U.S. Banks' Artificial Intelligence and Small Business Lending: Evidence from the Census Bureau's Annual Business Survey

by

Jeffery Piao
University of Missouri-Columbia

K. Philip Wang
University of Florida

Diana L. Weng
University of South Florida

This paper is a revised version of "U.S. Banks' Artificial Intelligence and Small Business Lending: Evidence from the Census Bureau's Annual Business Survey" (CES 25-07) from February 2025. A copy of the original paper is available upon request.

CES 25-07R September 2026

The research program of the Center for Economic Studies (CES) produces a wide range of economic analyses to improve the statistical programs of the U.S. Census Bureau. Many of these analyses take the form of CES research papers. The papers have not undergone the review accorded Census Bureau publications and no endorsement should be inferred. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Republication in whole or part must be cleared with the authors.

Papers in the series are posted on www.census.gov/library/working-papers/series/ces-wp.html. For information about the series, contact Danielle H. Sandler, Editor, Discussion Papers, U.S. Census Bureau, Center for Economic Studies, 4600 Silver Hill Road, Washington, DC 20233, CES.Working.Papers@census.gov.

Abstract

Utilizing confidential microdata from the Census Bureau's new technology survey (technology module of the Annual Business Survey), we shed light on U.S. banks' use of artificial intelligence (AI) and its effect on their small business lending. We find that on average 11% of banks use AI from 2017 to 2022. Banks with greater AI usage lend significantly more to distant borrowers, about whom they have less soft information. In contrast, we do not find similar effects for cloud systems, other software, or hardware surveyed by Census, highlighting AI's uniqueness. Moreover, AI's effect on distant lending is more pronounced in counties with more constrained credit and more minority-owned small businesses. Last, banks with greater AI usage experience lower default rates from and charge higher interest rates to distant borrowers. Altogether, our evidence suggests that AI reduces banks' reliance on soft information and that its gains in hard information appear to overcome those losses, net reducing the information asymmetry between banks and distant borrowers.

* Disclaimer: Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2686 (CBDRB-FY26-P2686-R13238 and CBDRB-FY26-0293). This paper is circulated outside of the U.S. Census Bureau under the alternate title "U.S. Banks' Artificial Intelligence and Small Business Lending: Evidence from the Census Bureau's Technology Survey."

Acknowledgments: We thank Jesse Chan, Kevin Chen, Keith Czerney, Yonca Ertimur, Elia Ferracuti, John Hackney (discussant), Tom Hagenberg, Kenneth Kelly, Seil Kim, Kalin Kolev, Hoyoun Kyung, Edward Li, Sara Malik, Trung Nyugen, Min Shen, and Elizabeth Tori for their thoughtful comments and suggestions. We thank conference participants at the 2024 Federal Statistical Research Data Center Conference at the University of Utah and 2025 Community Banking Research Conference at the Federal Reserve Bank of St. Louis and workshop participants at the University of Missouri-Columbia, Emerging Scholars Brownbag Series, Baruch CollegeCUNY, Georgia State University, University of Florida, Florida State University, Eugene M. Lang Foundation, University of South Florida, Temple University, and Boston University for their helpful suggestions and comments. K. Philip Wang acknowledges financial support from the Luciano Prida, Sr. Professorship. Diana L. Weng thanks the PSC-CUNY Research Award, Cycle 56 and Eugene M. Lang Junior Faculty Research Fellowship for financial support.

1. Introduction

How does artificial intelligence affect U.S. banks? This question has attracted considerable interest from academics, industry practitioners, and policymakers, yet empirical evidence remains limited. Optimists point to AI's substantial potential to transform banks' credit provision (McKinsey 2021), and media coverage frequently highlights banks embracing AI (e.g., Idzelis 2021; Lau 2024; Pathe 2024). Skeptics, however, question whether AI can live up to these expectations (Acemoglu 2025; Challapally et al. 2025), and some scholars argue that its effects, if any, may take considerably longer than expected to materialize (Brynjolfsson et al. 2019; Baslandze et al. 2026). Meanwhile, growing evidence of AI washing suggests that banks may overstate their AI use in public disclosures to manage investor perceptions (Donelson et al. 2025; Barrios et al. 2024; Kelley 2026), further complicating efforts to assess its true impact. These concerns underscore the need for empirical evidence on whether and how AI shapes bank operations.

This study addresses this gap using confidential microdata from the Census Bureau's new technology survey. Implemented in 2018, the survey is described as "one of the largest and most up-to-date datasets available on advanced technology adoption in the world" (Zolas et al. 2020, p.5) and offers several unique advantages. First, its confidential nature and penalties for misreporting substantially reduce managers' incentives to overstate AI use, directly addressing the AI washing concern. Second, unlike AI measures derived from job postings or hiring, which cannot capture AI use when firms purchase outsourced solutions from FinTech vendors (Babina 2026), the survey directly measures the extent of each firm's AI use. Third, the survey's mandatory response requirements mitigate the selection bias inherent in AI measures based on voluntary disclosure (Jia et al. 2024). Finally, the survey covers both private and public firms, allowing us

to provide a more comprehensive picture of AI use than studies restricted to public companies (e.g., Chen and Srinivasan 2024).

Using confidential Census microdata, we document several stylized facts about AI use among U.S. banks. Approximately 11% of U.S. banks use AI between 2017 and 2022, with 7% doing so at a moderate or high level. Banks appear ahead of the curve in AI adoption, using AI at higher rates than non-financial firms and earlier than other financial firms. However, AI use among banks does not follow a monotonic upward trend and declines modestly in 2022, possibly because monetary policy tightening shifted some banks' priorities away from AI deployment and toward liquidity and risk management. We also observe that AI use became increasingly concentrated among larger banks over time. Merging Census microdata with banks' Call Reports, we find that bank size is the only characteristic that consistently predicts AI use across both pooled and year-by-year regressions.

Conceptually, AI may affect banks' use of hard information in lending through three channels. First, it reduces banks' cost of collecting hard information, thereby enabling them to gather more data about borrowers. Anecdotal evidence suggests that banks use image recognition tools and AI assistants to directly read borrowers' raw financial records (Biz2X 2022; Crosman 2024). Second, it helps banks standardize and centralize unstructured data, lowering the cost of incorporating hard information into lending decisions (Bowman 2024; Gargano 2024). Third, it allows banks to use hard information more effectively. Machine learning, for example, can identify nonlinear patterns that traditional statistical models overlook, enhancing banks' ability to predict borrowers' default (Dryer 2018; Son 2017). As a result of improvement in banks' hard information, AI may reduce banks' reliance on soft information, which can only be gathered through local interaction with borrowers.

We empirically examine the effect of AI in the context of small business lending. We focus on small business loans rather than consumer loans, mortgages in particular, for three reasons. First, banks' tradeoff between hard and soft information is well established in small business lending (Petersen and Rajan 2002; Agarwal and Hauswald 2010), but less so in mortgage lending due to the prevalence of securitization (Liberti and Petersen 2019). Second, small businesses are inherently more difficult to evaluate and possess substantial yet largely unstructured financial records that banks do not currently utilize (Dryer 2018; Liu 2022). AI can help banks collect and standardize such unstructured data, an effect less likely to arise in mortgage markets.[1] Third, rich small business lending datasets allow us to examine the impact of AI on banks' borrower screening. In contrast, publicly available mortgage performance datasets typically include only loans sold to government-sponsored enterprises (GSEs), where banks have little incentive to screen and monitor borrowers beyond meeting GSE eligibility requirements (Kielty et al. 2023).

We merge Census AI-use microdata with Community Reinvestment Act (CRA) data, which contains the annual volume of small business loans at the county level originated by banks with total assets above $1 billion. To ensure that our results are not attributable to the Paycheck Protection Program (PPP), which provided guaranteed, forgivable loans to small businesses in 2020 and 2021 (Granja et al. 2022b), we exclude these two years from the sample. Following prior literature (e.g., DeYoung et al. 2008; Agarwal and Hauswald 2010), we measure banks' reliance on soft versus hard information based on how their lending varies with distance to borrowers. We include county-year fixed effects to hold local credit demand constant, and bank fixed effects to isolate the effect of AI use while controlling for time-invariant, unobserved bank characteristics.

[1] Government Accountability Office (2021, p.1) reports that "few mortgage loans have been underwritten with alternative data," suggesting that banks predominantly rely on standardized borrower information from credit bureaus in mortgage lending.

We find that while banks with greater AI use do not extend more total credit to small businesses, they lend significantly more to distant borrowers, about whom banks have less soft information. A one-standard-deviation increase in AI use attenuates the negative relation between lending distance and small business loan volume by 12%. Discretizing lending distance into five bins, we find that AI's effect increases monotonically with distance. These results suggest that AI reduces banks' reliance on soft information in lending.

A potential concern is that any technological improvement would increase banks' distant lending, in which case AI would be no different from other technologies. To assess this possibility, we utilize data on banks' use of *other* advanced technologies from the Census technology survey, which includes cloud systems, non-AI software, and hardware.[2] Many of these technologies have grown increasingly prevalent in banking; cloud systems, for instance, has expanded rapidly as banks seek to reduce data storage costs (Nguyen 2022). However, we find no evidence that greater use of cloud systems, other software, or hardware is associated with increased lending to distant borrowers. These results underscore the distinct role of AI relative to other recent technological advancements and alleviate concerns that the observed effects reflect broad technological change rather than AI specifically.

We next examine the mechanism through which AI affects distant lending. A recent Federal Reserve survey shows that 85% of small businesses face financial challenges, yet only 42% of them have their financing needs met (Federal Reserve Banks 2022). Anecdotal evidence suggests that AI helps banks identify creditworthy small businesses in areas overlooked by traditional risk assessment models and thus are historically underserved (Business Wire 2024). To

[2] Cloud systems is the only other relevant technology consistently surveyed by Census from 2018 to 2023. Other software technologies (e.g., automation, enterprise resource planning) are mostly only surveyed in one year, so we group them. Examples of hardware surveyed include server technologies, internet-connected devices, and robotics.

empirically examine this mechanism, we directly measure unmet credit demand using county-level unfulfilled small business loan application rates from the Census Annual Business Survey. We supplement this measure with the county-level share of minority-owned small businesses from the same source, given longstanding evidence that minority-owned firms face greater barriers to accessing credit (Fairlie et al. 2021). We find that AI's effect on distant lending is more pronounced in counties with larger unmet credit needs and higher shares of minority-owned small businesses, supporting this mechanism.

Although we show that AI helps banks extend credit to distant borrowers, this does not necessarily mean that AI helps banks identify more creditworthy borrowers. In other words, AI's gains in hard information may not be enough to offset the loss in soft information. Indeed, early technological advances in the 1990s, such as credit scoring, have been shown to worsen loan performance (Berger et al. 2005; DeYoung et al. 2008). Therefore, an alternative explanation for the growth in distant lending is that banks with greater AI use simply take on more risk. To examine the effect of AI on banks' borrower screening at origination, we follow Granja et al. (2022a) and use Small Business Administration (SBA) loan-level data.[3]

We find that while AI use is on average not significantly associated with loan performance, as measured by charge-offs, distant loans originated by banks with greater AI use perform significantly better *ex post*. These results suggest that AI's gains in hard information appear to outweigh losses in soft information for distant borrowers, enabling banks to identify more creditworthy borrowers. When we discretize lending distance into five bins, we find that AI's effect on loan performance is concentrated among the most distant borrowers.

[3] The CRA dataset does not contain loan performance or interest rates.

While AI improves borrower screening, its effect on loan pricing is theoretically ambiguous. On one hand, AI reduces the bank's information asymmetry with the borrower, allowing it to charge a lower risk premium. On the other hand, AI makes the bank better informed about borrower quality than competing lenders, and this informational advantage increases the bank's market power, enabling it to charge a higher markup without losing borrowers to rivals (Agarwal and Hauswald 2010; Beyhaghi et al. 2026).

We find that banks with greater AI usage charge higher interest spreads on average, and this AI interest premium increases with lending distance. When we discretize lending distance into five bins, we find that AI's effect on pricing is concentrated among the most distant borrowers, the exact same group for which we observe AI's effect on loan performance. These results suggest that AI's ability to identify distant creditworthy borrowers softens price competition and allows the bank to informationally capture these borrowers.

This study is among the first empirical effort to examine AI use among U.S. banks and its impact on credit supply, loan performance, and loan pricing. In doing so, we respond to Demerjian's (2024, p.5) call for greater investigation into the impact of FinTech on traditional banks. This area is growing rapidly, with increasing focus on how technology affects bank competition. Examples include Koont (2025), who finds that mobile application adoption intensifies bank competition by expanding access to distant customers; Chen et al. (2025), who examine how digital technologies moderate the effect of newspaper closures on local bank competition; and Jiang et al. (2026), who show that 3G network rollout drives divergent competitive strategies across banks depending on their customer bases. In contrast to these studies, we focus specifically on AI and its direct effects on banks' tradeoff between hard and soft information.

