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 empirically 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. Instrumental variable regressions at the bank level further show that IT makes banks' credit supply more responsive to changes in local house prices, and weakens the importance of geographical distance between borrowers and lenders. These results suggest that banks' IT adoption can increase dynamism by improving startups' access to finance.

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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 credit supply, as one of banks' key functions 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. Startups are not only often financially constrained and rely on external debt sources (Robb and Robinson, 2014; Babina, 2020),[1] but contribute disproportionately to job creation, innovation, and growth (Haltiwanger, Jarmin and Miranda, 2013; Klenow and Li, 2020). Understanding how the IT revolution in banking affects startups' access to finance and job creation is hence of paramount importance, but direct evidence is scarce.

This paper analyzes theoretically and empirically how the rise of IT in the financial sector affects entrepreneurship. We first build a parsimonious model of bank screening and lending. Banks face 'old' and 'young' firms that are of heterogeneous quality and opacity. They can screen firms by either acquiring information about firms' projects or by requiring collateral. Crucially, IT makes it relatively cheaper for banks to analyze hard information, thus engage in collateralized lending.[2] This benefits startups, as they have not yet produced sufficient information (i.e. they are *opaque*) and have to provide collateral. The key predictions of the model are thus that IT in banking spurs entrepreneurship, and the more so when collateral value rises.

We provide evidence at the county and bank level consistent with the model's predictions. To do so, 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).[3] First, at the county level, we find that counties where IT-intensive banks operate expe-

[1]According to Robb and Robinson (2014) and Kerr and Nanda (2015), banks (often through owner-backed loans) play an outsized role in financing startups.

[2]As IT facilitates real estate appraisal and transactions (Kummerow and Lun, 2005; Sawyer et al., 2005) and the flow of information within banks (Petersen and Rajan, 2002), we assume that screening through collateral is relatively cheaper for IT-intensive banks.

[3]The absence of major financial regulatory changes during our sample period from 1999-2007 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, 2022), thus creating a potential confounding factor.

rience stronger job creation by startups. Moreover, the presence of IT-intensive banks strengthens the responsiveness of job creation by entrepreneurs to changes in local real estate values. This pattern is especially pronounced within industries that rely more on real estate collateral. Second, in bank-county level regressions we show that small business lending of IT-intensive banks is more responsive to changes in local house prices and that IT attenuates the importance of distance, and hence informational frictions, in lending to small firms. Instrumental variable (IV) regressions confirm these findings.

To measure banks' IT adoption, we follow seminal papers on IT adoption among non-financial firms (see Bresnahan et al. (2002), Brynjolfsson and Hitt (2003), Beaudry et al. (2010), and Bloom et al. (2012)). We measure bank-level IT adoption as the ratio of PCs per employee within each bank. 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, but has much better data coverage.[4] We purposely 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 their historical geographic footprint to compute county-level *exposure* to IT in the financial sector. 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. Consequently, we find that county exposure is not systematically correlated with several county-level characteristics, such as the unemployment rate, level of education, industry composition, or the use of IT in the *non-financial* sector.

The first part of the empirical analysis shows that higher county-level IT exposure is associated with significantly higher entrepreneurial activity, measured as the employment share of new firms (Adelino et al., 2017). Economically, our estimates imply that a one-

[4]Later waves of the CiTBDs Aberdeen data on IT usage 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 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).

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 small fraction of banks' overall lending, which makes it unlikely that banks' overall IT adoption is driven solely by an expected increase in startup activity in some counties. 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 these concerns, we first show that including a wide set of county-level controls, such as the industrial composition, education and income levels, or the 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 the link between IT exposure and startup activity to the inclusion of granular fixed effects. Exploiting county-industry variation, 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 pattern remains similar in regressions without and with industry and county fixed effects, even though the R-squared increases significantly. This suggests that the relationship between entrepreneurship and IT is likely driven by better access to finance, and not other unobservable county or industry factors (Altonji et al., 2005; Oster, 2019).[5] However, even in specifications with granular fixed effects, IT exposure could reflect exposure to other (unobservable) bank-specific factors. We revisit this argument in bank-county-level regressions, where we use an instrumental variable approach.

Guided by the model, we then investigate the channels underlying the relationship between county exposure and entrepreneurship. The model assumes a comparative advantage of high-IT banks to lend against collateral. This assumption is based on two reinforcing trends. First, advances in technology reduce the costs of several real estate-

[5]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.

related processes, for example by expediting appraisal, research, and sales (Jud et al., 2002; Kummerow and Lun, 2005; Sawyer et al., 2005).[6] Second, IT facilitates the flow of (hard) information, such as on collateral values, between banks' headquarters and local branches (Petersen and Rajan, 2002).[7]

We investigate whether IT exposure affects the relation between higher collateral values and startup activity by exploiting variation in house price growth across counties (Mian and Sufi, 2011). We thereby follow literature showing that entrepreneurs often pledge their home equity as collateral (Adelino et al., 2015; Bahaj et al., 2020). 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 amplifying effect of IT exposure is strongest in industries where home equity is of high importance for startups – measured either by firms' propensity to use home equity or the amount of startup capital required to start a business (Hurst and Lusardi, 2004; Adelino et al., 2015; Doerr, 2021). Exploiting county-industry variation 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, despite increasing the R^2 substantially. This pattern mitigates the concern that unobservable factors explain the correlation between IT in banking, house prices, and entrepreneurship (Altonji et al., 2005; Oster, 2019).

Two further implications of the model concern recourse and startup quality. First, the ability to recourse borrowers' assets or income in the case of default can partially substitute for the need of screening borrowers through collateral (Ghent and Kudlyak, 2011). Exploiting differences in laws on recourse loans across states, we find that in recourse states the positive relationship between IT exposure and entrepreneurship, as well as the amplifying effect of exposure on the responsiveness of entrepreneurship to changes on house prices, is weaker. These findings support the central role of collateral underlying the relation between IT in banking and entrepreneurship in the model. Second, the model predicts that financing more startups does not lower their quality, as it results

[6]For example, Kummerow and Lun (2005) argue that "firms [used to] access sales data on microfiche, a tedious, time-consuming search process. [. . .] The result of being able to obtain sales information more quickly by fax or email was to increase the number of valuations completed per day. [. . .] A process that used to take several days could be compressed to a few hours. Valuers who used to do 3–4 valuations a day, now can complete 7–8 per day, including property inspections".

[7]Consistent with a cost advantage of high IT banks for collateralized lending, in an accessory analysis we use loan-level data on corporate lending to show that banks with a higher degree of IT adoption are more likely to request collateral for their lending, even when controlling for unobservable borrower characteristics.

from a better screening technology through IT. 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 pattern indicates that stronger firm formation does not result in more exits, which would indicate that firms of lower quality were started. IT in banking could thus spur aggregate business dynamism, innovation and growth.

The second part of the empirical analysis uses granular bank-county level data on small business lending to shed light on the effects of IT adoption on bank lending. This analysis allows us to measure IT at the bank-level directly, which brings two main advantages. First, it allows us to include granular fixed effects that control for potentially confounding factors. And second, we can use an instrumental variable to obtain exogenous variation in banks' IT adoption.

