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Investing in Lending Technology: IT Spending in Banking

Zhiguo He,[a,b,*] Sheila Jiang,[c] Douglas Xu,[c] Xiao Yin[d,e]

[a] Graduate School of Business, Stanford University, Stanford, California 94305; [b] NBER, Cambridge, Massachusetts 02138; [c] Warrington College of Business, University of Florida, Gainesville, Florida 32611; [d] Department of Economics, University College London, London WC1H 0AN, United Kingdom; [e] School of Management, University College London, London E14 5AA, United Kingdom

*Corresponding author

Contact: hezhg@stanford.edu, https://orcid.org/0009-0005-0076-1488 (ZH); sheila.jiang@warrington.ufl.edu (SJ); douglas.xu@warrington.ufl.edu (DX); xiao.yin@ucl.ac.uk (XY)

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Abstract. Banks' lending technology hinges on their handling of soft and hard information in dealing with different types of credit demand. Through assembling a novel data set on banks' investment in information technologies (IT), this paper provides concrete empirical evidence on how banks adapt their lending technologies. We find investment in communication IT is associated with improving banks' ability to produce and transmit soft information, whereas investment in software IT helps enhance banks' hard information processing capacity. We exploit policies that affect geographic regions differentially to show causally that banks respond to an increased demand for small business credit (mortgage refinance) by increasing their spending on communication (software) IT spending. We also find that the entry of fintech induces commercial banks to increase their investment in IT—more so in the software IT category.

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1. Introduction

Commercial banks have long relied on cutting-edge technology to deliver innovative products such as ATMs and online banking, streamline loan-making processes, and improve back-office efficiency. According to a 2012 McKinsey Report, across the globe, commercial banks spend about 4.7%–9.4% of their operating income on information technology (IT); for comparison, insurance companies and airlines only spend 3.3% and 2.6% of their income on IT, respectively. Recently, the impact of information technology on the banking sector and on financial stability has been a headline topic in policy discussions (Banna and Alam 2021, Pierri and Timmer 2022a).

Although the financial services industry—especially the banking industry—is increasingly becoming a tech-like industry, the academic literature lags behind in understanding the economics of IT spending in banking. Which banks, large or small, have invested more in IT? Do banks adapt their information technologies in response to different credit demand shocks?

How do traditional banks react to the entry of fintech in recent years? We take the first step toward understanding the key empirical patterns on these issues and further explore the mechanism that underlies the connection between these expenditures and the core functioning of banking.

To place our research in the literature, think about the information transmission between a loan officer and a borrower, or between layers of loan officers within a bank organization. As highlighted by Stein (2002), a less hierarchical structure within a bank facilitates the effective transmission of "soft" information. At the same time, fast-developing technologies in recent decades provide more options for the banking sector to cope with such problems.[1] So, can information technologies reduce frictions in communicating soft information and potentially improve banks' credit approval decisions? Likewise, with the explosive development of big data analytics, which combine "hard" information such as credit scores with other alternative data, have traditional banks started adopting these technologies?

Our study relies on a comprehensive data set, the Harte Hanks Market Intelligence Computer Intelligence Technology database, which has been used in the literature on the economic implications of technology in nonfinancial sectors (e.g., Forman et al. 2012, Bloom et al. 2014). This data set, which aligns well with the regulatory Y-9C data set in measuring total IT spending, provides detailed branch-level information on specific spending categories. We focus on two major categories in banks' IT spending: *software* and *communication*.[2] *Software* IT products mainly aim to improve information processing accuracy and speed through automation, specialized programming, AI technologies, etc. *Communication* IT products facilitate smoother exchanges of information within bank branching networks, across banks, and with borrowers.

In Section 3, we start by documenting that IT expenditure in the U.S. banking sector has been growing rapidly over the last decade. Growth in IT spending varies by bank size: large banks' IT spending increased steadily, whereas there was almost no growth in IT spending for the smallest banks.