This study also contributes to the growing literature on AI's economic impacts in three ways. First, while recent studies examine how AI shapes information processing on the investor side (e.g., Bertomeu et al. 2025; Chang et al. 2026; Ecker et al. 2026), we examine the firm side, specifically how AI helps banks process borrower information. Second, unlike studies that examine AI's effects on broad firm-level outcomes such as performance and employment (Babina et al. 2024; Baslandze et al. 2026), we zoom in on a specific yet consequential aspect of bank operations: commercial lending. Third, we respond to Babina's (2026) call for direct measurement of AI use, as outsourced AI solutions have grown increasingly popular yet remain difficult to capture with existing measures.

Finally, our findings speak to regulators' concerns about whether banks use technological innovations to take on excessive risk. Federal Reserve Governor Michelle Bowman recently asked, "how can regulators best balance the risks AI may pose to bank safety and soundness and financial stability with the need to allow for continued innovation?" (Bowman 2024). We offer evidence that AI enables banks to expand credit access without increasing risk, alleviating regulatory concerns about banks' AI use in small business lending.

2. How could AI affect banks' lending?

In making small business lending decisions, banks collect two types of information about borrowers when evaluating their risk: hard and soft information (Liberti and Petersen 2019; Vashishtha 2019). Hard information is numerical and standardized data that can be transmitted in impersonal ways, while soft information is qualitative and unverifiable data that is intricately linked to its context. Banks have limited hard information about small business borrowers, which restricts their ability to evaluate borrowers' risk and thus increases their demand for soft information (Minnis 2011).

However, banks' limited hard information is often not due to lack of availability, but because of the high cost of collecting and analyzing it. For example, a small restaurant may have a large volume of financial records, but they are less organized, some scanned or even hand-written, and the data are in heterogeneous formats across restaurants. Since collecting this data can be costly while the profit from small business loan origination is limited, many banks in practice screen small businesses only using a narrow set of hard information such as the debt service coverage ratio and the business owner's credit score (Dryer 2018).[4] Consistent with this anecdotal evidence, Liu (2022) uses loan-level data from a small business lender and shows empirically that loan officers process only a small portion of hard information that is useful for predicting borrower defaults.

AI can affect small business lending in three aspects. First, it reduces banks' cost of collecting data. For example, an AI module developed by Biz2X allows banks to read and automatically extract borrowers' raw financial records using image recognition and natural language processing (Biz2X 2022). Cascading AI, another FinTech startup, developed an AI assistant to help Bankwell Bank collect borrowers' information. By reducing information acquisition costs, AI allows banks to obtain more data about borrowers within the same budget (Blankespoor et al. 2020; Even-Tov et al. 2024).

Second, AI reduces banks' cost of integrating data into decision-making. For example, Citigroup partners with Numerated, a FinTech company, to centralize borrower data "from disparate sources in diverse formats" into a singular dashboard (Gargano 2024). Similarly, Michelle Bowman, the Federal Reserve governor, points out that AI is frequently used by banks

[4] For example, Dryer (2018) states that "bankers, being human, have limited time and brainpower. Faced with an edge-case scenario, they'll look at additional variables that complete the bigger picture. But if those additional variables require tracking down more data manually, bankers reach a limit to how much energy they can devote to one loan application."

for “reviewing and summarizing unstructured data” (Bowman 2024). David Donovan, head of a digital consulting firm, observes that many banks adopt AI to integrate alternative data into their loan approval processes (Gargano 2024).

Third, AI helps banks use hard information more effectively (Crosman 2024). For example, a Moody’s report states that “[a] machine learning model, unconstrained by some of the assumptions of classic statistical models, can yield much better insights that a human analyst could not infer from the data” (Moody's 2017). Similarly, Gord Baizley, CEO of JUDI.AI–a FinTech company that partnered with Seattle Bank–explains, “our small business-specific credit model, powered by machine learning, uses real-time, customer-permissioned bank transaction data to offer a more accurate snapshot of the financial health of the business” (Lau 2024).

AI’s effect on banks’ hard information has implications for banks’ credit supply and loan performance. Conceptually, the improvement in hard information allows banks to rely less on soft information while still maintaining the accuracy of their risk assessments. As a result, banks could extend credit to borrowers about whom they have less soft information. However, whether AI improves banks’ hard information in practice may not be obvious. For example, a premature image recognition tool may assign extracted numbers to incorrect data fields, compromising input data quality. Machine learning may produce prediction errors due to insufficient training data or unrealistic model assumptions. Given these potential problems, whether banks are willing to trust AI and place significant weight on the hard information it generates (and thus less weight on soft information) is an empirical question.

Regarding loan performance, AI’s effect is also not obvious. On one hand, if AI reduces banks’ demand for soft information, the loss of soft information can result in worse loan performance (Agarwal and Ben-David 2018; Gallo et al. 2023). On the other hand, hard and soft

information can be correlated, so the newly collected hard information could substitute for some soft information (He et al. 2024; Fuster et al. 2022). Last, recent studies show that using soft information does not always improve banks' risk assessment, depending on loan officers' cognitive constraints and behavioral biases (Campbell et al. 2019).

3. Data Sources

3.1 Census Bureau's technology survey

Lack of data has been a key impediment to researching AI's impacts (Seamans and Raj 2018). Partnering with the National Center for Science and Engineering Statistics, the Census Bureau introduced the Annual Business Survey (ABS) in 2018. The ABS technology module represents Census's first effort to identify adoption rates of advanced technologies and the extent to which each technology is used. Notably, Zolas et al. (2020, p.33) states that "one of the primary goals of the ABS technology module is to provide the first comprehensive look into the adoption rates of Artificial Intelligence (AI) by US firms." The technology module last appears in ABS 2023, due to module rotation to reduce respondent burden, thus concluding our sample period.

ABS is conducted on a company basis rather than on an establishment (i.e., branch) basis. All surveyed firms are required by law to respond (*Census Act, 13 U.S.C. § 224* 1954), significantly alleviating selection and nonresponse bias. The first ABS was sent out in June 2018, with a reference period of calendar year 2017. It surveys a representative sample using stratified systematic sampling of approximately 850,000 firms every 5 years and approximately 300,000 firms annually (Zolas et al. 2020). As a result, the sample in the initial year of each ABS cycle (i.e., 2018 and 2023) covers more firms than in the intervening years (i.e., 2019 to 2022), with smaller firms less representative in the intervening years. To account for sampling differences across years, we rebalance each sample year toward its underlying population distribution by weighting

observations based on bank size throughout our descriptive statistics and regression analyses following recent studies using the same survey (e.g., Ando et al. 2025; Acemoglu et al. 2022).[5]

The list of technologies included in the module varies across years. For example, in 2019, the module asked respondents about their use of AI, cloud systems, robotics, specialized software, and specialized equipment. However, in 2022, it instead asked about AI, advanced (cloud) computing, advanced sensing, autonomous systems and robotics, additive manufacturing, biotechnology, human-machine interfaces, communication and networking technologies, advanced financial technologies, advanced semiconductors and microelectronics, advanced engineering materials, renewable energy generation and storage, advanced gas turbine engine technologies, and advanced nuclear energy technologies.

This technology survey offers three unique advantages to our study. First, it allows us to directly measure a bank's AI use. Second, it provides data on banks' use of other advanced technologies, so we could contrast AI's impact with those of other advanced technologies. Third, other ABS modules provide information on the financing needs and demographic characteristics of small business owners, which allow us to conduct cross-sectional tests.

3.2 The Community Reinvestment Act (CRA) dataset

Following prior literature (e.g., Granja et al. 2022a; Cortés et al. 2020), we use data on small business loan originations collected by the Federal Financial Institutions Examination Council (FFIEC) pursuant to the Community Reinvestment Act (CRA). Small business loans are defined as non-farm commercial or industrial loans whose principal amount does not exceed $1 million. All commercial banks regulated by the Office of the Comptroller of the Currency (OCC),

[5] We sort the population of banks each year by total assets into 20 equally-sized groups. Each sample bank-year observation is assigned a weight, calculated as the number of population banks in its group-year divided by the number of sample banks in its group-year. Because Census generally samples fewer smaller companies (as a percentage of the population), this reweighting will generally give smaller banks larger weights.

Federal Reserve System, and Federal Deposit Insurance Corporation (FDIC) that exceed asset thresholds are required to report the number and aggregated dollar amount of loans originated in each county each year. The asset threshold was raised from $250 million to $1 billion in 2005 and is adjusted annually for inflation. During our sample period, the asset threshold ranges from $1.252 billion (2018) to $1.503 billion (2023).

3.3 The Small Business Administration (SBA) dataset

Because the CRA dataset aggregates loans at the bank-county-year level, it does not contain loan-level information such as default or interest rates. Therefore, following Granja et al. (2022a), we use the SBA dataset of loans originated under the 7(a) program, SBA's primary lending program, to conduct loan-level tests. This dataset identifies lenders and includes information about borrowers (e.g., identity, address, and industry), loan terms (e.g., approval date, loan amount, guaranteed portion, maturity, and interest spread plus base rate), and *ex-post* loan performance (e.g., the loan balance that has been charged off).

SBA guarantees a portion of the loan principal balance against losses upon defaults. Specifically, SBA guarantees up to 50% for express loans, the largest category of the 7(a) program, and otherwise guarantees up to 85% for loans under $150,000 and up to 75% for loans over $150,000. The guaranteed rate does not always reach the allowable maximum because borrowers often try to lower guarantee fees, which increase with the guaranteed rate (Huang 2024). Note that SBA does not take a first-loss position upon default; instead, it covers the guaranteed portion of the *remaining* outstanding balance and delinquent interest (Glennon and Nigro 2005). As a result, lenders still retain significant incentive to screen borrowers at loan origination to minimize default risk.

3.4 Other datasets

Banks' financial data: We obtain commercial banks' financial information from their Call Reports. We merge banks' financial data to Census' ABS using the nine-digit Employer Identification Number (EIN) assigned by the IRS.

Banks' branch data: FDIC's Summary of Deposits (SOD) data provides branch-level data on geographic locations of banks' headquarters and branches on an annual basis. We use this data to calculate the distance between lenders and borrowers in the CRA and SBA datasets.

Economy data: We obtain GDP data from the Federal Reserve Economic Data (FRED) website of the Federal Reserve Bank of St. Louis.

4. Empirical Results

All results that use confidential Census microdata need to go through a disclosure avoidance review process, in which Census personnel vet each reported number, prior to release to ensure that no individual responses can be inferred. Because Census has concerns about volume of output, we do not tabulate coefficients and standard errors for control variables in regression analyses.

4.1 The AI use rate

To shed light on AI use in the U.S. banking industry, we rely on banks' responses to AI-related question(s) in each year's ABS. ABS 2019, 2022, and 2023 directly asked about AI, but ABS 2018 and 2021 did not and instead asked about more specific technologies.[6] Therefore, following Zolas et al. (2020) and McElheran et al. (2024), we define "machine learning," "machine vision," and "natural language processing" as AI in these two years.[7] Because banks' AI use can

[6] We exclude ABS 2020 because the survey asks about AI use for "innovation activities," which somehow significantly inflated AI use for all industries (including banks) (McElheran et al. 2024). We consulted with Emin Dinlersoz, a Principal Economist at the Census Bureau, who has also worked with this technology survey, on this issue.

[7] Zolas et al. (2020) also identify "automated guided vehicles" and "voice recognition" as AI, but we do not include them as they are not relevant to banks' lending.

change across years, we do not extrapolate AI levels for unsurveyed years using values from surveyed years to avoid introducing measurement error. Appendix B provides details of the construction of the AI variable.

Merging ABS with banks' Call Reports results in a sample of 2,600 (rounded) bank-year observations from 1,500 (rounded) unique banks. We find that, on average, 11% of banks use AI between 2017 and 2022. Figure 1, Panel A shows that the share of banks using AI rose from 7% in 2017 to 14% in 2018, remained roughly stable through 2021, and then declined to 8% in 2022. The 2022 decline likely reflects the onset of monetary policy tightening, which redirected some banks' resources and attention, particularly smaller banks, away from AI deployment and toward liquidity and risk management.

We further compare AI use rates in the banking industry against two benchmarks: non-bank financial industries and non-financial industries. Because non-bank firms are on average smaller than banks, raw differences in AI use rates may partly reflect a size effect rather than industry differences. We reweight both groups according to firm size to ensure comparability with the banking industry.[8] Figure 1, Panel A plots AI use rates for non-bank financial and non-financial firms. We find that banks were early movers relative to non-bank financial firms, though the latter caught up by 2021. Across the full sample period, both banks and non-bank financial firms generally have greater AI use than non-financial firms.

Decomposing AI use by intensity reveals that, on average, 3.8% of banks use AI to a low extent, 6.6% to a moderate extent, and 0.8% to a high extent. Figure 1, Panel B plots these shares

[8] Census does not have firms' total assets, so we follow Zolas et al. (2020) and Acemoglu et al. (2022) in measuring firm size using employees. We sort the population of banks each year by employees into 20 equally-sized groups. We then assign the samples of non-bank financial and non-financial firms each year into 20 (unequally-sized) groups using bank size thresholds, excluding firms smaller than the smallest bank and larger than the largest bank. Each sample firm-year observation is assigned a weight, calculated as the number of population *banks* in its group-year divided by the number of sample *firms* in its group-year.

over time, revealing no particularly notable pattern. Figure 1, Panel C plots the year-by-year difference in log average total assets between banks with and without AI use. We show that this gap widens over time, suggesting that AI use is increasingly concentrated among larger banks.