We require an instrumental variable to address the concern that banks' IT adoption could be correlated with other (unobservable) bank characteristics that also drive lending to small businesses. For example, IT adoption could be correlated with banks' organizational forms and managerial quality (Bresnahan et al., 2002; Bloom et al., 2012). Our instrument is based on the distance between a bank's headquarters (HQ) and the nearest land-grant colleges. Students of these institutions, established at the end of the nineteenth century to provide technical education, are significantly more likely to major in technical subjects and less likely to major in business and management sciences. The establishment of these colleges is thus similar to a shift in the availability of local technical knowledge, rather than managerial capabilities. Important for our setting, the location of land-grant colleges is practically random from today's perspective (Moretti, 2004) and unrelated to economic conditions other than the supply of skilled labor (Kantor and Whalley, 2019). Moreover, the location of banks' headquarters is mostly explained by historical heritage and usually predates the IT revolution by decades.[8] We establish a strong negative correlation between the distance between the bank' HQ to land-grant colleges and banks' IT adoption (see also He et al. (2021); Pierri and Timmer (2022)).

The key identifying assumption underlying our instrument is that the distance between banks' headquarters and the nearest land-grant colleges affects banks' ability to

[8]As shown in Pierri and Timmer (2022), the location of land-grant colleges does not predict the presence of banks' HQ in a county, indicating the distance between locations is independent with respect to relevant factors affecting the banks' business. They also show that students at land-grant colleges have higher SAT scores in math but not in writing, further supporting the argument that land-grant colleges increase only the availability of technical skills.

lend to small businesses through banks' IT adoption. It should not have an effect on credit demand or through other bank-specific channels. Since we focus on large banks, whose lending portfolio is usually geographically diversified, this is less of a concern than if we were to focus on smaller banks. Moreover, exploiting bank-county level data and hence focusing mostly on bank lending outside its headquarters' county strengthens this assumption – and so does the inclusion of granular fixed effects at the county level that absorb potentially confounding factors that could affect credit demand.[9] Finally, we show that the strong negative relation between banks' IT and the HQ distance to nearest colleges remain when we condition on bank size. While larger banks could benefit from economies of scale, which has been shown to be associated with IT adoption, our results suggest that the instrument does not affect IT though this channel.

We first revisit the models' predictions on the interaction of IT, house prices, and entrepreneurs' access to credit. We find that small business lending, obtained from Community Reinvestment Act (CRA) data, 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 on job creation at the county-level. This finding is robust to specifications in which we account for unobservable time-varying factors at the county level through county*year fixed effects. In such regressions we essentially compare small business lending by two similar banks that differ in their IT intensity to borrowers in the *same* county. This mitigates concerns that the relation between bank lending and house prices is due to (unobservable) confounding factors, such as employment growth. In addition, our IV results confirm findings from OLS regressions: IT-savvy banks, where their IT adoption is instrumented with the distance between the bank's headquarters and the nearest land-grant colleges, lend more to small businesses when house prices rise, even when holding unobservable county factors (such as loan demand) constant.

As we show theoretically, 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 (see also Petersen and Rajan (2002); Liberti and Petersen (2017); Vives and Ye (2020)). We hence study how physical 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

[9] We also find that excluding the HQ county of each bank, in which non-financial firms could be directly affected through the supply of skilled workers, leaves our results unaltered.

in income per capita (Adelino et al., 2017). We show that, first, banks' small business lending is less sensitive to a local income shock in a county further away from banks' HQ, even when we include county*time fixed effects. This is in line with the interpretation that a greater distance implies higher frictions. Consistent with the model, however, the effect of distance on the sensitivity of lending to a rise in business opportunities is significantly lower for IT-intensive banks. Again, IV regressions yield similar results in terms of economic and statistical significance.

We also perform a series of additional exercises to examine the robustness of our findings. We show that our results are insensitive to alternative constructions of IT exposure based on either the unweighted average of the IT adoption of banks that operate in a county, or the share of local deposits. Excluding firms in the financial and education industries, or individual regions that have particularly high IT exposure or entrepreneurial activity, does not affect our results. And neither does excluding the top 20 counties in terms of venture capital (VC) funding activity (which receive almost 80% of total VC funding). Further, normalizing the share of employment in startups by the previous year's total employment leaves our conclusion unaltered. We also show that our main findings are present in tradable industries, which are less affected by local economic conditions. Finally, investigating the increase in IT adoption over time, we find that counties more exposed to the *increase* in IT in banking also experienced relatively higher startup rates.

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 (Petersen and Rajan, 2002; Liberti and Mian, 2009; Liberti and Petersen, 2017).[10] 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,

[10] DeYoung et al. (2008) show that the distance between borrowers and lenders increased over recent years and argue that this reflects banks' digitalization. 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.

2015; Schmalz et al., 2017; Bahaj et al., 2020). 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 often require 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 the first evidence that banks' IT adoption increases the importance of real estate collateral in the financing of young firms.[11]

Finally, we speak to the recent literature on the rise of financial technology (FinTech) and its effects on credit scoring and credit supply. Several papers investigate how FinTech changes information processing, as well as the consequences for households (Berg et al., 2019; Di Maggio and Yao, 2018; Fuster et al., 2019, 2021). While recent work highlights an increasing importance of FinTechs and IT in small business lending (Hau et al., 2018; Erel and Liebersohn, 2020; Gopal and Schnabl, 2020; Beaumont et al., 2021; Kwan et al., 2021), traditional banks remain an important source of credit for young and small firms (see 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 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 at the county level and Section 5 at the bank-county level. Section 6 provides additional evidence supporting the model assumptions, as well as robustness tests. 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

[11] We also relate to the literature on firm dynamics and the macroeconomy (Decker et al., 2016). While the slowdown in productivity after the Great Financial Crisis has been attributed 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.

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. Our focus on bank lending to startups is motivated by work showing that banks (often through owner-backed loans) play an outsized role in financing startups (Robb and Robinson, 2014; Kerr and Nanda, 2015).

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:[12]

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

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:

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

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 and convey these pieces of information to its headquarters, consistent with lending based on hard information. This channel builds on literature that has shown that IT has facilitated the appraisal of real estate, especially across distance (Kummerow and Lun, 2005; Sawyer et al., 2005).[13]

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. 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 concen-

[12]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.

[13]Kummerow and Lun (2005) argue that "appraisal firms [used to] access sales data on microfiche, a tedious, time-consuming search process. [...] being able to obtain sales information [electronically] more quickly [means that] process that used to take several days could be compressed to a few hours. Valuers who used to do 3–4 valuations a day, now can complete 7–8 per day, including property inspections." Sawyer et al. (2005) highlight that "the use of digital forms [...] and online applications [...] provide[s] semi-automation [and] leads to an increasing percentage of the transaction information being shared in digital form, discussions about standardizing the form and structure of data, and the use of this data for analysis and additional value-adding functions." More recent industry reports suggest that the process continues today: "Leveraging big data streamlines the appraisal process, reducing to seconds complex analyses that used to take hours" (see How Technology is Shaping the Appraisal Process and Profession). Further, Table A4 provides evidence consistent with this assumption, showing that high-IT banks issue more secured loans in the syndicated loans market.

tration does not affect the relationship between IT and entrepreneurship (see Table A5).

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.[14] 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.

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.

[14] 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 $r^*_{HighIT} = \theta p_G x + (1 - \theta)(1 + v_{HighIT})$.

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.