Another noticeable distinction between large and small banks is that the latter, which presumably engage in more small business lending, consistently allocate a higher share of their IT budget toward communication technology than the former. As we will elaborate, this pattern points to the role communication IT plays in conducting small business lending. Furthermore, we document how banks of different sizes adopt various types of technologies using granular installation-level data on IT systems across bank branches. To make the data analytically tractable, we use a large language model to classify technologies into five functional categories: core infrastructure, customer engagement, cybersecurity, data systems, and enterprise applications. Our analysis shows that whereas banks across all size groups increasingly invest in technologies that improve enterprise productivity, large banks invest more broadly across all categories. In particular, they allocate relatively more resources toward cybersecurity and customer engagement technologies compared with smaller banks.

We then examine the relationship between banks' IT spending and their lending activities. Among the three main categories of loan types in call reports, the share of commercial and industrial (C&I) loans is positively associated with the lenders' communication spending, but uncorrelated with their software spending. In contrast, the share of personal loans is positively associated with the lenders' software spending, but not with communication spending. Going one step further, within C&I loans, we show that small business lending stands out as a subcategory that drives the overall positive association with communication IT spending, whereas within personal loans, mortgage refinance is the main contributor to the positive correlation between personal loans and software spending. As different types of loans often require different technologies in dealing with relevant information, these positive associations (or the lack thereof) offer important guidance in understanding banks' IT spending profiles from the perspective of lending technology.

Aside from broad credit categories of loan portfolios, we also explore how banks' IT investment is shaped by other factors affecting their business operations. Regarding the complexity of internal hierarchical structure, banks with more internal layers tend to have higher communication spending. Further, hierarchical complexity has an impact on the responsiveness of banks' IT spending to their loan profiles—a more complex hierarchical structure makes banks' communication spending respond more to their small business lending but displays no systematic effect on the relation between software spending and mortgage refinancing.[3] Finally, in the context of the syndicated lending market, frequent lead lenders spend significantly more on communication than participant lenders, as lead banks take more direct responsibility in interacting with borrowers.

In Section 4, we delve deeper into the underlying economics behind the connection between banks' IT investment and their lending activities. Conceptually, we distinguish two fundamentally different types of lending technologies. The first heavily relies on the gathering and augmentation of soft information from borrowers; in the context of Berger and Udell (2002), "relationship lending" is a concrete example of the first type. The second type of lending technology relies primarily on the processing and quantification of hard information; leading examples include "transactions lending"; that is, loans that are based on a specific credit scoring system and quantified financial statement metrics (Berger and Udell 2006).

We formulate our first hypothesis along the dimension of soft information. Increased demand for loans that involve intensive soft information production/transmission (e.g., small business loans) should lead banks to invest more in communication technologies, say, video conferencing, as they not only enable banks to more effectively collect soft information from entrepreneurs but also allow for a smoother transmission of such otherwise hard-to-verify soft information within a bank organization. Taking advantage of an arguably exogenous demand shifter, we show an increase in banks' small business credit demand—because of a higher ex ante exposure of local counties to the policy shock exploited in our analysis—leads to a positive and significant growth in banks' communication spending, without much impact on the bank's software spending.[4] Furthermore, we find that such responses are more pronounced for banks operating in regions with more young firms, for whom effective transmission of soft information is particularly important.

In our second hypothesis, a positive demand shock for loans that rely heavily on hard information processing (e.g., mortgage refinancing) should push banks to engage in more IT investment in software (which facilitates lenders in processing such existing data).

For causal identification, we utilize the cross-county variation in interest savings of outstanding mortgages to construct a shifter to the mortgage refinance demand across different regions.[5] We show that an increase in mortgage refinancing by a bank (because of its local exposure to high refinance savings) results in higher software spending without any significant impact on its communication spending.

The last part of our analysis concerns how the entry of fintech lenders into local credit markets affects banks' IT spending. In the past decade, we have witnessed a growing penetration of fintech into the traditional banking sector. Utilizing the staggered entry of LendingClub into seven states after 2010 as an experimental setting, we investigate how the traditional banking sector reacted to the penetrating fintechs. Right after the regulatory approval of LendingClub's operation in a state, banks operating in that state saw a significant increase in their IT investment. Importantly, shocked banks' software spending experienced an economically and statistically significant growth (around 7%), whereas the change in their communication spending was insignificant.