4.2 What bank characteristics are associated with AI use?

Zolas et al. (2020, p.3) state that "our understanding of how and why firms adopt new technologies is still rather imprecise," suggesting limited research on what affects firms' use of AI. To explore this question in the banking industry, we run the following model using the bank-year sample:

$$\begin{aligned} AI \quad &= Size + Public + ROA + Leverage + Liquid\ Assets + Securities + Loans \\ &+ Residential\ Loans + Commercial\ Loans + Nonperforming\ Loans + Derivatives \\ &+ Deposits + Remote\ Specialist + \text{Year FEs} + \text{State FEs} + \varepsilon \end{aligned} \quad (1)$$

AI, the extent to which a bank uses AI, equals 0 if no use or testing, 1 if low use, 2 if moderate use, and 3 if high use. We include 13 bank characteristics as possible determinants of AI. These characteristics include basic financials (*Size, ROA, Leverage*), an indicator for public banks (*Public*), asset composition (*Liquid Assets, Securities, Loans*), loan composition (*Residential Loans, Commercial Loans, Nonperforming Loans*), and banks' other major business components (*Derivatives, Deposits*). Motivated by recent evidence of increasing industry specialization in small business lending (Di and Pattison 2023), we include an indicator variable for whether a bank is a *Remote Specialist*, defined as a bank that originates loans nationwide but focuses on a narrow set of industries. Appendix A provides variable definitions. We include year fixed effects and cluster standard errors by bank.

Table 1, Panel A presents the descriptive statistics. In our sample, loans constitute 59% of bank assets on average, of which 41% are residential and 13% are commercial. Nonperforming loans account for less than 1% of total loans. Table 2 presents the results of the determinants

analysis for both the pooled and year-by-year regressions. We find that *Size* is the only determinant of AI use with consistent sign and significance across specifications. The finding that larger banks are more likely to use AI is consistent with studies examining the determinants of AI adoption outside the banking industry (McElheran et al. 2024; Acemoglu et al. 2022). Beyond *Size*, most bank characteristics show little consistent association with AI use, either insignificant across all years (e.g., *ROA*) or significant in only one year (e.g., *Leverage*). Of the three characteristics significant in two of five years, two (*Residential Loans* and *Deposits*) exhibit opposite signs. Only *Remote Specialist* shows a consistent sign across two years, but it is nevertheless insignificant in the pooled regression. Overall, these results do not point to a clear pattern in which AI adoption is systematically driven by the technological demands of specific business lines.

We rerun the determinants analysis using two alternative binary AI variables. *AI (use/no)* equals one if a bank reports low, moderate, or high AI use, and zero if it reports no use or testing. *AI (high/low)* equals one for moderate or high use, and zero for no use, testing, or low use. We find the results are qualitatively similar. For brevity, we report them in Online Appendix A1.

4.3 The effect of AI on the quantity of small business loans

To examine the effect of AI on small business lending, we use the CRA dataset, which aggregates loans by number and volume at the bank-county-year level. One complication is that CRA data includes and does not separately report PPP loans originated during the COVID-19 pandemic (Federal Reserve Board 2020). Because PPP loans are fully government-guaranteed, they differ fundamentally from conventional small business loans for which banks bear default risk. Therefore, we exclude all observations in 2020 and 2021 from this analysis. Further, following Adams et al. (2023), we exclude observations in Alaska, Hawaii, and U.S. territories (e.g., U.S. Virgin Islands, Puerto Rico, etc.), because they introduce discrete jumps in the distance

between the borrowers' county and the bank. Merging the bank-year sample with AI and bank controls to the CRA dataset yields 180,000 (rounded) bank-county-year observations. Panel B of Table 1 reports the descriptive statistics for this sample. In our sample, the distance between a bank and borrower's county averages 414 miles, and a bank originates an average of $1.49 million in loans from a given county per year.

We run the following model using this sample:

$$\begin{aligned} Ln(SBL)_{i,c,t+1} = {} & \beta_1 AI_{i,t} + \beta_2 Ln(Distance_{i,c}) + \beta_3 AI_{i,t} \times Ln(Distance_{i,c}) \\ & + \beta_4 Size_{i,t} \times Ln(Distance_{i,c}) + \beta_5 \Delta GDP_{t,t+1} \times Ln(Distance_{i,c}) \\ & + \text{Bank Controls}_{i,t} + \text{County} \times \text{Year FEs} + \text{Bank FEs} + \varepsilon \end{aligned} \quad (2)$$

Following prior studies (Petersen and Rajan 2002; Granja et al. 2022a), we measure a bank's reliance on hard versus soft information based on how its lending varies with the distance from its borrowers (i.e., *Ln*(*Distance*)). Because soft information is generated through frequent in-person contact, banks that rely more heavily on it tend to lend disproportionately less to distant borrowers (Liberti and Petersen 2019).

Consistent with Granja and Leuz (2024) and Dagostino (2025), we define *Ln*(*SBL*) as the natural logarithm of the total dollar amount (in thousands) of small business loans by bank *i* in county *c* from year *t*+1. Because only borrowers' county is available in the CRA dataset, we calculate *Distance* as the geodetic distance between the centroid of the borrower county and the bank's closest branch. If AI helps banks increase overall credit supply, we expect β_1 to be positive in the model that excludes the *AI* × *Ln*(*Distance*) interaction. If AI helps banks rely less on soft information and thus extend more credit to distant borrowers, we expect β_3 to be positive.

We include all bank characteristics used in Equation (1), borrower county × year fixed effects, and bank fixed effects. We control for Δ*GDP* × *Ln*(*Distance*) because Granja et al. (2022a) show that banks lend more to distant borrowers when the economy is booming. We do not include

ΔGDP itself in the model because it would be absorbed by county × year fixed effects. We also control for *Size* × *Ln*(*Distance*) because *Size* is the only bank characteristic consistently associated with *AI* in the determinants analysis. Because the *AI* variable measures the level of AI usage rather than a binary adoption decision, we include bank fixed effects to isolate the effect of within-bank changes in AI use over time. In doing so, our approach mirrors Babina et al.'s (2024) strategy to identify the effect of AI adoption on firm outcomes over a long horizon. Following Cortés et al. (2020), we cluster standard errors by bank-year.

Table 3 presents the regression results for Equation (2). Column (1) shows that AI is not associated with *Ln*(*SBL*), suggesting that AI does not impact a bank's overall quantity of small business lending. In Column (2) where we include *AI* × *Ln*(*Distance*), we find that banks with greater AI use lend significantly more as bank-borrower distance increases, suggesting that AI reduces banks' reliance on soft information. Because larger banks are more likely to use AI, we additionally control for *Size* × *Ln*(*Distance*) in Column (3) and show that our results are not driven by bank size. Regarding economic magnitude, a one-standard-deviation increase in AI use attenuates the negative relation between lending distance and bank loan growth by 12% for small business loans.[9] Last, consistent with the notion that banks tend to lend more to local borrowers, we find a negative coefficient on *Ln*(*Distance*) in all columns. The results are robust to clustering standard errors by bank or two-way clustering by bank and county (untabulated). Note that the coefficients on *AI* in Columns (2) and (3), where we include *AI* × *Ln*(*Distance*), are not meaningful, because they reflect *AI*'s effects when *Ln*(*Distance*) equals zero, which barely exists in the sample

[9] The calculation details are as follows: 12% = 1.019 (standard deviation of AI from Panel B of Table 1) × 0.078 (coefficient on *AI* × *Ln*(*Distance*) in Column (2)) / 0.663 (absolute value of coefficient on *Ln*(*Distance*) in Column (2)). Note that we rely on Column (2) to interpret the magnitude because adding *Size* × *Ln*(*Distance*) in Column (3) means that the coefficient on *Ln*(*Distance*) reflects the slope of *Ln*(*Distance*) when *Size* equals 0 (i.e., bank total assets equals $10 million).

period (Burks et al. 2019; Aiken and West 1991, p.38).

To investigate the distances at which borrowers are affected by AI, we discretize distance within each bank's portfolio into five distance bins. We replace *Ln*(*Distance*) with four binary variables using the closest bin as the benchmark and interact AI with these four variables. Figure 2 plots the coefficients on these four binary variables and their interaction terms with AI. Consistent with the notion that banks on average lend more to local borrowers, we find that the coefficients on the distance bin indicators are all significantly negative and monotonically decrease as lending distance increases. More importantly, coefficients on *AI* × distance bin indicators are all significantly positive and monotonically increase as lending distance increases. Further analyses show that the coefficients on distance bin interactions three through five are statistically different from that of the second quintile (untabulated). These results together suggest that AI helps banks to extend credit to borrowers across all observed distant ranges in our sample.

4.4 Do all advanced technologies increase distant lending?

We next examine whether other advanced technologies have a similar effect on distant lending as AI does. Earlier research shows that technological advancements from the 1970s to the 1990s led to an increase in distance between banks and borrowers at the time (e.g., Petersen and Rajan 2002). Therefore, it is possible that any type of technological improvement could lead to more distant lending, suggesting that AI's impact might not be unique.

We utilize other questions in the ABS technology module to conduct these tests. Specifically, non-AI technologies in ABS 2018 include cloud service, augmented reality, automated storage and retrieval system, radio-frequency identification inventory system, robotics, and touchscreens/kiosks for customer interface. Non-AI technologies in ABS 2019 and 2023 include cloud-based computing systems and applications, specialized software, robotics, and

specialized equipment. Non-AI technologies in ABS 2021 include cloud service, augmented reality, radio-frequency identification system, robotics, touchscreens/kiosks for customer interface, and additive manufacturing. Non-AI technologies in ABS 2022 include advanced (cloud) computing, advanced sensing, autonomous systems and robotics, additive manufacturing, biotechnology, human-machine interfaces, communication and networking technologies, advanced financial technologies (blockchain), advanced semiconductors and microelectronics, advanced engineering materials, renewable energy generation and storage, advanced gas turbine engine technologies, and advanced nuclear energy technologies.

Among all non-AI technologies, cloud systems is the only one surveyed consistently throughout our sample period, albeit with slightly different wording across years. Therefore, we categorize the non-AI technologies into three groups: cloud systems, other software, and hardware. Other software includes automated storage and retrieval systems, radio-frequency identification inventory system, and touchscreens/kiosks for customer interface in 2017; specialized software in 2018 and 2022; radio-frequency identification system and touchscreens/kiosks for customer interface in 2020; and autonomous systems and robotics, human-machine interfaces, communication and networking technologies, and advanced financial technologies (blockchain) in 2021. Hardware includes robotics in 2017; robotics and specialized equipment in 2018 and 2022; robotics and additive manufacturing in 2020; and additive manufacturing, advanced semiconductors and microelectronics, advanced engineering materials, and renewable energy generation and storage in 2021. Similar to how we define *AI* in Appendix B, we construct three continuous measures to capture the extent to which the bank uses cloud systems (*Cloud*), other software (*Other Software*), and hardware (*Hardware*).

The mean of *Cloud* is 1.61, meaning that banks' average use of cloud systems is between

low and modest. The mean of *Other Software* (i.e., 1.67) is slightly higher than that of cloud systems, while the mean of *Hardware* (i.e., 0.53) is lower. The standard deviations of all three other technologies are larger than that of *AI*, suggesting that there is meaningful variation in the use of these technologies among U.S. banks.

Table 4 presents the regression results after we replace *AI* with *Cloud*, *Other Software*, or *Hardware* in Equation (2). We find that the coefficients on the interaction terms between these non-AI technologies and distance are not statistically significant, suggesting that banks with more non-AI technologies do not lend more to distant borrowers. The results are robust to clustering standard errors by bank or two-way clustering by bank and county (untabulated). These results contrast with those of AI, suggesting that the effect on distant lending is unique to AI rather than driven by banks' broad embrace of technology.

4.5 Are AI's effects stronger for underserved areas?

A possible mechanism for the increase in distant lending by AI is that AI helps banks identify creditworthy borrowers who have been overlooked by traditional credit assessment models. Testing this mechanism requires identifying borrowers with historically less access to bank loans. Because CRA data are aggregated at the bank-county level, we construct two novel county-level measures using granular ABS data.

Motivated by survey evidence that only 42% small businesses have their financing needs met (Federal Reserve Banks 2022), we first measure the degree to which small businesses are underserved in each county. Specifically, ABS 2021 and 2023 ask surveyed firms whether they applied for new credit in the prior 12 months and, if so, how much of the requested amount they received. We classify a small business as credit-constrained if it applied for but did not receive

new credit.[10] We then aggregate responses from both survey years to the county level to calculate the share of applicants with unmet credit needs. Counties with higher shares of such applicants are characterized as more credit-constrained.