Some of our model's implications are related to evidence documented in other work. The positive impact of collateral values on entrepreneurship is consistent with the evidence in Adelino et al. (2015), among others. 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' HQ, 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 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 and exposure. 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 by branch on a bank (group) fixed effect, while controlling for the location of the establishment and other characteristics.[15] 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, which account for through branch-location fixed effects, (c) using a larger pool of observations reduces measurement error, and (d) this estimation procedure yields bank-level IT adoption measures that are uncorrelated with a bank's business model (assets or funding), size, or profitability, suggesting that this approach purges potential correlation between IT and management quality or other confounding factors (Pierri and Timmer, 2022).

To compute county exposure to IT in the financial sector, we then merge the resulting Aberdeen-BHC data set to the FDIC summary of deposits (SOD) data. These data that provide information on the number of branches of each bank in a county. We combine

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

$$PCs/Emp_{i,t} = \widetilde{IT_b} + \theta_{type} + \theta_c + \theta_t + \gamma \cdot log(emp) + \epsilon_{i,t},$$

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

$\widetilde{IT}_b$ with the branch network of each bank in 1999, thus prior to the period of analysis. The average IT adoption of all banks present in a county is defined as:

$$IT\ exposure_c = \sum_{b=1}^{N} \widetilde{IT}_b * \frac{No.\ branches_{b,c}}{No.\ branches_c}, \tag{10}$$

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, $IT\ exposure_c$ 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.

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 has 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.

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. There is significant variation in job creation rates by startups both across and within states, and entrepreneurial activity is high also outside of 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). In addition, we collect information on the reported capital required to start a company in each industry. Following Rajan and Zingales (1998), we measure industry-level dependence on external finance as capital expenditure minus cash flow over capital expenditure, average over the decade prior to our sample period.

The US Department of Agriculture provides a list of land-grant colleges and universities that were established in the nineteenth century (1862 and 1890). Data on enrolment by major and test scores are obtained from from the Integrated Postsecondary Education Data System survey for 1996.

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) repeat sales House Price Index (HPI), and Bureau of Economic Analysis Local Area Personal Income.

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 bank-county-year 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 and then compute loan growth as log differences. We also compute loan growth for loans of origination amount smaller than \$100,000.

Descriptive statistics. Table 1 reports summary statistics of our main variables at the county and bank 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.

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.

4.1 IT exposure and 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:

$$\begin{aligned} \text{startups}_{c,i} = {} & \beta_1\ \mathit{IT\ exposure}_{c,99} + \beta_2\ \mathit{constraint}_i \\ & + \beta_3\ \mathit{IT\ exposure}_{c,99} \times \mathit{constraint}_i + \mathit{controls}_{c,99} + \theta_c + \phi_i + \varepsilon_{c,i}. \end{aligned} \tag{11}$$

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. $\mathit{IT\ exposure}_c$ denotes county exposure to IT-intensive banks as of 1999, measured by the IT adoption of banks' historical presence in the county. The variable $\mathit{constraint}_i$ captures industry-level dependence on external finance. Standard errors are clustered at the county level, and regressions are weighted by county size.

The relationship between IT exposure and local entrepreneurship could be driven by other local characteristics. To mitigate this concern, we include a rich set of county-level controls, all as of 1999. By controlling for county size (log of the total population) we avoid comparing smaller rural counties to larger urban ones. We further control for the share of population age 65 and older, as younger individuals may be more likely to start successful companies and also have better IT knowledge (Ouimet and Zarutskie, 2014; Bernstein et al., 2021). Similarly, we control for the share of adults with a bachelor degree or higher. 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 differences in the industrial structure of counties (proxied by employment shares in the major 2-digit SIC industries 23, 31, 44, 62, and 72). Finally, we control for IT in non-financial firms (measured as the average PCs per employee in non-financial firms) to address the concern that startup activity may thrive in location where IT is more readily available in general.

Abstracting from interaction terms, **Prediction 1** implies that $\beta_1 > 0$. Before moving to the regression analysis, panel (a) in Figure 1 provides a binscatter plot at the county level, with the share of employment among firms age 0–1 on the vertical axis and county exposure on the horizontal axis. There is a significant positive relationship between IT exposure and startup employment. 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 and significance 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. The results in columns (2)–(3) suggest that the effect of counties' IT exposure on job creation by startups is orthogonal to observable county and unobservable industry characteristics, reducing potential concerns about self-selection and omitted variable bias (Altonji et al., 2005; Oster, 2019). The magnitude of the coefficient 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, IT spurs entrepreneurship through a bank lending channel. We thus expect the positive correlation in columns (1)–(3) to be stronger in industries that depend more on external finance. We therefore augment the regression with an interaction term between IT adoption and industry-level dependence on external finance (β_3 in Equation (11)). In column (4), the coefficient on the interaction term between IT exposure and external financial dependence is positive 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.

Robustness. To show that the relation between exposure and entrepreneurship is robust, we perform a series of additional tests, discussed in more detail in Section 6 below. We show that our results are insensitive to an alternative construction of IT exposure based on either the unweighted average of the IT adoption of banks that operate in a county, or the share of local deposits. Further, excluding firms in the financial and education industries, or individual regions that have particularly high IT exposure or entrepreneurial activity, does not affect our results. Excluding the top 20 counties in terms of venture capital (VC) funding activity (which receive almost 80% of total VC funding) yields results similar to our baseline. Similarly, normalizing the share of employment in startups by the previous year's total employment leaves our conclusion unaltered. We also show that our main findings are present in tradable industries, which are less affected by local economic conditions. Finally, investigate the increase in IT adoption over time. We find that counties more exposed to the *increase* in IT in banking also experienced relatively higher startup rates.

4.2 IT, collateral, and entrepreneurship (Predictions 2 & 3)

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. The role of collateral in our model is directly motivated by a large literature that highlights the importance of rising house prices for employment among small and young firms, as rising real estate prices increase collateral values, thereby overcoming informational frictions and relaxing borrowing constraints for constrained firms (Rampini and Viswanathan, 2010; Adelino et al., 2015; Schmalz et al., 2017; Bahaj et al., 2020).

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. We estimate the following regression:

$$\begin{aligned} \text{startups}_{c,i,t} = \gamma_1 \; IT\ exposure_{c,99} + \gamma_2 \; \Delta HPI_{c,t} \\ + \gamma_3 \; IT\ exposure_{c,99} \times \Delta HPI_{c,t} \\ + controls_{c,t-1} + \theta_{c,i} + \tau_t + \varepsilon_{c,i,t}. \end{aligned} \tag{12}$$

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.

Table 4, column (1) confirms that higher IT exposure is associated with a higher share of young firm employment. This is in line with results in Table 3 on **Prediction 1** ($\gamma_1 > 0$). We then explicitly test **Prediction 2**, which implies that $\gamma_2 > 0$. Column (2) shows that a rise in house prices is associated with an increase in entrepreneurship at the local level, conditional on year fixed effects that absorb common trends and in line with previous literature. Column (3) confirms this finding when controlling for IT adoption at the county level.

We then test **Prediction 3** by including the interaction term between changes in local house prices and county exposure to IT in banking (γ_3). Based on **Prediction 3**, we expect $\gamma_3 > 0$, i.e. 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. Column (4) shows that higher house prices spur entrepreneurship in areas with more IT, consistent with **Prediction 3**. To further tighten identification, columns (5) and (6) add time-varying county controls, as well as industry×year fixed effects that account for unobservable changes at the industry level. The interaction coefficient remains similar in terms of sign, size and significance across specifications.