Additionally, we also examine whether banks' IT investments help preserve market share in response to fintech competition, using the staggered entry of LendingClub as an exogenous shock in the personal loan market. We find no significant changes in market share postentry. This suggests that whereas banks do invest in IT following fintech entry, such investments likely mitigate losses rather than expand market presence.[6]

There is also significant heterogeneity across bank size groups in their technology spending reactions in response to fintech entry. In particular, the increased IT investment is predominantly observed among large banks, whereas small banks barely respond.[7] Our findings suggest an overall "competition reaction" from the traditional banking sector in that banks—particularly larger ones—are catching up with fintech challengers. Consistent with this competition interpretation, such "catching-up" behavior by commercial banks is especially noticeable in improving their automating and information processing technology through increased software spending, which is precisely the domain of lending technology in which fintech lenders have a comparative advantage.

1.1. Related Literature

1.1.1. Bank Lending Technology and the Nature of Information. Berger and Udell (2006) provide a comprehensive framework of the two fundamental types of bank lending technology, that is, relationship lending and transactions lending, in the small and medium enterprise (SME) lending market; see also related work by Bolton et al. (2016).

A key difference between these two types of lending is related to the role played by information, as highlighted by Stein (2002), who provides an explanation for why soft information production favors an organizational structure with fewer hierarchical layers.[8]

We contribute to this literature by linking banks' IT spending to their lending technology, especially with regard to the distinction between soft information production/transmission and hard information processing. We further establish causal linkages from the informational components in credit demand to banks' IT spending. It is, to our knowledge, the first attempt in the literature to show how credit demand shocks drive banks' investment in their information-driven lending technologies.[9]

1.1.2. Information Technology in the Banking Industry. Our paper belongs to the literature on the interaction between the development of information technology and the evolution of the banking industry. For instance, Berger (2003) shows that progress in both information and financial technologies led to significant improvement in banking services, and Petersen and Rajan (2002) document that communication technology greatly increased the lending distance of small business loans. Using the number of computers per employee as a measurement for IT adoption, two recent papers show that IT adoption helps banks weather financial crisis (Pierri and Timmer 2022b) and spur entrepreneurial activities (Ahnert et al. 2021). Our paper, with the aid of detailed IT spending data, studies the specific economic mechanisms that connect banks' lending technology with their IT spending.[10]

Our paper is closely related to Modi et al. (2022), who construct IT spending data using the call reports; we compare our sample with them in Section 2.1. Whereas their analysis also investigates the linkages between banks' IT spending and their lending behaviors (e.g., mortgage lending and reactions to monetary policies), our analysis differs in our focus on linking different categories of IT investment to banks' lending activities associated with different types of information nature (i.e., soft information versus hard information). Furthermore, our analysis aims to establish a causal linkage between banks' adaptation of their lending technology and credit demand shocks, which is not the focus of Modi et al. (2022).

1.1.3. Fintech Entry and Banks' IT Spending. The emergence of fintech reflects the recent developments in information technologies.[11] Our study aligns closely with studies on how the emergence of the fintech industry is affecting (or has affected) the traditional banking sector.[12] Whereas a common theme of this research has mostly focused on bank-fintech competition during which traditional banks are largely viewed as a *passive* player, little attention has been paid to the banks' *active* responses; we take the latter angle by studying whether and how traditional banks are catching up with penetrating fintech lenders.

Along a similar line, Modi et al. (2022) also document that banks with more fintech exposure in the mortgage market tend to spend more on IT and that their lending behaviors are also likely to resemble fintech companies.