As a complementary measure, we calculate the share of minority-owned small businesses for each county-year. A substantial body of evidence documents that minority-owned businesses face discrimination in credit markets, resulting in more limited access to financing (e.g., Blanchflower et al. 2003; Cavalluzzo and Wolken 2005; Fairlie et al. 2021). Using race information from ABS, we classify a firm as minority-owned if owners from minority groups (i.e., Black or African American, Hispanic, American Indian, Alaska Native, Native Hawaiian, or Other Pacific Islander) hold a majority equity stake of more than 50%.[11]

If AI helps banks identify creditworthy borrowers overlooked by conventional risk assessment models or loan officers, its effect on distant lending should be more pronounced in counties with greater unmet credit needs and a higher prevalence of minority-owned small businesses. Table 5 reports the results after we partition the sample based on these two measures. We find that the coefficient on $AI \times Ln(Distance)$ is significantly positive across all four subsamples. The coefficient is significantly larger for counties with greater unmet credit needs and counties with higher presence of minority-owned businesses, suggesting that AI enables banks to extend credit to borrowers that traditionally have less credit access. Our cross-sectional results resonate with anecdotal evidence that lenders use AI to expand credit for credit-constrained and minority-owned small businesses, highlighting AI's potential to reduce discrimination and promote financial inclusion in underserved communities (U.S. Department of the Treasury 2024).

[10] Following SBA's guidelines, we define small businesses as firms with 500 or fewer employees (SBA 2026).
[11] We apply Census-provided sampling weights to both measures to correct for differences in sampling across survey years, rebalance each sample toward the underlying population distribution, and ensure the measures are comparable over time.

4.6 AI's effect on loan performance

To examine the effect of AI on loan performance, we rely on the SBA dataset, which is at the individual loan level. Consistent with our other tests, we only include loans where the lenders and borrowers are both located in the 48 contiguous U.S. To calculate lender-borrower distance, we exclude borrowers without valid street addresses, such as those with addresses listed as post office boxes or lot numbers. We then manually clean borrowers' street addresses before converting the addresses into geographical coordinates using the Census Bureau TIGER/Line shapefiles. Following Brown and Earle (2017) and Granja et al. (2022a), we exclude canceled loans. Merging the bank-year sample with AI and bank controls to the SBA dataset yields 69,500 (rounded) loans.

We run the following model using this sample:

$$\begin{aligned} ChargeOff_{l,\,t+1} = {} & \beta_1\, AI_{i,\,t} \times Ln(Distance_{i,\,j}) + \beta_2\, AI_{i,\,t} + \beta_3\, Ln(Distance_{i,\,j}) \\ & + \beta_4\, Size_{i,\,t} \times Ln(Distance_{i,\,j}) + \beta_5\, \Delta GDP_{t,\,t+1} \times Ln(Distance_{i,\,j}) \\ & + \text{Loan Controls}_{l} + \text{Bank Controls}_{i,\,t} + \text{SBA program FEs} \\ & + \text{County} \times \text{Year FEs} + \text{Borrower Industry FEs} + \text{Bank FEs} + \varepsilon \end{aligned} \quad (3)$$

where l indexes loans, i indexes banks, j indexes borrowers, and t indexes origination years. *ChargeOff* equals the amount that has been charged off scaled by the loan's principal amount. If the loan does not have any charge-off, *ChargeOff* equals 0. Because the SBA dataset contains borrowers' addresses, we calculate *Distance* as the geodetic distance between borrower j's address and bank i's closest branch. If AI helps banks lower the default rate of loans to distant borrowers, we expect β_1 to be negative.

We include the same interaction variables (*Size* × *Ln*(*Distance*) and Δ*GDP* × *Ln*(*Distance*)), the same set of bank controls (*Size*, *Public*, *ROA*, *Leverage*, *Liquid Assets*, *Securities*, *Loans*, *Residential Loans*, *Commercial Loans*, *Nonperforming Loans*, *Derivatives*, *Deposits*, *Remote Specialist*), county × year fixed effects, and bank fixed effects as Equation (2). In addition, we include loan controls (*Loan Amount*, *Maturity*, and *Guaranteed*), borrower industry

(3-digit NAICS code) fixed effects, and SBA program fixed effects (i.e., SBA Express and Preferred Lending Program). See variable definitions in Appendix A. Consistent with our credit supply tests, we cluster standard errors by bank-year.

Panel C of Table 1 reports the descriptive statistics of this sample. The average charge-off percentage is 0.2%, and the average lending distance is 162.7 miles. Compared with the CRA sample, the SBA sample has a shorter lending distance, likely because the unit of observation is at the bank-county-year level for our CRA tests, but at the individual loan level for our SBA analyses. The mean portion guaranteed by SBA is 65%, suggesting that banks retain significant "skin in the game."

Table 6 presents the regression results. In Column (1), we do not find that AI use is associated with charge-off, suggesting that AI does not help banks improve loan performance on average. In Column (2) where we include *AI* × *Ln*(*Distance*), we find that the coefficient on *AI* × *Ln*(*Distance*) is significantly negative, suggesting that distant loans originated by banks with greater AI use experience lower defaults *ex post*. The results hold after controlling for *Size* × *Ln*(*Distance*) in Column (3). Regarding economic magnitude, a one-standard-deviation increase in AI use attenuates the positive relation between lending distance and default by 60% for small business loans.[12] The results are robust to clustering standard errors by bank or two-way clustering by bank and county (untabulated).

To identify the distances at which AI affects loan performance, we follow the same discretization approach as in the credit supply analysis, dividing distance within each bank's portfolio into five bins. Replacing *Ln(Distance)* with four binary indicators, with the closest bin

[12] The calculation details are as follows: 60% = 1.048 (standard deviation of AI from Panel C of Table 1) × 0.019 (absolute value of coefficient on *AI* × *Ln*(*Distance*) in Column (2)) / 0.033 (coefficient on *Ln*(*Distance*) in Column (2)).

as the benchmark, we interact each indicator with *AI* and plot the resulting coefficients on the indicators and interactions in Figure 3. While the coefficients on all *AI* × distance bin interactions are negative, only the furthest bin interaction is statistically significant, suggesting that AI's ability to identify creditworthy borrowers is most consequential at the greatest distances.

4.6. AI's effect on interest spread

To examine the effect of AI on interest spread, we use the same loan-level SBA sample as the loan performance test and re-run Equation (3) with *Interest Spread* as the dependent variable. *Interest Spread* is the interest rate at loan origination minus the concurrent Treasury rate with the closest maturity (i.e., the risk-free rate). SBA sets a maximum rate of the prime rate plus 2.25% (2.75%) for loans with principal amount of more than $50,000 and maturity of less than seven years (seven years or more). The standard deviation of interest spread is 1.787% (Table 1, Panel C), representing meaningful variation in interest spreads in our sample despite SBA's ceilings.

Table 7 presents the regression results. Column (1) shows that banks with greater AI use charge higher interest rates on average, possibly reflecting a premium borrowers pay for ancillary benefits such as improved service quality or faster application processing (Fuster et al. 2019). In Column (2) where we include *AI* × *Ln*(*Distance*), we find that the coefficient on *AI* × *Ln*(*Distance*) is significantly positive, suggesting that banks with greater AI use charge significantly higher interest rates to distant borrowers. The results hold even after controlling for *Size* × *Ln*(*Distance*) in Column (3). The results are robust to clustering standard errors by bank or two-way clustering by bank and county (untabulated). These results are consistent with the notion that AI helps banks gain an informational advantage over non-AI rivals, allowing them to extract greater rent from creditworthy distant borrowers.

We follow the same discretization approach as in the loan performance analyses, dividing distance within each bank's portfolio into five bins. We replace *Ln(Distance)* with four binary indicators and interact each with *AI*. Figure 4 plots the resulting coefficients on the indicators and interactions. We find that while the *AI* × distance bin coefficients generally increase with lending distance, only the furthest bin interaction is significantly positive, consistent with AI enabling banks to extract greater rents primarily from the most distant creditworthy borrowers.

4.7. Robustness Tests

We conduct several tests regarding our main results. First, AI usage response options are based on explicit cutoffs in some survey years and subjective assessments in others. Although these categories capture meaningful variation in AI intensity, they may not be fully comparable across survey waves. To address this concern, we replace *AI* with two alternative binary measures, *AI (use/no)* and *AI (high/low)*, and re-estimate the credit supply, loan performance, and loan pricing tests. We report these results in Table 8, Panel A and show our inferences remain the same.

Second, we exclude ABS 2020 from the main analysis because its AI usage question differs substantially from those in all other survey years. To confirm that this exclusion does not affect our results, we re-estimate the loan performance and loan pricing tests including 2019 (ABS 2020), following Ando et al. (2025) in treating low AI use as no use in that year. Table 8, Panel B reports these results, which are qualitatively unchanged from the baseline. Note that we do not conduct this robustness test for the credit supply analysis, because 2019 (loans in 2020) is excluded regardless due to PPP loan contamination in the CRA dataset.

Third, unlike the CRA dataset, the SBA dataset does not include PPP loans, so we do not exclude the PPP period from the main analysis. Nevertheless, to rule out potential spillover effects

of PPP lending on conventional small business loans, we re-estimate the loan performance and loan pricing tests after excluding loans originated during the PPP period (April 3, 2020, to May 31, 2021). As reported in Table 8, Panel C, results are qualitatively unchanged.

5. Conclusion

Despite the growing importance of AI and abundant anecdotal evidence of its rapid adoption in U.S. banking, rigorous empirical evidence on its effects remains scarce. We fill this gap using confidential microdata from the Census Bureau's new technology survey. We document AI use rates across the U.S. banking industry and, in the context of small business lending, provide empirical evidence on how AI shapes banks' lending practices. Our evidence suggests that AI reduces banks' reliance on soft information, enabling them to lend more to distant borrowers, an effect we do not observe for other advanced technologies. Cross-sectional tests point to a specific mechanism: AI helps banks reach distant, credit-constrained small businesses.

Our loan performance and pricing analyses reveal two benefits of AI use for banks. First, AI does not lead banks to take on more risk; if anything, it lowers bank's risk by helping them identify creditworthy distant borrowers. Second, AI builds banks' informational advantage over rivals, enabling them to extract greater rent from distant borrowers. Taken together, these findings suggest that AI improves banks' overall assessment of borrower quality, reducing credit rationing for distant borrowers.

References

Acemoglu, D. 2025. The simple macroeconomics of AI*. *Economic Policy* 40 (121):13-58.

Acemoglu, D., G. W. Anderson, D. N. Beede, C. Buffington, E. E. Childress, E. Dinlersoz, L. S. Foster, N. Goldschlag, J. C. Haltiwanger, Z. Kroff, P. Restrepo, and N. Zolas. 2022. Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey. Cambridge, MA: National Bureau of Economic Research.

Adams, R. M., K. P. Brevoort, and J. C. Driscoll. 2023. Is lending distance really changing? Distance dynamics and loan composition in small business lending. *Journal of Banking & Finance* 156:107006.

Agarwal, S., and I. Ben-David. 2018. Loan prospecting and the loss of soft information. *Journal of Financial Economics* 129 (3):608-628.

Agarwal, S., and R. Hauswald. 2010. Distance and Private Information in Lending. *The Review of Financial Studies* 23 (7):2757-2788.

Aiken, L. S., and S. G. West. 1991. *Multiple regression: Testing and interpreting interactions*. Thousand Oaks, CA, US: Sage Publications, Inc.

Ando, Y., E. Dinlersoz, J. Greenwood, and R. Piazzesi. 2025. Technifying Ventures. *National Bureau of Economic Research Working Paper Series* No. 33993.

Babina, T. 2026. Understanding Firms' AI Efforts and Their Economic Impact. *National Bureau of Economic Research Working Paper Series* No. 35123.

Babina, T., A. Fedyk, A. He, and J. Hodson. 2024. Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics* 151:103745.

Barrios, J. M., J. L. Campbell, R. G. Johnson, and C. Liu. 2024. Signals or Smoke? The Determinants and Informativeness of Corporate Artificial Intelligence (AI) Disclosures: Social Science Research Network.

Baslandze, S., Z. Edwards, J. Graham, T. McClure, B. H. Meyer, M. Sparks, S. R. Waddell, and D. Weitz. 2026. Artificial Intelligence, Productivity, and the Workforce: Evidence from Corporate Executives. *National Bureau of Economic Research Working Paper Series* No. 34984.

Berger, A. N., W. S. Frame, and N. H. Miller. 2005. Credit Scoring and the Availability, Price, and Risk of Small Business Credit. *Journal of Money, Credit and Banking* 37 (2):191-222.

Bertomeu, J., Y. Lin, Y. Liu, and Z. Ni. 2025. The impact of generative AI on information processing: Evidence from the ban of ChatGPT in Italy. *Journal of Accounting and Economics* 80 (1):101782.

Beyhaghi, M., C. Fracassi, and G. Weitzner. 2026. Adverse Selection in Corporate Loan Markets. *The Journal of Finance* 81 (1):239-284.