Finally, we provide complementary evidence on the role of collateral, building on previous demonstrating that the importance of real estate collateral differs across industries. Specifically, 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). Focusing on differences between industries within the same county and year also allows us to additionally include county×year fixed effects. We thus purge our estimates from the impact of any time-varying county-level shocks, in addition to controlling for industry-specific trends. Columns (7) and (8) show that the positive effect of rising house prices on startups in more-IT exposed counties is especially pronounced in those industries whose financing is expected to be more sensitive to changes in collateral values.

In sum, Table 4 provides evidence in line with **Predictions 2 & 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 11, where the dependent variable is the average transition rate between 1999 and 2007. Columns (1)-(3) in Table 5 show that there is no systematic correlation between a county's exposure to IT in banking and the transition rates of local startups to age 2–3, 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 IT adoption by banks has aggregate implications. If the additional startups created due to IT adoption are of similar quality as other startups, this should bring benefits to the aggregate economy – for example in terms of business dynamism, employment 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 or default 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 **Prediction 5**, we exploit 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 11) for counties in recourse versus non-recourse states.[16]

[16] Ghent and Kudlyak (2011) relies on recourse / non-recourse classifications of states from the 21^{st}

Columns (1) and (2) in Table 6 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 column (9) in Table 4).

5 Banks' IT and Small Business Lending

In this section, we use CRA data on banks' small business lending in each county to provide additional tests of the model predictions. We first investigate **Prediction 6**, i.e. that with increasing IT adoption, lending should become more responsive to new investment opportunities in more-distant counties. We then revisit **Predictions 2 & 3** on the importance of collateral values in stimulating job creation by providing direct evidence on banks' small business lending. An advantage of bank-county level regressions is that we can measure IT adoption directly at the bank-level, which allows us to implement an instrumental variable approach, and to include granular fixed effects. We discuss the construction of our IV, which is based on the historical location of land-grant colleges, in what follows.

5.1 An instrument for IT adoption

Measuring IT-adoption at the bank-level directly, rather than through geographic variation in banks' footprints, allows us to obtain exogenous variation in IT-adoption through an instrumental variable. Specifically, we exploit the quasi-random allocation of land grant colleges, which acted as a shift in the availability of local technical expertise (Moretti, 2004) and has been shown to predict banks' IT adoption (He et al., 2021; Pierri and Timmer, 2022). The Morrill Act of 1862, and its follow-up in 1890, endowed states with federal land to found universities, with a focus on teaching science, agri-

edition (2004) of the National Mortgage Servicer's Reference Directory to show that recourse clauses impact borrowers' behavior.

culture, and other technical subjects. The presence of a land-grant college remains an important determinant of the supply of skilled labour in a city even today, especially for the IT sector. Their exact location, however, is largely due to historical accidents and close to random from today's perspective.[17] It is also unrelated to current local economic factors (Kantor and Whalley, 2019), and is also unrelated to the presence of banks' HQ in the same county (Pierri and Timmer, 2022).

Land-grant colleges could spur banks' IT adoption through different channels. They directly increase the supply of tech-inclined graduates that banks could hire, which could incentivize their IT adoption. Additionally, a lower distance to campuses could lead to knowledge spillovers and the diffusion of ideas and technology (Keller, 2002), making bank mangers more likely to invest in IT. We thus base our instrument on the distance of a bank's HQ to the nearest land grant colleges. In a first step, we compute the distance in log miles (plus one) between the county of each land-grant college j and a bank's HQ county, weighted by the size of the college in terms of STEM enrollment. In a second step, we compute a measure of the average distance to land-grant colleges. Since there is no clear economic reason to expect why the distance to only the nearest, second- or third-nearest college should matter, we take an agnostic approach and take the first principal component of the distance to the nearest two land-grant colleges as our baseline instrumental variable, The IV thus captures the salient variation in distance to the nearest colleges. We also compute the first principal component of the distance to the nearest three or five colleges for robustness tests.

The key identification assumption underlying our instrument is that the distance to the nearest land-grant colleges affects the ability to lend to small businesses through banks' IT adoption, and not by changing credit demand or through other bank-specific channels. As shown in Pierri and Timmer (2022), students of land-grant colleges are significantly more likely to major in technical subjects and less likely to major in business and management sciences. The introduction of these colleges is thus similar to a shift in the availability of local technical knowledge for banks, rather than overall managerial capabilities. We consequently find a strong negative association between the distance to the nearest land-grant colleges and banks' IT adoption (see Figure 2, panel a). Further, in regressions we control for an extensive set of bank-level controls – most importantly bank size, which is commonly associated with economies of scale that facilitate IT adoption. As panel (b) of Figure 2 shows, the strong relation between distance to the nearest land-grant

[17] For a detailed discussion, see Moretti (2004).

colleges and IT adoption remains when we condition on bank size (log assets).

Yet the presence of land-grant colleges could also affect non-financial firms in close proximity. We address this concern with help of our granular bank-county level data. First, we focus mostly on large BHCs which do a large share of their lending outside their HQ county. Second, fixed effects at the borrower-county level (discussed below) absorb potentially confounding factors that could affect local credit demand by non-financial firms. And third, we show that excluding the HQ county of each bank, as well as counties with land-grant colleges, from the sample leaves the results unaltered (Table A3).

5.2 IT and the role of distance in lending (Prediction 6)

In the model, banks verify the value of collateral at cost v. IT is assumed to lower v, because high-IT banks can better verify the existence and market value of collateral, and transmit the information to their (distant) HQ. This mechanism is consistent with work that suggests that IT adoption by banks reduces the importance of distance in lending decisions, as it enables a more effective transmission of hard information (Petersen and Rajan, 2002; Vives and Ye, 2020).

Prediction 6 thus states that with increasing IT adoption, lending should become more responsive to new investment opportunities in more distant counties. Following a large literature that shows that informational frictions increase with lender-borrower distance (Liberti and Petersen, 2017), we test whether the relationship between local investment opportunities and lender-borrower distance varies with banks' use of IT. We consider the following specification from 1999 to 2007 at the bank-county-year level:

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

The dependent variable is the log difference in total CRA small business loans by bank b to borrower county c in year t. The variable $log(distance)$ measures the log of the distance between banks' HQ county and the county of the borrower. We proxy investment opportunities in borrower countries with the log change in county-level income per capita (Adelino et al., 2017). Regressions further include standard county controls, as well as year or county*year fixed effects. Bank-level controls are the log of total 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. Standard errors are clustered at the bank and county level. An increase in local investment opportunities is expected to increase local lending ($\beta_1 > 0$), and the more so, the shorter the lender-borrower distance ($\beta_3 < 0$). If banks' IT adoption reduces the importance of distance, then β_3 should be significantly smaller for *high IT* banks.

Results in Table 7 are in line with the hypotheses. Column (1) shows that rising local incomes are associated with higher local loan growth. Greater 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 bank lending in counties located further away is present only among low IT banks; for high IT banks, distance has no 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. Results are similar when we focus on the smallest loans with origination amounts below $100,000 – arguably a better measure of lending to startups. Note that coefficients increase in magnitude, which is consistent with the common finding that informational frictions are more severe among smaller firms.