1.1.4. Microlevel Evidence on Technology Adoption. Our paper also broadly contributes to the literature studying firms' technology adoption behavior using microlevel data. Using the same IT spending data as this paper, Forman et al. (2012) study the impact of firms' technology adoption on regional wage inequality, Bloom et al. (2014) investigate the effect of information technology on firms' internal control, and Ridder (2023) explores how software adoption explains the decline in business dynamism and the rise of market power.[13]

2. Data and Background

We explain our main data sources in this section, together with detailed descriptions of various categories of IT spending.

2.1. Data Source for Bank IT Spending and Sample Construction

The data on banks' IT spending comes from the Harte Hanks Market Intelligence Computer Intelligence Technology database, which covers over three million establishment-level observations from 2010 to 2019 obtained while conducting IT-related consulting for firms. Harte Hanks collects and sells this information to technology companies, which then use it for marketing purposes or to better serve their clients. Firms have incentives to report their IT spending data truthfully to Harte Hanks, as they also want to receive tailored advice for better IT services in the future.

2.1.1. Our Paper Focuses on Commercial Banks.[14] The sample consists of 1,450 commercial banks in the United States, which covers more than 80% of the U.S. banking sector in terms of asset size (Figure A1 in the Online Appendix). The sample is more representative for large banks, as shown in Table 1, which reports our coverage by bank asset size group. For the three groups of relatively large banks (with assets above $1 billion), the coverage in frequency and assets is both over 80%. However, for small banks with size below $100 million, our sample covers only 9.47% (11.36%) of the total number (assets) of commercial banks in the U.S. system.

Table 2 displays the summary statistics of banks' IT spending. In our sample, total IT spending as a share of net income ranges from 1.7% (25th percentile) to 8.5% (75th percentile), suggesting a large cross-sectional variation across banks. Median IT spending as a share of net income is 5.2%, consistent with a 2012 McKinsey survey (Figure A5 in the Online Appendix) reporting that banks' IT spending as a share of net operating income ranges from 4.7% to 9.4%.

2.1.2. Matching Procedure and Matching Quality. We provide detailed descriptions of the matching algorithm for our sample construction in Online Appendix C.1.1. This matching mainly involves mapping sites in Harte Hanks to bank branches, where we take bank names from the call report. To evaluate the matching quality, we conduct several cross-checks of our sample with other data sources, especially call reports, regarding certain key bank-level variables. More specifically, Online Appendix C.1.2 shows a close alignment of our sample with the call report in terms of the total number of banks' branches at both the bank level and bank-county level, as well as banks' total revenue and total number of employees.

Table 1. Sample Coverage

Coverage of data	Sample		Call report		Frequency (%)	Asset (%)
Average assets 2010–2019	Number of banks	Average asset size	Number of banks	Average asset size		
>$250 billion	6	1,196.15	6	1,196.15	100	100
$10 billion–$250 billion	98	43.82	106	43.69	92.45	92.72
$1 billion–$10 billion	418	2.95	590	2.78	70.85	85.62
$100 million–$1 billion	734	0.42	4,161	0.32	17.64	23.43
<$100 million	194	0.06	2,048	0.05	9.47	11.36

Notes. This table demonstrates the sample coverage of banks across five categories of banks' size groups. The call report bank population is constructed by applying the commercial bank restriction ("charter type" being 200) following Federal Financial Institutions Examination Council (FFIEC) definition. The first two columns show the number of banks and the average asset sizes of banks in our sample across five size groups. Column (3) and column (4) show the total number of banks and average asset sizes of all banks in the call report. Column (5) shows the percentage of sample coverage in terms of frequency compared with the population in the call report, and column (6) shows the percentage of sample coverage in terms of total asset size compared with the population in the call report.