Biz2X. *Understanding the Role of Artificial Intelligence in Lending* 2022 [cited. Available from https://www.biz2x.com/blog/understanding-the-role-of-artificial-intelligence-in-lending/.

Blanchflower, D. G., P. B. Levine, and D. J. Zimmerman. 2003. Discrimination in the Small-Business Credit Market. *The Review of Economics and Statistics* 85 (4):930-943.

Blankespoor, E., E. deHaan, and I. Marinovic. 2020. Disclosure Processing Costs, Investors' Information Choice, and Equity Market Outcomes: A Review. *Journal of Accounting and Economics* 70 (2-3):1-46.

Bowman, M. D. 2024. Speech by Governor Bowman on banking policy developments. *Board of Governors of the Federal Reserve System*.

Brown, J. D., and J. S. Earle. 2017. Finance and Growth at the Firm Level: Evidence from SBA Loans. *The Journal of Finance* 72 (3):1039-1080.

Brynjolfsson, E., D. Rock, and C. Syverson. 2019. Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. In *The Economics of Artificial Intelligence: An Agenda*: University of Chicago Press, 0.

Burks, J. J., D. W. Randolph, and J. A. Seida. 2019. Modeling and interpreting regressions with interactions. *Journal of Accounting Literature* 42 (1):61-79.

Business Wire. 2024. New Abrigo small business lending gives financial institutions automation and AI tech to grow their portfolios and communities.

Campbell, D., M. Loumioti, and R. Wittenberg-Moerman. 2019. Making sense of soft information: interpretation bias and loan quality. *Journal of Accounting and Economics* 68 (2):101240.

Cavalluzzo, K., and J. Wolken. 2005. Small Business Loan Turndowns, Personal Wealth, and Discrimination. *The Journal of Business* 78 (6):2153-2178.

Census Act, 13 U.S.C. § 224.

Challapally, A., C. Pease, R. Raskar, and P. Chari. 2025. The GenAI Divide: State of AI in Business 2025: MIT.

Chang, A. Y., X. I. Dong, X. Martin, and C. Zhou. 2026. AI Democratization and Trading Inequality. *Journal of Accounting Research* n/a (n/a).

Chen, W., J. K. Kang, and A. Mohan. 2025. Data-driven Technologies and Local Information Advantages in Small Business Lending. In *Harvard Business School Working Paper*: Harvard Business School.

Chen, W., and S. Srinivasan. 2024. Going digital: implications for firm value and performance. *Review of Accounting Studies* 29 (2):1619-1665.

Cortés, K. R., Y. Demyanyk, L. Li, E. Loutskina, and P. E. Strahan. 2020. Stress tests and small business lending. *Journal of Financial Economics* 136 (1):260-279.

Crosman, P. 2024. Bankwell Bank pilots generative AI in small-business lending. *American Banker*.

Dagostino, R. 2025. The impact of bank financing on municipalities' bond issuance and the real economy. *Journal of Financial Economics* 166:104022.

Demerjian, P. 2024. Financial statements vs. FinTech: A discussion of Minnis, Sutherland, and Vetter. *Journal of Accounting and Economics*:101716.

DeYoung, R., D. Glennon, and P. Nigro. 2008. Borrower–lender distance, credit scoring, and loan performance: Evidence from informational-opaque small business borrowers. *Journal of Financial Intermediation* 17 (1):113-143.

Di, W., and N. Pattison. 2023. Industry Specialization and Small Business Lending. *Journal of Banking & Finance* 149:106797.

Donelson, D. C., M. Kim, S. Kim, and M. A. Yip. 2025. Strategic AI Disclosures: Determinants and Consequences of Obfuscated and Overstated AI Investments: Social Science Research Network.

Dryer, T. 2018. How machine learning is quietly transforming small business lending. *Forbes*.

Ecker, F., X. Li, Y. Li, and F. A. N. Wu. 2026. How Stock Market Participants Use Generative Artificial Intelligence: Evidence from User-Platform Interaction Data. *Journal of Accounting Research* n/a (n/a).

Even-Tov, O., A. Su, and K. P. Wang. 2024. Do information processing costs matter to regulators? Evidence from the U.S. mortgage companies' supervision. *The Accounting Review* (Forthcoming).

Fairlie, R., A. Robb, and D. T. Robinson. 2021. Black and White: Access to Capital Among Minority-Owned Start-ups. *Management Science* 68 (4):2377-2400.

Federal Reserve Banks. 2022. 2022 Report on Employer Firms: Based on the 2021 Small Business Credit Survey.
Federal Reserve Board. 2020. CRA Consideration for Activities in Response to the Coronavirus Disease (COVID-19): Frequently Asked Questions (FAQs). In *Consumer Affairs (CA) Letter 20-10*. Washington, D.C.: Federal Reserve Board.
Fuster, A., P. Goldsmith-Pinkham, T. Ramadorai, and A. Walther. 2022. Predictably Unequal? The Effects of Machine Learning on Credit Markets. *The Journal of Finance* 77 (1):5-47.
Fuster, A., M. Plosser, P. Schnabl, and J. Vickery. 2019. The Role of Technology in Mortgage Lending. *The Review of Financial Studies* 32 (5):1854-1899.
Gallo, L., E. Labro, and J. Omartian. 2023. Overreliance on Data in Forecasting. *Working Paper*.
Gargano, F. 2024. Citi streamlines commercial lending with the help of AI. *American Banker*.
Glennon, D., and P. Nigro. 2005. Measuring the Default Risk of Small Business Loans: A Survival Analysis Approach. *Journal of Money, Credit and Banking* 37 (5):923-947.
Government Accountability Office. 2021. Mortgage Lending: Use of Alternative Data Is Limited but Has Potential Benefits. Washington, D.C.: U.S. Government Accountability Office.
Granja, J., and C. Leuz. 2024. The death of a regulator: Strict supervision, bank lending, and business activity. *Journal of Financial Economics* 158:103871.
Granja, J., C. Leuz, and R. G. Rajan. 2022a. Going the Extra Mile: Distant Lending and Credit Cycles. *The Journal of Finance* 77 (2):1259-1324.
Granja, J., C. Makridis, C. Yannelis, and E. Zwick. 2022b. Did the paycheck protection program hit the target? *Journal of Financial Economics* 145 (3):725-761.
He, Z., J. Huang, and C. Parlatore. 2024. Information Span and Credit Market Competition. *National Bureau of Economic Research Working Paper Series* No. 33141.
Huang, R. 2024. The Financial Consequences of Online Review Aggregators: Evidence from Yelp Ratings and SBA Loans. *Management Science* 71 (1):59-82.
Idzelis, C. 2021. Bank of America Adopts AI, Finds More Significant Credit Stresses From Covid-19. *Institutional Investor*.
Jia, N., N. Li, G. Ma, and D. Xu. 2024. Corporate Responses to Generative AI: Early Evidence from Conference Calls. *Working Paper*.
Jiang, E. X., G. Y. Yu, and J. Zhang. 2026. Bank Competition Amid Digital Disruption: Implications for Financial Inclusion. *Journal of Finance*.
Kelley, L. 2026. Did A.I. Take Your Job? Or Was Your Employer 'A.I.-Washing'? *The New York Times*, 2026/02/01.
Kielty, P. D., K. P. Wang, and D. L. Weng. 2023. Simplifying Complex Disclosures: Evidence from Disclosure Regulation in the Mortgage Markets. *The Accounting Review* 98 (4):191-216.
Koont, N. 2025. How Does the Digital Revolution Alter Competition in Banking? New York: Columbia University / SSRN.
Lau, A. *How A Community Bank Simplified Small Business Lending with Open Banking Innovation* 2024 [cited. Available from https://www.geekwire.com/sponsor-post/how-a-community-bank-simplified-small-business-lending-with-open-banking-innovation/.
Liberti, J. M., and M. A. Petersen. 2019. Information: Hard and Soft. *The Review of Corporate Finance Studies* 8 (1):1-41.
Liu, M. 2022. Assessing Human Information Processing in Lending Decisions: A Machine Learning Approach. *Journal of Accounting Research* 60 (2):607-651.

McElheran, K., J. F. Li, E. Brynjolfsson, Z. Kroff, E. Dinlersoz, L. Foster, and N. Zolas. 2024. AI adoption in America: Who, what, and where. *Journal of Economics & Management Strategy* 33 (2):375-415.

McKinsey. 2021. Building the AI bank of the future.

Minnis, M. 2011. The Value of Financial Statement Verification in Debt Financing: Evidence from Private U.S. Firms. *Journal of Accounting Research* 49 (2):457-506.

Moody's. *Machine learning: Challenges, lessons, and opportunities in credit risk modeling* 2017 [cited. Available from https://www.moodys.com/web/en/us/insights/credit-risk/machine-learning-challenges-lessons-and-opportunities-in-credit-risk-modeling.html.

Nguyen, L. 2022. Banks Tiptoe Toward Their Cloud-Based Future. *New York Times*.

Pathe, T. 2024. Rich Data Co Inks First US Deal for AI Decisioning Platform with M&T Bank. *FinTech Futures*, 2024/05/29.

Petersen, M. A., and R. G. Rajan. 2002. Does Distance Still Matter? The Information Revolution in Small Business Lending. *The Journal of Finance* 57 (6):2533-2570.

SBA. *Basic requirements for federal contracting* 2026 [cited. Available from https://www.sba.gov/federal-contracting/contracting-guide/basic-requirements.

Seamans, R., and M. Raj. 2018. Artificial Intelligence, Labor, Productivity, and the Need for Firm-Level Data. In *The Economics of Artificial Intelligence: An Agenda*: National Bureau of Economic Research, Inc, 553-565.

Son, H. *JPMorgan Software Does in Seconds What Took Lawyers 360,000 Hours* 2017 [cited. Available from https://www.bloomberg.com/news/articles/2017-02-28/jpmorgan-marshals-an-army-of-developers-to-automate-high-finance.

U.S. Department of the Treasury. 2024. Managing Artificial Intelligence-Specific Cybersecurity Risks in the Financial Services Sector. Washington, D.C.: U.S. Department of the Treasury.

Vashishtha, R. 2019. Discussion of "Making sense of soft information: Interpretation bias and loan quality". *Journal of Accounting and Economics* 68 (2):101239.

Zolas, N., Z. Kroff, E. Brynjolfsson, K. McElheran, D. N. Beede, C. Buffington, N. Goldschlag, L. Foster, and E. Dinlersoz. 2020. Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey. *National Bureau of Economic Research Working Paper Series* No. 28290.

Appendix A
Variable Definitions

Variable	Definition
Ln(*SBL*)	Natural logarithm of the total dollar amount (in thousands) of small business loans by bank *i* in county *c* in year *t*+1.
Ln(*Distance*)	Natural logarithm of the geodetic distance between the centroid of the borrowers' county (address) and the bank's closest branch for CRA (SBA).
AI	Level of AI use; 0 for no use or testing, 1 for low use, 2 for moderate use, and 3 for high use.
Size	Natural logarithm of total assets (in $10 million).
ROA	Net income divided by total assets.
Leverage	Total liabilities divided by total assets.
Loans	Total loans divided by total assets.
Public	= 1 if the bank is publicly traded, 0 otherwise.
Liquid Assets	Sum of cash, federal funds sold, and securities purchased under agreements to resell, scaled by total assets.
Securities	Sum of held-to-maturity and available-for-sale securities, scaled by total assets.
Residential Loans	Loans secured by residential properties, scaled by total loans.
Commercial Loans	Commercial and industrial loans, scaled by total loans.
Nonperforming Loans	Sum of loans past due more than 90 days and nonaccrual loans, scaled by total loans.
Derivatives	Derivative assets minus derivative liabilities, scaled by total assets.
Deposits	Deposits divided by total liabilities.
Remote Specialist	= 1 if the bank's median borrower-lender distance exceeds 100 miles and its top-five industry share exceeds 32%, 0 otherwise (Di and Pattison 2023). We use all non-canceled SBA loans approved between 2010 and 2024 for this classification.
Loan Amount	Natural logarithm of the loan's principal amount (in thousands).
Maturity	Length of loan term (in months).
Guaranteed	Amount of the loan guaranteed by SBA divided by loan amount.
Interest Spread	Interest rate at loan origination minus the concurrent Treasury rate with the closest maturity (in percentage).
ChargeOff	Amount charged off within two years of origination scaled by loan amount (in percentage).
Δ*GDP*	Percentage change in real GDP from year *t* to *t*+1.