Finally, columns (7)–(8) replicate columns (5)–(6), but instrument banks' IT with the IV based on distance to the nearest two land-grant colleges. The main coefficients are similar in terms of sign and significance, but larger in magnitude. This mostly reflects that variation in IT when predicted with land-grand colleges is around 0.15 times as large as variation in IT adoption (0.156 vs 0.932). Hence, when we adjust for the difference in standard deviations across actual and predicted IT, coefficients are similar in magnitude in columns (5)–(6) vs (7)–(8). Note that regressions include county*time fixed effects and hence absorb unobservable changes at the borrower-county level. This approach strengthens our identification assumption, as these fixed effects control for potentially confounding factors that could be correlated with the local presence of land-grant colleges, and hence the demand for credit. In the appendix, we show that our results are insensitive to using an IV based on distance to the three or five nearest land-grant colleges, or when we exclude banks' HQ counties (see Table A3).

5.3 IT, house prices and small business lending

We now revisit **Predictions 2 & 3** to provide supporting evidence that banks' IT improves access to finance for entrepreneurs, especially when house prices increase. To this end, we investigate how high- and low-IT banks adjust their small business lending in response to house price changes. We estimate the following regression equation from 1999 to 2007 at the bank-county-year level:

$$\begin{aligned}\Delta loans_{b,c,t} = {} & \beta_1\ IT_b + \beta_2\ \Delta\ HPI_{c,t} + \beta_3\ IT_b \times \Delta HPI_{c,t} \\ & + bank\ controls_{b,t-1} + county\ controls_{c,t-1} + \tau_t + \varepsilon_{b,c,t}.\end{aligned} \tag{14}$$

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 in the borrower county. The regression includes baseline county and bank controls. We cluster standard errors at the bank and county level. If IT-intensive banks rely more on hard information, as indicated by the county-level analysis in Section 4, we expect their lending to be more sensitive to changes in local collateral values, i.e. house prices ($\beta_3 > 0$).

Figure 3 suggests that while small business lending grows faster when house prices increase, the sensitivity is higher for loans by IT-intensive banks. Results in Table 8 confirm this pattern. Columns (1) shows a larger responsiveness of small business lending by high-IT banks to rising house prices, as indicated by the significant coefficient on the interaction term. Since borrower counties could differ along several dimension, we enrich our specifications with time-varying fixed effects at the county level in column (2). We now 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. Results show that despite a more than fourfold increase in the R-squared, estimated coefficient estimates remain near-identical (the coefficient on the change in house prices is now absorbed). Columns (3)–(4) repeat the exercise for loans of size \$100,000 or less and show similar results. Again, magnitudes are larger, indicating that smaller firms are subject to greater informational frictions and their financing conditions hence more sensitive to changes in collateral values.

Instrumental variable regressions in columns (5)–(6) confirm this finding. Higher IT adoption by banks leads to a greater sensitivity of small business lending to local house prices. Again, by including county*time fixed effects we control for county-level characteristics that could correlate with the distance to land-grant colleges. As we show in the appendix, these patterns are robust to using an IV based on distance to the three or five nearest land-grant colleges, or when we exclude banks' HQ counties (see Table A3).

6 Collateralized Lending, Competition, and Further Tests

In this section we present additional evidence that speaks to assumptions and implications of the model, as well as further robustness tests.

IT and the use of collateral. A key assumption of the model is that high IT banks have a relative cost advantage in screening through collateral. While we do not have loan-level information on collateralized lending to startups, we can provide empirical evidence on the presence of collateral for large corporate loans with data from DealScan (Ivashina and Scharfstein, 2010). Figure A1 shows that the share of loans that are collateralized is positively correlated with bank IT adoption. To ensure that this correlation is not driven by (unobservable) borrower heterogeneity, we estimate the following linear probability model:

$$secured_{b,i,t} = \beta \; IT_b + \tau_t + \theta_i + \varepsilon_{b,i,t}, \tag{15}$$

where b denotes a bank that granted a loan in year t to corporate borrower i and $secured_{b,i,t}$ is a dummy equal to one whenever the loan is collateralized. Results in Table A4 confirm that more IT-intensive banks are more likely to require collateral than other banks, even when controlling for borrower characteristics through borrower fixed effects.

The role of local competition. The model abstracts from interactions between local competition and IT adoption in the banking sector. Instead, banks and borrowers share the surplus from lending if a loan is granted. To ensure that local competition does not affect our key empirical results, we re-estimate Equation 11, but control for market concentration (measured through the HHI) and its interaction with IT. Results are presented in Table A5, where columns (1)–(2) construct the HHI from CRA loan shares and columns (3)–(4) from deposit shares. In general, higher concentration is associated with higher startup activity. This could reflect that lenders in less competitive markets have a sufficiently high surplus to acquire costly soft information or that they might be more prone to lend to startups because know they expect to extract more surplus in the future as young firms grow (Petersen and Rajan, 1995). However, there is no significant interaction between concentration and local IT adoption in banking, and the positive impact of IT on startups remains largely unaffected when we account for the local market structure. This result supports the model's assumption to abstract from local competition.

Extensions and robustness. Table A1 presents robustness tests to our main results at the county level. Column (1) replicates the baseline result for comparison (see column (3) in Table 3). In column (2), IT exposure is the unweighted average of the IT adoption of banks that operate in a county and in column (3) exposure is weighted by the share of local deposits (rather than the number of branches). The positive association between IT exposure and entrepreneurial activity remains, highlighting that it is not driven by any specific choice of the construction of the IT exposure measure. Column (4) excludes employment in startups in the financial and education industries and column (5) excludes Wyoming, the state with the highest exposure to banks' IT adoption. Results remain unaltered. Column (6) includes state fixed effects and shows that results are also present when we exploit within-state variation only. Column (7) normalizes the share of employment in startups by the previous year's total employment and column (8) shows that our results are not driven by a decline in total employment. Column (9) focuses in firms in tradable industries, which are less affected by local economic conditions.[18] Finally, columns (10) and (11) address the concern that the availability of other forms of external financing, venture capital (VC) in particular, may be correlated with IT exposure. AS VC funding is highly concentrated in a small fraction of the US territory, we exclude the top 20 counties (representing almost 80% of VC funding at the time) or seven states with the highest VC activity,[19] and find results similar to baseline.

[18]We rely on the tradable classification of 4 digit industries by Mian and Sufi (2014), which we aggregate to the 2 digit level.

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

Increase in IT adoption over time. An alternative approach to test **Prediction 1** is to analyze the relationship between the *increase* in IT adoption and *changes* in entrepreneurship at the county-level. To do so, we compute the change in county exposure as

$$\Delta IT_c = \sum_{b=1}^{N} \Delta \widetilde{IT}_b * \frac{No.\ Branches_{b,c}}{No.\ Branches_c}, \tag{16}$$

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 an increase in IT in banking also experienced stronger performance of startups, as illustrated by panel (b) in Figure 1. 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. Note that this first-difference approach implicitly controls any county-level (time invariant) observable and unobservable characteristics.