Table 2. IT Spending Summary Statistics

	Mean	Standard deviation	P25	Median	P75
Total IT Spending (Million)	11.125	160.239	0.024	0.159	0.796
No. of IT Employees	178.756	1,828.766	5.000	20.682	56.912
IT Spending/Income	0.020	0.039	0.006	0.012	0.021
IT Spending/Net income	0.068	0.113	0.017	0.037	0.084
IT Spending/Expenses	0.022	0.027	0.008	0.014	0.026
IT Spending/Noninterest expense	0.051	0.036	0.009	0.018	0.035
Communication/Total	0.089	0.108	0.028	0.051	0.110
Software/Total	0.334	0.172	0.219	0.315	0.468
Hardware/Total	0.172	0.111	0.066	0.161	0.235
Services/Total	0.327	0.129	0.243	0.329	0.415
Other/Total	0.066	0.104	0.009	0.022	0.111

Notes. This table presents summary statistics on banks' IT spending. *Total IT Spending* is the sum of all types of IT spending in millions of dollars. *IT Spending/Revenue* is total IT spending scaled by banks' total gross income (*Revenue* is RIAD4000 of the call report), *IT Spending/Noninterest expense* is total IT spending scaled by noninterest expenses (*Noninterest expenses* is RIAD4093 in the call report), and *IT spending/Net income* is total IT spending scaled by total income minus the gross total expenses (*Net income* is total income minus the sum of interest expenses and noninterest expenses, or the sum of RIAD4073 and RIAD4093 in the call report). The different categories of IT spending are the four categories of IT spending scaled by total IT spending.

2.1.3. Cross-Validation of Bank IT Expense Measure. To confirm the reliability of Harte Hanks data in measuring banks' IT spending, we conduct thorough validity checks against various alternative sources, including the FR Y-9C Consolidated Financial Statements for Holding Companies, which contain regulatory data on IT spending at the bank holding company (BHC)–year level. As explained in Online Appendix C.2, we follow Kovner et al. (2014) to construct BHCs' IT expenses by summing up two standardized "other noninterest expenses" in the Y-9C data set, the "data processing expenses" and the "telecommunication," together with the unstandardized write-in items reported in "other noninterest expenses" containing IT-related keywords. For the top 50 BHCs sorted by assets, Figure C9 offers a BHC-by-BHC comparison of IT spending between Y-9C and Harte Hanks (adjusted for BHC subsidiaries) at years that Y-9C IT expenses are not missing or zero.[15] Further, for the overall matched sample, Table C4 reports that a regression of the logarithm of the IT spending in Harte Hanks on that in Y-9C has a slope coefficient close to one (0.935) and a constant close to zero (0.037). Overall, we find a decent match between Y-9C regulatory filings and Harte Hanks data (adjusted for BHC subsidiaries), suggesting a high quality of the Harte Hanks data in measuring banks' IT expenses.

We also compare our IT spending measure with that in Modi et al. (2022), who construct the IT spending using only IT-related write-in expenses in call reports. We find a decent correlation ($\rho = 0.77$) between the two IT expense measures. Furthermore, Figure C12 in the Online Appendix separates banks into different size groups as in Modi et al. (2022) and shows similar time trends in banks' IT expenses during 2010–2019 across bank size groups in these two data sets.[16] Data Appendix C.3 provides several further comparisons with our sources on the empirical measures for banks' IT investment, from which overall consistent results are obtained.[17]

2.1.4. Data Collection Practice by Harte Hanks. Our analysis uses the "IT budget data" offered by Harte Hanks.[18] According to the official description provided by the data collection team of Harte Hanks, the construction of this data set is mainly based on data collected from surveys conducted at the site-year level; in addition, the IT budget data reflect the purchases of ready-to-use IT products or services and do not include expenditures on IT-related R&D activities, which might take a longer time to accomplish. Furthermore, because the usage of IT products or services (e.g., software programs) is often license based, the IT expense is therefore likely to be spread across branches of a given bank based on branch-level usage, rather than concentrated at the headquarters of the bank. As one piece of supporting evidence, we find no significant differences between the IT expenses at bank headquarters and local bank branches. Data Appendix C.4 provides more details for supplemental materials and analysis regarding the IT data collection practices of Harte Hanks.

2.2. IT Investment Categorization

Our data set offers a detailed decomposition of banks' IT investments in four major categories specified by Harte Hanks: *hardware*, *software*, *communication*, and *services*. We now explain these categories, with formal definitions given in Figure A6, (a)–(d) in the Online Appendix.