Appendix B
Survey Questions on the Use of AI and Other Technologies

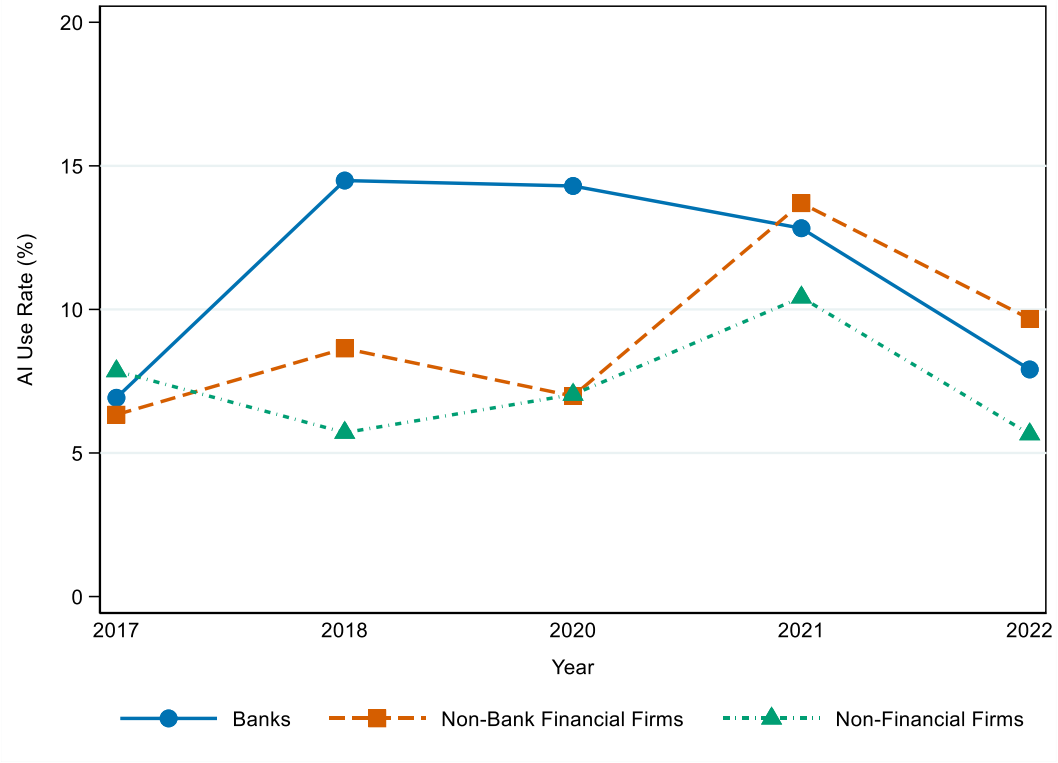
Following Zolas et al. (2020) and McElheran et al. (2024), we define AI as machine learning, natural language processing, and machine vision in 2017 (ABS 2018) and 2020 (ABS 2021), the only years when AI was not directly surveyed. Because there are multiple technologies in ABS 2018 and 2021, we define AI use based on the highest level of usage among them. We code AI usage as follows:

Reference Year	ABS	0 (no use or testing)	1 (low use)	2 (moderate use)	3 (high use)
2017	2018	"No use" or "Testing but not using in production or service"	"In use for less than 5% of production or service"	"In use for between 5% and 25% of production or service"	"In use for more than 25% of production or service"
2018	2019	"Did not use" or "Tested, but did not use in production or service"	"Low use"	"Moderate use"	"High use"
2020	2021	"Not in use nor testing" or "In testing, but not in use"		"In use"	
2021	2022	"Not at all"	"A little"	"Somewhat"	"A lot"
2022	2023	"This technology is not applicable to this business," "Applicable, but did not test or use," or "Tested, but did not use as part of the processes or methods"	"Used as part of the processes or methods" and "Not important"	"Used as part of the processes or methods" and "Somewhat important"	"Used as part of the processes or methods" and "Very important"

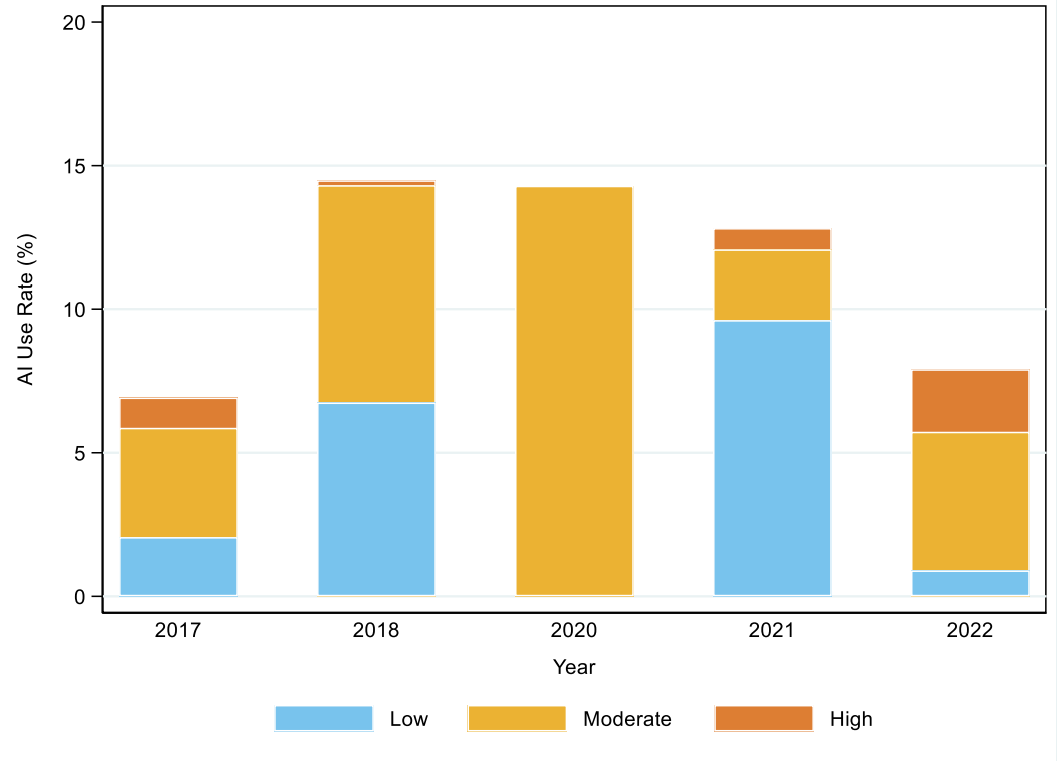
We define other technologies' variables (*Cloud*, *Other Software*, and *Hardware*) following the same procedure. When multiple technologies are involved, we define the variable based on the highest level of usage among them.

Figure 1
AI Use

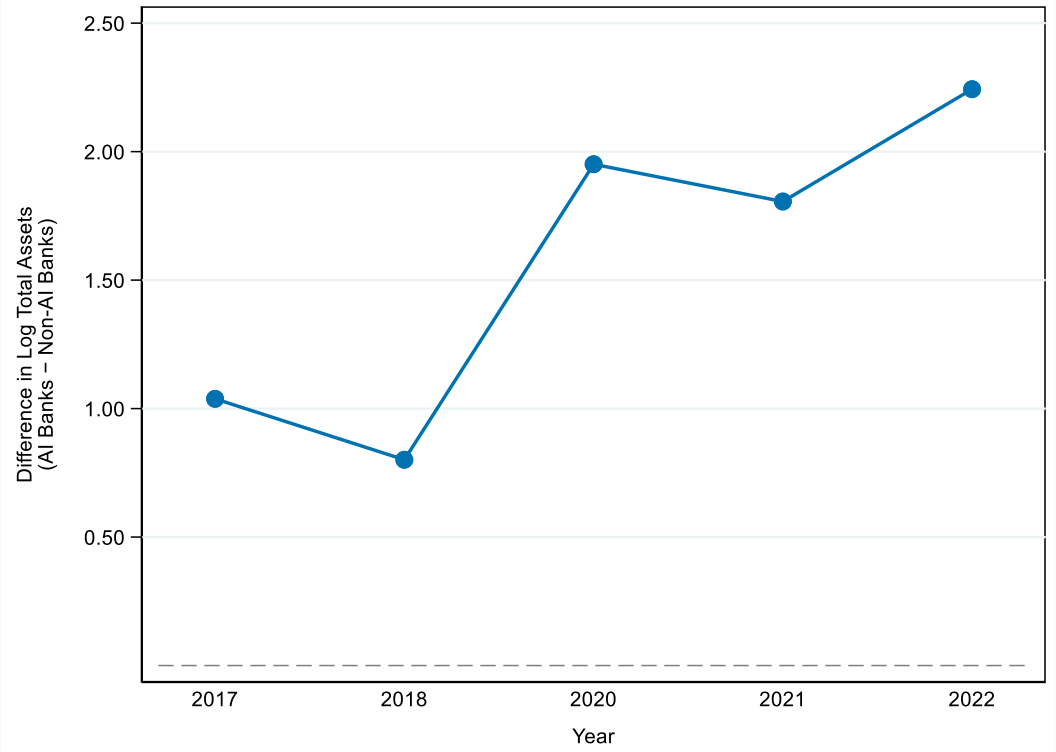
Panel A: AI use rate by industry



Panel B: Banks' AI use by intensity

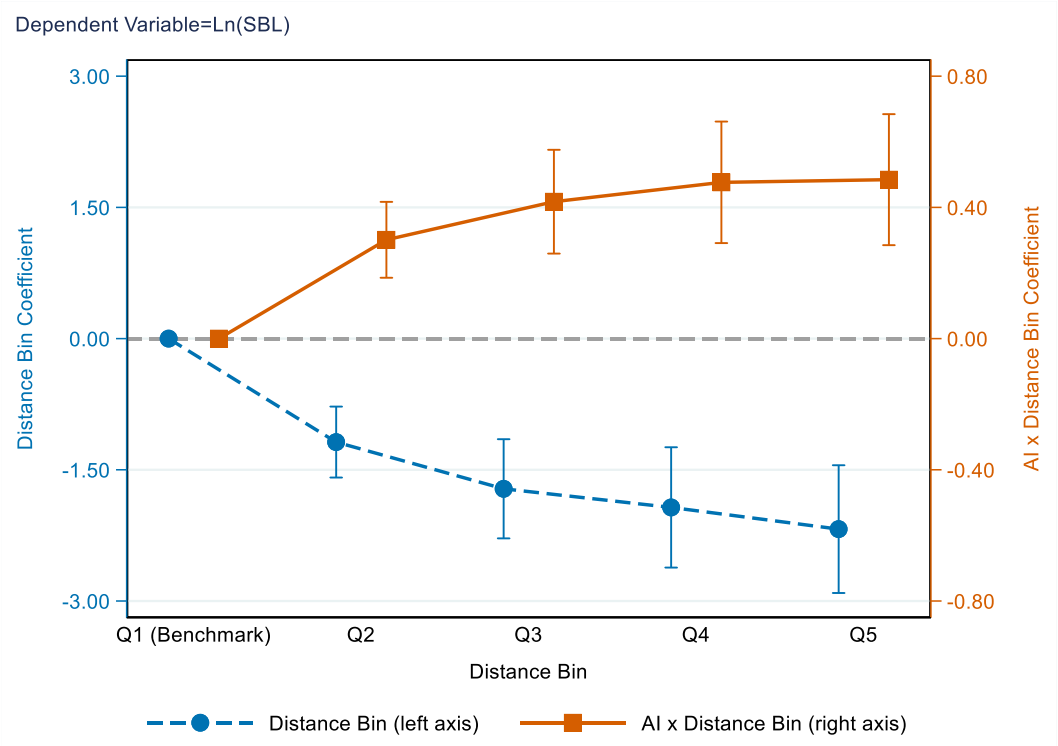


Panel C: Bank Size of AI users versus non-AI users



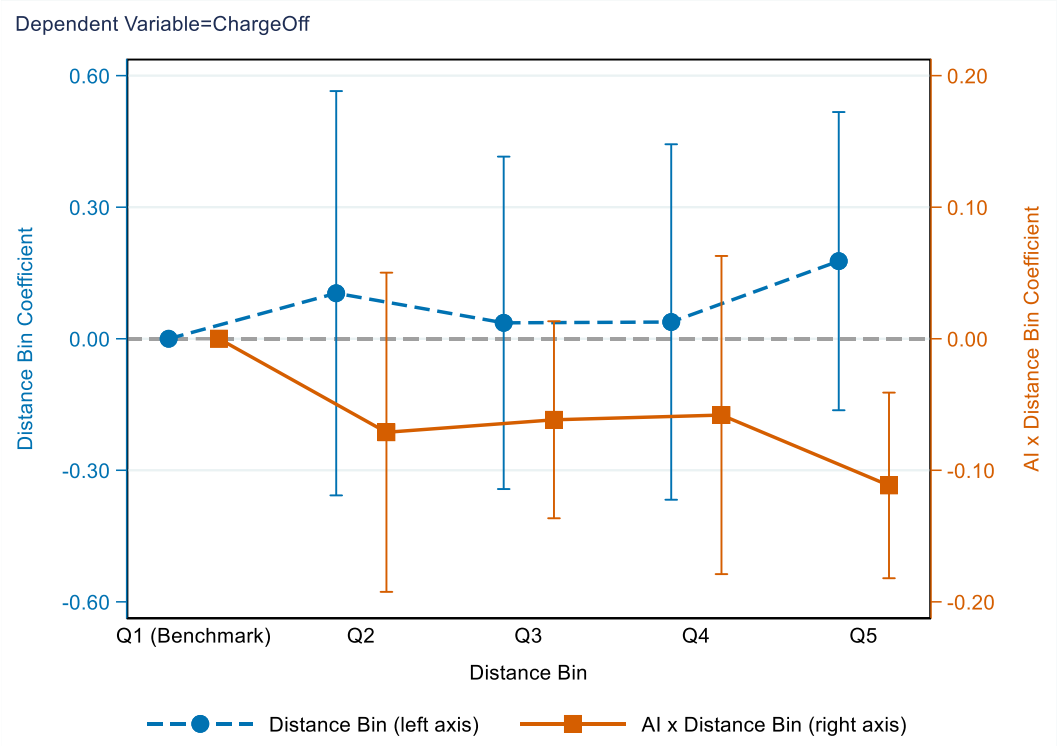
Notes: Figure 1, Panel A, plots the share of AI users for U.S. banks, size-adjusted U.S. non-bank financial firms, and size-adjusted U.S. non-financial firms. To make our bank statistics representative of the U.S. bank population and to account for sampling differences across years, we weight observations according to bank size following recent studies using the same survey (e.g., Ando et al. 2025; Acemoglu et al. 2022). Because non-bank financial and non-financial firms are on average smaller than banks, raw differences in AI use rates may partly reflect size effects rather than industry differences. We therefore reweight both groups according to firm size to match the size distribution of the banking industry. Panel B plots the share of banks by AI intensity across time. Note that ABS 2021 (AI use in 2020) only asks whether AI technologies are in use, without distinguishing intensity levels, so we code all positive responses as "moderate" (this year is excluded in the credit supply tests due to PPP loans). Panel C plots the annual difference in log average total assets between banks with and without AI use.