7 Conclusion

Over the last decades, banks have invested in information technology at a grand scale. However, there is little evidence on the effects of this 'IT revolution' in banking on lending and the real economy. In this paper we focus on the effects of IT on startups. We do so because startups matter greatly for aggregate employment, innovation, and growth, and because they are usually opaque borrowers that are likely to be especially sensitive to technologies that affect lenders' informational acquisition.

We find that IT adoption in the financial sector has spurred entrepreneurship. In regions where banks with higher 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 and transmit the value and quality of collateral, banks with higher IT adoption are more likely to lend against increases the value of entrepreneurs' collateral. We confirm these findings in instrumental variable regressions.

Our results could have implications for policy. Banks have been ardent adopters of technology during the last years. Meanwhile the role of FinTech companies that rely on IT, rather than loan officers, to provide credit to small businesses has been steadily increasing (Gopal and Schnabl, 2020). These developments have triggered a debate on the impact of IT adoption in financial sector on the real economy, for example through its impact on the relative importance of soft and hard information, or the need for collateral (Gambacorta et al., 2020). Our findings suggest that IT adoption can spur job creation by young firms by making lending against collateral, or hard information more general, easier. From a policy perspective, this finding raises the prospect that improvements in financial technology ease financial constraints for young and dynamic firms.

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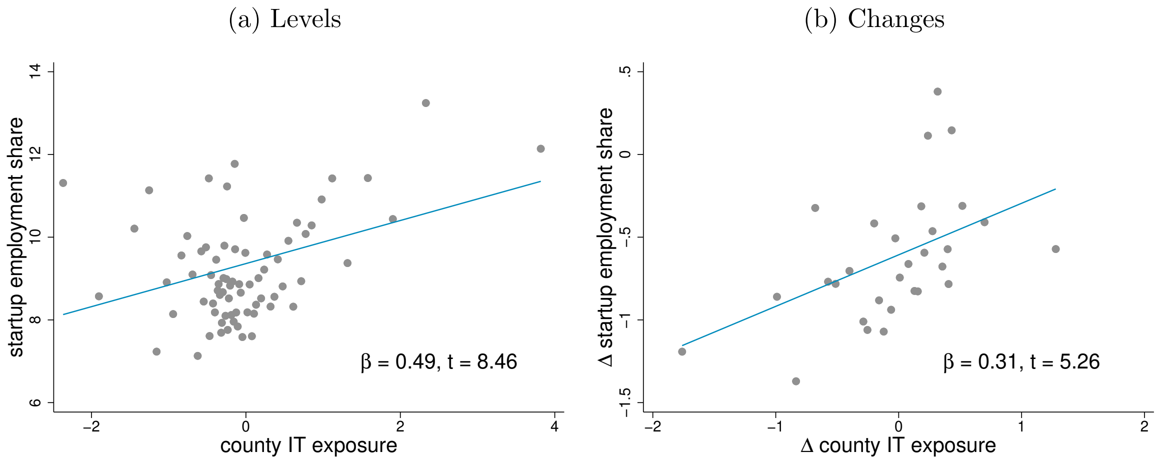
Figures and Tables

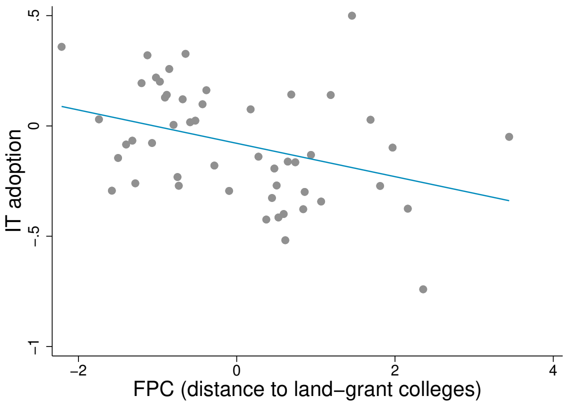
Figure 1: **Job creation by young firms and banks' IT adoption**



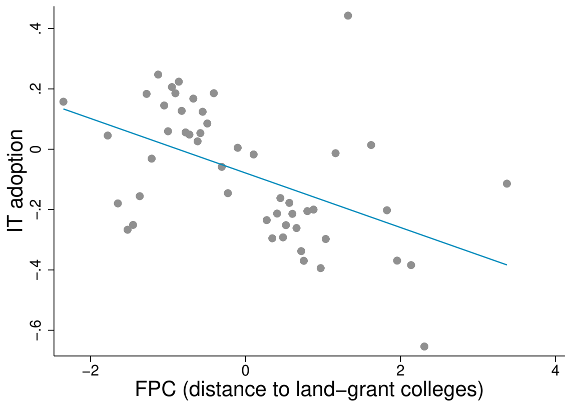
Panel (a) shows a binscatter plot of the share of employment by young firms over total employment in a county-industry cell, averaged over the period from 2000 to 2007, on the vertical axis and county-level exposure to banks' IT adoption, as defined in Section 3, on the horizontal axis. Panel (b) shows a binscatter plot of the change in the startup rate in a county-industry between 2000 and 2007 (in percentage points) on the y-axis and the exposure of a county to banks' *change* in IT adoption between 2000 and 2007 (standardized) on the x-axis.

Figure 2: **Distance to land-grant colleges and IT adoption**

(a) Unconditional

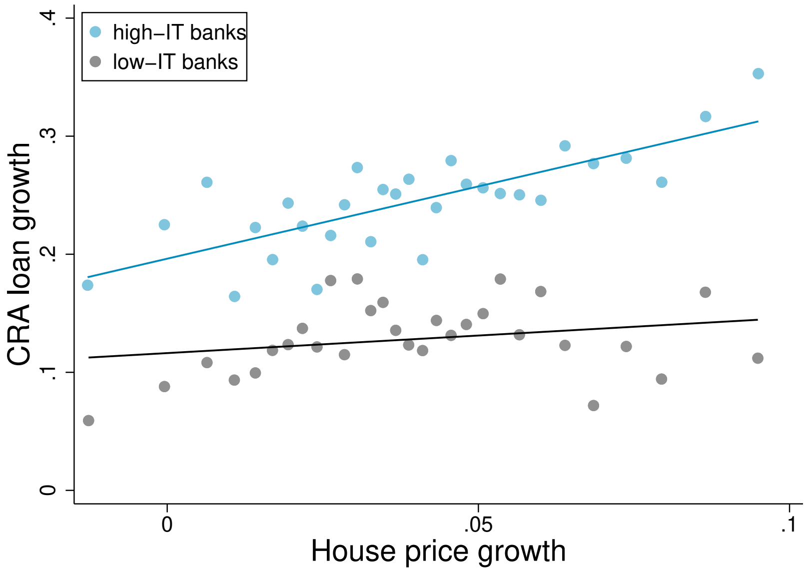


(b) Conditional on bank size



Panel (a) shows a binscatter plot of banks' IT adoption on the vertical axis against the first principal component (FPC) of the distance of banks' HQ to the nearest two land-grant colleges on the horizontal axis. Panel (b) shows the same binscatter plot but conditional on bank size, measured via the log of total bank assets.

Figure 3: **Banks' IT, house prices, and loan growth**



This figure shows a binscatter of CRA loan growth on the vertical axis and county-level house price growth on the horizontal axis. The sample is split into banks above and below the median along the IT distribution. In a regression of CRA loan growth on house price growth ($\Delta CRA_{b,c,t} = \Delta$ *house price growth*$_{c,t} + \varepsilon_{b,c,t}$), the respective coefficients (t-values) for high- and low-IT banks are 1.22 (5.93) and 0.30 (1.77).

Table 1: **Descriptive statistics**

Panel (a): County level

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

Panel (b): Bank level

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
IT adoption	4489	0	1	-2.596	2.596	-.526	-.101	.517
log(assets)	4489	13.812	1.684	8.964	20.958	12.677	13.452	14.635
deposit ratio	4489	.84	.151	0	.997	.796	.877	.936
non-interest income	4480	.17	.105	.006	.704	.103	.144	.209
secured assets	4489	.204	.112	0	.682	.127	.191	.269
return on assets	4481	.003	.002	-.011	.01	.002	.003	.004
equity ratio	4489	.096	.043	.043	.929	.076	.087	.102

This table reports summary statistics at the county and bank 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 11). The dependent variable is the share of the employment in firms of age 0-1 in county c and industry i. $IT\ Exposure_c$ 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, 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 $\times$ Δ HPI				0.075***	0.070**	0.075**			0.271***
				(0.027)	(0.033)	(0.030)			(0.086)
IT exposure $\times$ Δ HPI $\times$ Low SU capital							0.136***		
							(0.051)		
IT exposure $\times$ Δ HPI $\times$ home equity								0.175**	
								(0.087)	
IT exposure $\times$ Δ HPI $\times$ 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 $\times$ NAICS FE	-	-	-	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	-	-	-	-
NAICS $\times$ Year FE	-	-	-	-	-	✓	✓	✓	✓
County $\times$ 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 12). The dependent variable is the share of the employment in firms of age 0-1 in county c and industry i in year t. *IT Exposure*$_c$ 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. Δ $HPI_{c,t}$ is the yearly change in house prices in county c. *low SU 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 5: **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 $\times$ 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. *IT Exposure*$_c$ 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 6: **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 11). The dependent variable is the share of the employment in firms of age 0-1 in county c and industry i. $IT\ Exposure_c$ 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. $Recourse\ State_s$ 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 $Recourse\ State_s$ and $IT\ Exposure_c$. 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 7: **Banks' IT, distance, and lending**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			low IT	high IT			IV	IV
VARIABLES	Δ loans	Δ loans	Δ loans	Δ loans	Δ loans	Δ loans (sm)	Δ loans	Δ loans (sm)
log(distance)	0.016***	0.020***	0.048***	-0.003	0.019***	0.017***	0.000	-0.002
	(0.003)	(0.003)	(0.005)	(0.006)	(0.003)	(0.003)	(0.007)	(0.006)
Δ income	0.019***							
	(0.004)							
Δ income × log(distance)	-0.003***	-0.004***	-0.009***	0.003***	-0.004***	-0.005***	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IT					0.057***	0.049***	1.206***	0.930***
					(0.017)	(0.015)	(0.227)	(0.187)
Δ income × IT					-0.017***	-0.020***	-0.193***	-0.165***
					(0.004)	(0.004)	(0.040)	(0.034)
log(distance) × IT					-0.008**	-0.003	-0.216***	-0.169***
					(0.003)	(0.003)	(0.037)	(0.031)
Δ income × log(distance) × IT					0.004***	0.005***	0.041***	0.037***
					(0.001)	(0.001)	(0.007)	(0.006)
Observations	144,722	144,144	73,865	47,146	144,144	125,756	144,144	125,756
R-squared	0.025	0.167	0.264	0.302	0.167	0.199		
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓
County Controls	✓	-	-	-	-	-	-	
Year FE	✓	C*T	C*T	C*T	C*T	C*T	C*T	C*T

This table reports results for regressions at the bank-county-year level (see Equation 13). The dependent variable is the change in total CRA loans by bank b to county c in year t or in CRA loans with an amount of less than $ 100,000. IT_b is the IT adoption of bank b. $\Delta\ Income_{c,t}$ is the change in per capita income in county c between year $t-1$ and t. $log(distance)_{b,c}$ is the log of the number of miles between bank b's headquarters and county *low/high IT* refers to banks in the bottom/top tercile of the IT distribution. Standard errors are clustered at the bank and county level. The Kleibergen-Paap Wald F-statistics for all instrumented variables considered in columns (7) and (8) jointly equal 8.17 and 7.80. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: **Banks' IT, house prices, and lending**

	(1)	(2)	(3)	(4)	(5)	(6)
					IV	IV
VARIABLES	Δ loans	Δ loans	Δ loans (sm)	Δ loans (sm)	Δ loans	Δ loans (sm)
IT	0.012**	0.013**	0.011**	0.011**	-0.090***	-0.107***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.032)	(0.031)
Δ house prices	-0.009		-0.073			
	(0.062)		(0.057)			
IT × Δ house prices	0.274***	0.267***	0.433***	0.413***	4.073***	5.375***
	(0.075)	(0.080)	(0.076)	(0.082)	(0.467)	(0.456)
Observations	136,821	136,106	121,400	124,757	136,106	120,495
R-squared	0.026	0.174	0.044	0.173		
Bank Controls	✓	✓	✓	✓	✓	✓
County Controls	✓	-	✓	-	-	-
Year FE	✓	C*T	✓	C*T	C*T	C*T

This table reports results for regressions at the bank-county-year level (see Equation 14). The dependent variable is the change in total CRA loans by bank b to county c in year t or in CRA loans with an amount of less than \$ 100,000. IT_b is the IT adoption of bank b, $\Delta HPI_{c,t}$ is the yearly change in house prices in county c. Columns with header 'IV' refer to regression that instrument bank-level IT with the land grant colleagues instrument. Standard errors are clustered at the bank and county level. The Kleibergen-Paap Wald F-statistics for all instrumented variables considered in columns (7) and (8) jointly equal 165.54 and 139.41. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table A1: **County-level 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. $\Delta IT\ Exposure_b$ 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: **Banks' IT adoption – robustness tests**

Panel (a): Distance

VARIABLES	(1) no HQ Δ loans	(2) no HQ Δ loans (sm)	(3) 2 Δ loans	(4) 2 Δ loans (sm)	(5) 3 Δ loans	(6) 3 Δ loans (sm)	(7) 5 Δ loans	(8) 5 Δ loans (sm)
log(distance)	-0.015**	-0.013**	0.016***	0.017***	0.000	-0.001	0.013***	0.015***
	(0.007)	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)
Δ income × log(distance)	0.002*	0.001	-0.001	-0.002*	0.000	-0.001	-0.002**	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IT	1.368***	1.157***	0.284**	0.146	0.913***	0.730***	0.531***	0.398***
	(0.160)	(0.141)	(0.130)	(0.094)	(0.189)	(0.159)	(0.094)	(0.080)
Δ income × IT	-0.208***	-0.196***	-0.163***	-0.110***	-0.178***	-0.138***	-0.106***	-0.111***
	(0.029)	(0.024)	(0.037)	(0.025)	(0.039)	(0.031)	(0.021)	(0.019)
log(distance) × IT	-0.245***	-0.207***	-0.020	0.005	-0.183***	-0.147***	-0.086***	-0.060***
	(0.027)	(0.024)	(0.026)	(0.018)	(0.034)	(0.029)	(0.017)	(0.014)
Δ income × log(distance) × IT	0.044***	0.043***	0.035***	0.026***	0.039***	0.032***	0.022***	0.022***
	(0.005)	(0.004)	(0.007)	(0.004)	(0.007)	(0.006)	(0.004)	(0.003)
Observations	142,080	123,690	144,144	125,756	144,144	125,756	144,144	125,756
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓
County*Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Panel (b): House prices