Figure 2
AI Use and Credit Supply by Distance



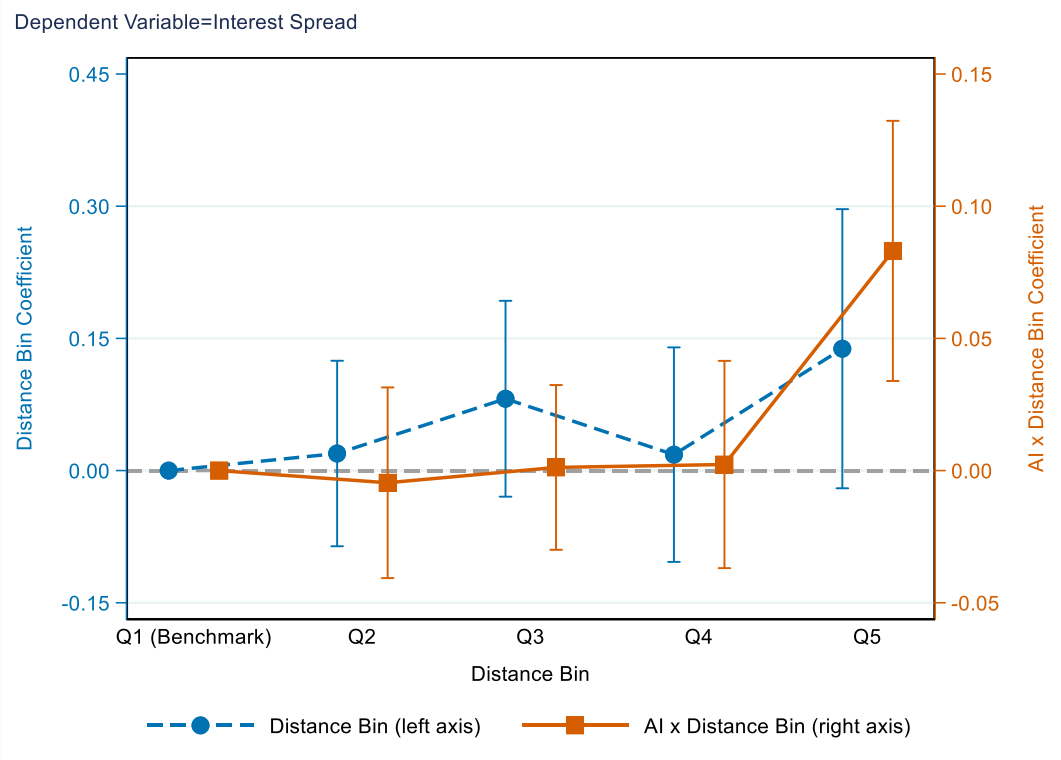
Notes: Figure 2 plots the estimated coefficients and 95% confidence intervals on the distance bin indicators and their interactions with *AI*. Specifically, we discretize bank-borrower distance within each bank's portfolio into five quintile bins, replacing *Ln(Distance)* and *Ln(Distance)* × *AI* with four distance bin indicators and their interactions with *AI*, using the closest distance bin as the omitted category, and re-estimate Equation (2). The solid orange line plots coefficients on the *AI* × distance bin interactions and the dashed blue line plots coefficients on the distance bin indicators. Because the two sets of coefficients are not directly comparable in magnitude, we use two y-axes: The right y-axis corresponds to the *AI* × distance bin interactions, and the left y-axis corresponds to the distance bin indicators.

Figure 3
AI Use and Loan Performance by Distance



Notes: Figure 3 plots the estimated coefficients and 95% confidence intervals on the distance bin indicators and their interactions with *AI*. Specifically, we discretize bank-borrower distance within each bank's portfolio into five quintile bins, replacing *Ln(Distance)* and *Ln(Distance)* × *AI* with four distance bin indicators and their interactions with *AI*, using the closest distance bin as the omitted category, and re-estimate Equation (3) with *ChargeOff* as the dependent variable. The solid orange line plots coefficients on the *AI* × distance bin interactions and the dashed blue line plots coefficients on the distance bin indicators. Because the two sets of coefficients are not directly comparable in magnitude, we use two y-axes: The right y-axis corresponds to the *AI* × distance bin interactions, and the left y-axis corresponds to the distance bin indicators.

Figure 4
AI Use and Loan Pricing by Distance



Notes: Figure 4 plots the estimated coefficients and 95% confidence intervals on the distance bin indicators and their interactions with *AI*. Specifically, we discretize bank-borrower distance within each bank's portfolio into five quintile bins, replacing *Ln(Distance)* and *Ln(Distance)* × *AI* with four distance bin indicators and their interactions with *AI*, using the closest distance bin as the omitted category, and re-estimate Equation (3) with *Interest Spread* as the dependent variable. The solid orange line plots coefficients on the *AI* × distance bin interactions and the dashed blue line plots coefficients on the distance bin indicators. Because the two sets of coefficients are not directly comparable in magnitude, we use two y-axes: The right y-axis corresponds to the *AI* × distance bin interactions, and the left y-axis corresponds to the distance bin indicators.

Table 1
Descriptive Statistics

Panel A: Determinants analyses

	Mean	S.D.
AI	0.194	0.580
Total Assets (in $10 million)	0.224	1.338
ROA	0.013	0.013
Leverage	0.835	0.203
Loans	0.594	0.216
Public	0.187	0.390
Liquid Assets	0.144	0.176
Securities	0.211	0.157
Residential Loans	0.408	0.221
Commercial Loans	0.132	0.123
Nonperforming Loans	0.008	0.011
Derivatives	0.000	0.001
Deposits	0.896	0.223
Remote Specialist	0.005	0.072

Panel B: Loan volume analyses

	Mean	S.D.
SBL (in thousands)	1,491	4,177
AI	0.791	1.019
Distance	414.0	496.6

Panel C: Loan performance and pricing analyses

	Mean	S.D.
ChargeOff (in %)	0.233	4.647
Interest Spread (in %)	4.788	1.787
AI	0.679	1.048
Distance	162.7	425.8
Loan Amount (in thousands)	440.3	748.7
Maturity	130.2	69.7
Guaranteed	0.653	0.150

Notes: Table 1 presents descriptive statistics for the variables used in our analyses. Panel A reports bank-year-level variables from the determinants analyses, Panel B reports bank-county-year-level variables from the credit supply analyses, and Panel C reports loan-level variables from the loan performance and pricing analyses. See Appendix A for variable definitions.

Table 2
Determinants of Banks' Use of AI

Dependent variable = *AI*	(1) Pooled	(2) 2017	(3) 2018	(4) 2020	(5) 2021	(6) 2022
Size	0.069***	0.030	0.073***	0.116***	0.055**	0.085***
	(0.012)	(0.019)	(0.022)	(0.030)	(0.023)	(0.020)
ROA	-0.834	n.s.	n.s.	n.s.	n.s.	n.s.
	(2.544)					
Leverage	-0.283	-*	n.s.	n.s.	n.s.	n.s.
	(0.365)					
Loans	-0.195	n.s.	n.s.	n.s.	-**	n.s.
	(0.660)					
Public	-0.006	n.s.	n.s.	+**	n.s.	n.s.
	(0.061)					
Liquid Assets	-0.243	n.s.	n.s.	n.s.	-**	n.s.
	(0.572)					
Securities	-0.255	n.s.	n.s.	n.s.	-**	n.s.
	(0.692)					
Residential Loans	-0.035	n.s.	+**	n.s.	-**	n.s.
	(0.089)					
Commercial Loans	-0.133	n.s.	-**	n.s.	n.s.	n.s.
	(0.133)					
Nonperforming Loans	-0.334	n.s.	n.s.	n.s.	n.s.	n.s.
	(1.396)					
Derivatives	22.26	n.s.	n.s.	n.s.	n.s.	n.s.
	(31.04)					
Deposits	-0.305	+*	n.s.	-**	n.s.	n.s.
	(0.246)					
Remote Specialist	-0.024	n.s.	n.s.	-***	-**	n.s.
	(0.108)					
Year FEs	✓					
Adj. R^2	0.07					
Observations (rounded)	2,600	750	350	300	400	850

Notes: Table 2 presents the regression results of estimating the determinants of banks' AI use. *AI* is banks' level of AI use in year *t*, with 0 as no use or testing, 1 as low use, 2 as moderate use, and 3 as high use. For Census Bureau disclosure avoidance purposes, we round the number of observations. Other than *Size*, we report only the signs and significance levels for the year-by-year determinants model due to Census disclosure avoidance concerns. See Appendix A for variable definitions. Standard errors are clustered by bank and reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 3
The Effect of AI Use on Credit Supply

Dependent variable = *Ln*(*SBL*)	(1)	(2)	(3)
AI* × *Ln(Distance)		**0.078*** **	**0.050*** **
		(0.022)	**(0.019)**
Ln(Distance)	-0.512***	-0.663***	-0.709***
	(0.106)	(0.100)	(0.098)
AI	-0.006	-0.367***	-0.237***
	(0.039)	(0.105)	(0.090)
Size × *Ln(Distance)*			✓
Δ*GDP* × *Ln(Distance)*	✓	✓	✓
Bank Controls	✓	✓	✓
Bank FEs	✓	✓	✓
County × Year FEs	✓	✓	✓
Adj. R^2	0.59	0.59	0.60
Observations (rounded)	180,000	180,000	180,000

Notes: Table 3 presents the regression results of estimating the effect of banks' AI use on the quantity of small business loans. The dependent variable, *Ln*(*SBL*), is the natural logarithm of the total dollar amount (in thousands) of small business loans originated by a bank in a county during year t+1. *AI* is banks' level of AI use in year t, with 0 as no use or testing, 1 as low use, 2 as moderate use, and 3 as high use. *Ln*(*Distance*) is the geodetic distance between the centroid of the county and the bank's nearest branch. For Census Bureau disclosure avoidance purposes, we round the number of observations and do not tabulate bank controls, which include all bank characteristics in Table 2. See Appendix A for variable definitions. Standard errors are clustered by bank-year and reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 4
The Effects of Non-AI Technologies on Credit Supply

Dependent variable = *Ln*(*SBL*)	(1)	(2)	(3)
Cloud* × *Ln(Distance)	**0.011**		
	(0.013)		
Other Software* × *Ln(Distance)		**-0.004**	
		(0.013)	
Hardware* × *Ln(Distance)			**-0.025**
			(0.015)
Cloud	✓		
Other Software		✓	
Hardware			✓
Ln(Distance)	✓	✓	✓
Size × *Ln(Distance)*	✓	✓	✓
Δ*GDP* × *Ln(Distance)*	✓	✓	✓
Bank Controls	✓	✓	✓
Bank FEs	✓	✓	✓
County × Year FEs	✓	✓	✓
Adj. R^2	0.61	0.59	0.59
Observations (rounded)	175,000	176,000	172,000

Notes: Table 4 presents the regression results of estimating the effect of banks' use of alternative advanced technologies on small business lending to distant borrowers. We focus on three technology categories: cloud computing, other (non-AI) software, and hardware. The dependent variable, *Ln*(*SBL*), is the natural logarithm of the total dollar amount (in thousands) of small business loans originated by a bank in a county during year *t*+1. *Cloud*, *Other Software*, and *Hardware* measure a bank's level of use of each respective technology in year *t*, coded consistently with *AI*: 0 (no use or testing), 1 (low use), 2 (moderate use), and 3 (high use). *Ln*(*Distance*) is the geodetic distance between the centroid of a county and a bank's nearest branch. For Census Bureau disclosure avoidance purposes, we round the number of observations and only tabulate the interaction term of interest. All other controls and fixed effects follow Table 3. See Appendix A for variable definitions. Standard errors are clustered by bank-year and reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 5
The Mechanism