VARIABLES	(1) no HQ Δ loans	(2) no HQ Δ loans (sm)	(3) 2 Δ loans	(4) 2 Δ loans (sm)	(5) 3 Δ loans	(6) 3 Δ loans (sm)	(7) 5 Δ loans	(8) 5 Δ loans (sm)
IT	-0.090***	-0.102***	0.097**	0.082**	-0.062**	-0.114***	0.024	-0.040**
	(0.032)	(0.032)	(0.047)	(0.038)	(0.026)	(0.024)	(0.020)	(0.019)
IT × Δ house prices	4.109***	5.438***	2.601***	2.894***	2.417***	3.786***	1.927***	3.188***
	(0.473)	(0.463)	(0.811)	(0.615)	(0.476)	(0.441)	(0.329)	(0.304)
Observations	134,098	118,485	136,106	120,495	136,106	120,495	136,106	120,495
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓
County*Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Panel (a) reports results for regressions at the bank-county-year level (see Equation 13). The dependent variable is the change in total CRA loans by bank b to county c in year t or in CRA loans with an amount of less than \$ 100,000. IT_b is the IT adoption of bank b. $\Delta\ Income_{c,t}$ is the change in per capita income in county c between year $t-1$ and t. $log(distance)_{b,c}$ is the log of the number of miles between bank b's headquarters and county *low/high IT* refers to banks in the bottom/top tercile of the IT distribution. Panel (b) reports results for regressions at the bank-county-year level (see Equation 14). The dependent variable is the change in total CRA loans by bank b to county c in year t or in CRA loans with an amount of less than \$ 100,000. IT_b is the IT adoption of bank b, $\Delta HPI_{c,t}$ is the yearly change in house prices in county c. Columns with header 'no HQ' refer to regression that exclude banks' HQ county. Columns with header '2/3/5' use the first principle component of distance to the nearest two, three, or five land-grant colleges. Standard errors are clustered at the bank and county level. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: **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

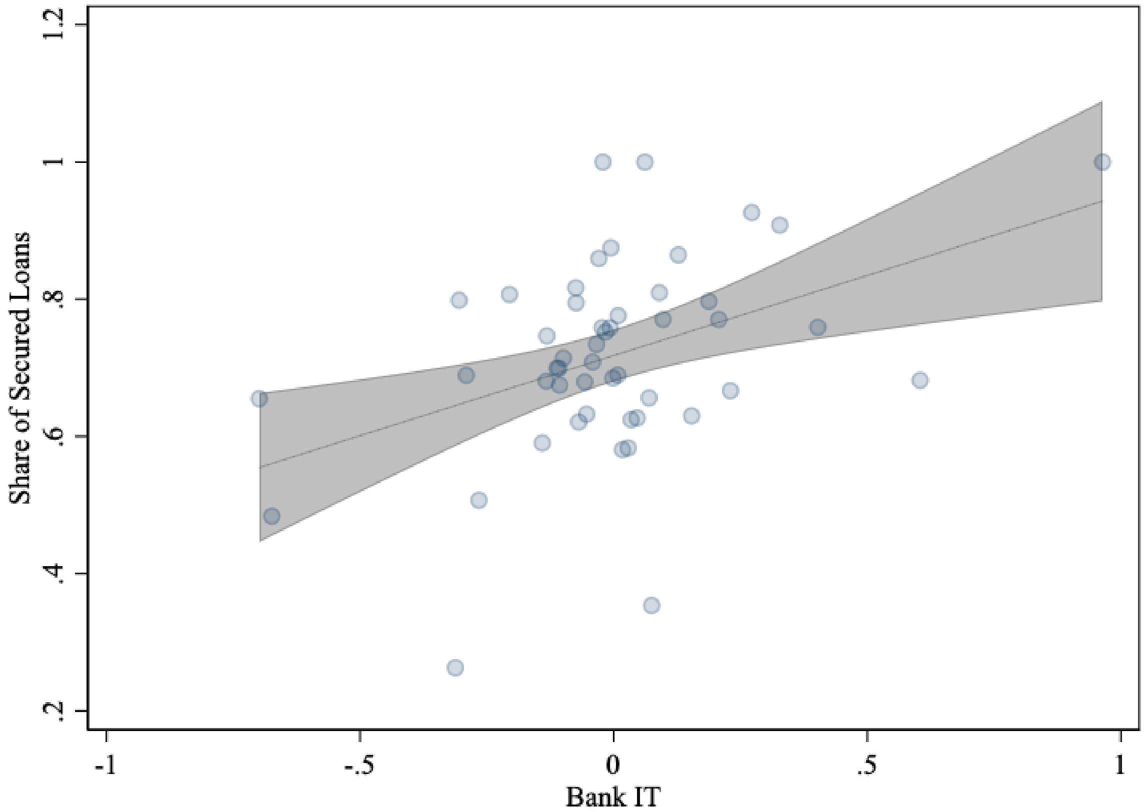
This table reports results from syndicated loan-level regression using data from Dealscan. The dependent variable is a dummy that equals one if the loan is secured and 0 otherwise. Standard errors are clustered at the bank-level *** p<0.01, ** p<0.05, * p<0.1.

Table A5: **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.

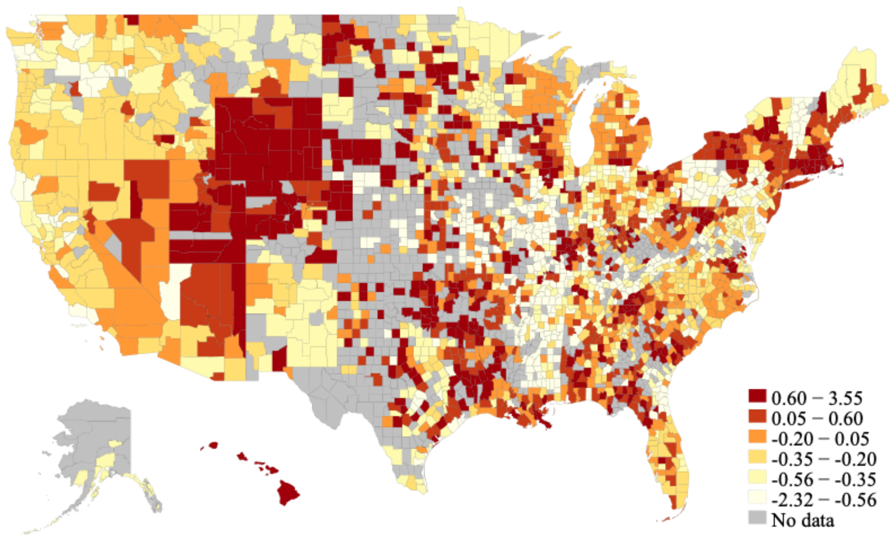
Figure A1: Share of Secured Loans



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

Figure A2: **Spatial distribution of startups and IT exposure**

(a) County exposure to IT in Banking



(b) Job creation by startups