Panel A: Small Businesses with Unmet Credit Demand

Dependent variable = *Ln*(*SBL*)	(1)	(2)
AI × *Ln(Distance)*	0.059***	0.038*
	(0.019)	(0.020)
Test of coefficient difference	χ^2 = **5.44****	
AI	✓	✓
Ln(Distance)	✓	✓
Δ*GDP* × *Ln(Distance)*	✓	✓
Size × *Ln(Distance)*	✓	✓
Bank Controls	✓	✓
Bank FEs	✓	✓
County × Year FEs	✓	✓
Partition	More credit constrained	Less credit constrained
Adj. R^2	0.62	0.57
Observations (rounded)	82,500	83,000

Panel B: Minority-owned Small Businesses

Dependent variable = *Ln*(*SBL*)	(1)	(2)
AI × *Ln(Distance)*	0.064***	0.039*
	(0.019)	(0.023)
Test of coefficient difference	χ^2 = **4.95****	
AI	✓	✓
Ln(Distance)	✓	✓
Δ*GDP* × *Ln(Distance)*	✓	✓
Size × *Ln(Distance)*	✓	✓
Bank Controls	✓	✓
Bank FEs	✓	✓
County × Year FEs	✓	✓
Partition	More minority-owned	Less minority-owned
Adj. R^2	0.62	0.57
Observations (rounded)	89,500	90,000

Notes: Table 5 presents cross-sectional analyses of the credit supply tests. The dependent variable, *Ln*(*SBL*), is the natural logarithm of the total dollar amount (in thousands) of small business loans originated by a bank in a county during year *t*+1. *AI* is banks' level of AI use in year *t*, with 0 as no use or testing, 1 as low use, 2 as moderate use, and 3 as high use. *Ln*(*Distance*) is the geodetic distance between the centroid of the county and the bank's nearest branch. Panel A partitions the sample at the median percentage of county-level small businesses with unmet credit needs and reports above-median results in Column (1) and below in Column (2). Panel B partitions the sample at the median percentage of county-level minority-owned small businesses and reports above-median results in Column (1) and below in Column (2). For Census Bureau disclosure avoidance purposes, we round the number of observations and only tabulate the interaction term of interest. All other controls and fixed effects follow Table 3. See Appendix A for variable definitions. Standard errors are clustered by bank-year and reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 6
The Effect of AI Use on Loan Performance

Dependent variable = *ChargeOff*	(1)	(2)	(3)
AI* × *Ln(Distance)		**-0.019*** **	**-0.027*** **
		(0.006)	**(0.008)**
Ln(Distance)	0.015	0.033*	0.033*
	(0.018)	(0.019)	(0.019)
AI	0.042	0.088**	0.103***
	(0.037)	(0.038)	(0.038)
Size × *Ln(Distance)*			✓
Δ*GDP* × *Ln(Distance)*	✓	✓	✓
Bank Controls	✓	✓	✓
Loan Controls	✓	✓	✓
Borrower Industry FEs	✓	✓	✓
SBA Program FEs	✓	✓	✓
Bank FEs	✓	✓	✓
County × Year FEs	✓	✓	✓
Adj. R^2	< 0.01	< 0.01	< 0.01
Observations (rounded)	69,500	69,500	69,500

Notes: Table 6 presents the regression results of estimating the effect of banks' AI use on loan performance. The dependent variable, *ChargeOff*, is the amount that has been charged off scaled by the loan amount. *AI* is banks' level of AI use in year *t*, with 0 as no use or testing, 1 as low use, 2 as moderate use, and 3 as high use. *Ln*(*Distance*) is the geodetic distance between the borrower's address and the bank's nearest branch. We include all bank characteristics in Table 2 along with additional loan-level controls including *Loan Amount*, *Maturity*, and *Guaranteed.* For Census Bureau disclosure avoidance purposes, we do not tabulate the coefficients on these control variables and round the number of observations. We include borrower industry fixed effects using 3-digit NAICS code and SBA program fixed effects. See Appendix A for variable definitions. Standard errors are clustered by bank-year and reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 7
The Effect of AI Use on Loan Pricing

Dependent variable = *Interest Spread*	(1)	(2)	(3)
AI × Ln(Distance)		**0.021*** **	**0.021*** **
		(0.006)	**(0.007)**
Ln(Distance)	0.059***	0.040***	0.040***
	(0.014)	(0.014)	(0.014)
AI	0.129***	0.080*	0.079*
	(0.037)	(0.042)	(0.043)
Size × Ln(Distance)			✓
ΔGDP × Ln(Distance)	✓	✓	✓
Bank Controls	✓	✓	✓
Loan Controls	✓	✓	✓
Borrower Industry FEs	✓	✓	✓
SBA Program FEs	✓	✓	✓
Bank FEs	✓	✓	✓
County × Year FEs	✓	✓	✓
Adj. R^2	0.67	0.67	0.67
Observations (rounded)	69,500	69,500	69,500

Notes: Table 7 presents the regression results of estimating the effect of banks' AI use on loan pricing. The dependent variable, *Interest Spread*, is the interest rate at loan origination minus the concurrent Treasury rate with the closest maturity (i.e., the risk-free rate). *AI* is banks' level of AI use in year *t*, with 0 as no use or testing, 1 as low use, 2 as moderate use, and 3 as high use. *Ln*(*Distance*) is the geodetic distance between the borrower's address and the bank's nearest branch. We include all bank characteristics in Table 2 along with additional loan-level controls including *Loan Amount*, *Maturity*, and *Guaranteed.* For Census Bureau disclosure avoidance purposes, we do not tabulate the coefficients on these control variables and round the number of observations. We include borrower industry fixed effects using 3-digit NAICS code and SBA program fixed effects. See Appendix A for detailed variable definitions. Standard errors are clustered by bank-year and reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 8
Robustness Tests

Panel A: Alternative AI measures

Dependent variable =	*Ln*(*SBL*)		*ChargeOff*		*Interest Spread*	
	(1)	(2)	(3)	(4)	(5)	(6)
AI (use/no) × Ln(Distance)	**0.068***		**-0.050*****		**0.036****	
	(0.036)		**(0.018)**		**(0.014)**	
AI (high/low) × Ln(Distance)		**0.112****		**-0.068*****		**0.049*****
		(0.047)		**(0.023)**		**(0.016)**
AI (use/no)	✓		✓		✓	
AI (high/low)		✓		✓		✓
Ln(Distance)	✓	✓	✓	✓	✓	✓
ΔGDP × Ln(Distance)	✓	✓	✓	✓	✓	✓
Size × Ln(Distance)	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
Loan Controls			✓	✓	✓	✓
Borrower Industry FEs			✓	✓	✓	✓
SBA Program FEs			✓	✓	✓	✓
Bank FEs	✓	✓	✓	✓	✓	✓
County × Year FEs	✓	✓	✓	✓	✓	✓
Adj. R^2	0.60	0.60	< 0.01	< 0.01	0.67	0.67
Observations (rounded)	180,000	180,000	69,500	69,500	69,500	69,500

Panel B: Include ABS 2020

	(1)	(2)
Dependent variable =	*ChargeOff*	*Interest Spread*
AI × Ln(Distance)	**-0.024*** **	**0.018*** **
	(0.008)	**(0.006)**
AI	✓	✓
Ln(Distance)	✓	✓
ΔGDP × Ln(Distance)	✓	✓
Size × Ln(Distance)	✓	✓
Bank Controls	✓	✓
Loan Controls	✓	✓
Borrower Industry FEs	✓	✓
SBA Program FEs	✓	✓
Bank FEs	✓	✓
County × Year FEs	✓	✓
Adj. R^2	< 0.01	0.66
Observations (rounded)	84,000	84,000

Panel C: Exclude Loans During PPP Period

	(1)	(2)
Dependent variable =	*ChargeOff*	*Interest Spread*
AI × Ln(Distance)	**-0.029*** **	**0.020*** **
	(0.008)	**(0.007)**
AI	✓	✓
Ln(Distance)	✓	✓
ΔGDP × Ln(Distance)	✓	✓
Size × Ln(Distance)	✓	✓
Bank Controls	✓	✓
Loan Controls	✓	✓
Borrower Industry FEs	✓	✓
SBA Program FEs	✓	✓
Bank FEs	✓	✓
County × Year FEs	✓	✓
Adj. R^2	< 0.01	0.68
Observations (rounded)	63,500	63,500

Notes: Table 8 presents the results of robustness tests. *Ln*(*SBL*) is the natural logarithm of the total dollar amount (in thousands) of small business loans originated by a bank in a county during year *t*+1. *ChargeOff* is the amount of the small business loan that has been charged off scaled by the loan amount. *Interest Spread* is the interest rate at loan origination minus the concurrent Treasury rate with the closest maturity (i.e., the risk-free rate). When the dependent variable is *Ln(SBL)*, *Ln*(*Distance*) is the geodetic distance between the centroid of the county and the bank's nearest branch. When the dependent variable is *ChargeOff* or *Interest Spread*, *Ln*(*Distance*) is the geodetic distance between the borrower's address and the bank's nearest branch. Panel A re-estimates the credit supply, loan performance, and loan pricing analyses using two alternative measures of banks' AI use. *AI (use/no)* is one if the bank reports low, moderate, or high AI use, and zero for no use or testing. *AI (high/low)* is one if the bank reports moderate or high AI use, and zero for no use, testing, or low use. Panel B re-estimates the loan performance and pricing analyses by including ABS 2020.

Following Ando et al. (2025), we adjust banks' AI use by coding low use as 0 in 2019. Panel C re-estimates the loan performance and pricing analyses by excluding small business loans originated during the Paycheck Protection Program period (i.e., April 3, 2020, to May 31, 2021). For Census Bureau disclosure avoidance purposes, we round the number of observations and only tabulate the interaction term of interest. See Appendix A for variable definitions. Standard errors are clustered by bank-year and reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Online Appendix A1
Determinants of Banks' AI Use Using Alternative AI Measures

Panel A: AI (use/no)

Dependent variable = *AI (use/no)*	(1) Pooled	(2) 2017	(3) 2018	(4) 2020	(5) 2021	(6) 2022
Size	+***	n.s.	+***	+***	+***	+***
ROA	n.s.	-**	n.s.	n.s.	n.s.	n.s.
Leverage	n.s.	n.s.	n.s.	n.s.	n.s.	-**
Loans	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Public	n.s.	n.s.	n.s.	+**	n.s.	n.s.
Liquid Assets	n.s.	n.s.	n.s.	n.s.	-**	n.s.
Securities	n.s.	n.s.	n.s.	n.s.	-*	n.s.
Residential Loans	n.s.	n.s.	+**	n.s.	n.s.	n.s.
Commercial Loans	n.s.	n.s.	-*	n.s.	n.s.	n.s.
Nonperforming Loans	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Derivatives	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Deposits	n.s.	n.s.	n.s.	-**	n.s.	n.s.
Remote Specialist	n.s.	✓	✓	✓	✓	✓
Year FEs	✓					
Observations (rounded)	2,600	750	350	300	400	850

Panel B: AI (high/low)

Dependent variable = *AI (high/low)*	(1) Pooled	(2) 2017	(3) 2018	(4) 2020	(5) 2021	(6) 2022
Size	+***	+*	+*	+***	n.s.	+***
ROA	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Leverage	n.s.	-**	n.s.	n.s.	+**	-**
Loans	n.s.	n.s.	n.s.	n.s.	-**	n.s.
Public	n.s.	n.s.	n.s.	+**	-**	n.s.
Liquid Assets	n.s.	n.s.	n.s.	n.s.	-**	n.s.
Securities	n.s.	n.s.	n.s.	n.s.	-**	n.s.
Residential Loans	n.s.	n.s.	n.s.	n.s.	-*	n.s.
Commercial Loans	n.s.	n.s.	-***	n.s.	n.s.	n.s.
Nonperforming Loans	n.s.	n.s.	-*	n.s.	n.s.	n.s.
Derivatives	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Deposits	n.s.	+**	n.s.	-**	n.s.	n.s.
Remote Specialist	✓	✓	✓	✓	✓	✓
Year FEs	✓					
Observations (rounded)	2,600	750	350	300	400	850

Notes: This table presents the determinants analyses using alternative measures of AI use. *AI (use/no)* is one if the bank reports low, moderate, or high use of AI, and zero for no use or testing. *AI (high/low)* is one if the bank reports moderate or high use of AI, and zero for no use, testing, or low use. For Census Bureau disclosure avoidance purposes, we round the number of observations and cannot report *Remote Specialist*. See Appendix A for variable definitions. Standard errors are clustered by bank and reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.