2.2.1. Software. Software is defined as software programs purchased from third parties, including those offered as a software as a service (SaaS) from a multitenant shared-license server accessible by a browser. More specifically, the category of software covers desktop applications, information management software, processing software, and risk and payment management software. For desktop applications, one representative example is Microsoft Office.[19]

Processing software specializes in automatically processing information from loan applicants' document packets through specialized programming and AI technologies with improved accuracy and speed, which would otherwise be done manually by loan officers.[20]

Risk management software provides ongoing risk assessment after loans have been issued through augmenting borrowers' repayment status as well as real-time industrial and economic conditions.[21]

2.2.2. Communication. Communication is defined as the network equipment that banks operate to support their communication needs. It includes routers, switches, private branch exchanges, radio and TV transmitters, Wi-Fi transmitters, desktop telephone sets, wide-area networks, local-area network equipment, video conferencing systems, and mobile phone devices. For effective project evaluation, these machines allow bankers to conveniently talk to and see borrowers who seek credit. In addition, communication equipment, such as private branch exchanges, facilitates the exchange of information, opinions, and decisions within the bank branching networks.

2.2.3. Hardware. Hardware as a form of IT investment includes classic computer hardware such as PCs, monitors, printers, keyboards, USB devices, storage devices, servers, and mainframes. In terms of lending services, hardware investment can complement and facilitate both the gathering of borrower information and the processing of that information. This is because hardware devices, such as PCs and servers, help provide storage and transmission of data in addition to serving as the carriers of software and toolboxes.

2.2.4. Services. Services are defined as project-based consulting services (including, say, IT strategy and security assessments) or systems integration services that vendors provide to banks, which are often provided by IT outsourcing companies on a contractual basis. Similar to hardware, services work as complements to other categories of information technology investment to facilitate banks' lending. Examples include Aquiety, a Chicago-based IT service company that provides cybersecurity services to banks and other firms, and Iconic IT, a New York–based IT service company that provides software and hardware procurement, together with installment and upgrade services.

Table 2 reports summary statistics on the detailed structure of banks' IT spending profiles. By size, software and services are the top two among all categories of IT spending, each constituting around 33% of total IT budget, whereas hardware (communication) constitutes about 17% (9%) of the total IT budget. We conduct analysis on banks' IT spending at the bank-year level in Section 3, whereas in Section 4, the analysis is at bank-county-year level, in which we aggregate the branch-level spending information of each bank at the county level.

2.3. Other Data Sets

To supplement our study on banks' lending technologies and their relation to IT spending, we combine loan-level information from multiple sources.

2.3.1. Bank Balance Sheet. We obtain bank-level balance sheet information from call reports; for detailed matching procedures, see Online Appendix D.1.1. In our ordinary least squares (OLS) analysis investigating the correlation between IT spending and loan portfolios, we calculate the dependent variable as IT spending in Harte Hanks as a share of "revenue" (RIAD4000 of the call report) at the bank level. In the identification part that involves bank-county analysis (Sections 4 and 5), because there is no bank-county revenue in regulatory data, we use revenue scaled by number of employees in Harte Hanks to control for the profitability at the bank-county level.

2.3.2. Loans and Local Characteristics. We obtain syndicated loan information on the frequency of a bank acting as the lead bank in syndicated loan packages from LPC Dealscan. Small business loan origination data are from the Community Reinvestment Act (CRA), which is at the bank-county-year level covering the sample period of 2010–2019. Mortgage refinance information is available through the Home Mortgage Disclosure Act (HMDA) from 2010–2019, and we use the county-level average mortgage interest rate before 2010, obtained from Freddie Mac, as the demand shifter for mortgage refinancing.

2.3.3. Bank Hierarchical Structure. We obtain banks' hierarchical structure information from Mergent Intellect platform, which covers 97 million public and private businesses, including their locations and industry classifications.[22] We restrict our sample to entities with the two-digit SIC code of "60," which designates "depository institutions."

The database provides the complete family trees of the companies, with detailed information on its family members. Importantly, this database classifies each family member of a company into one of the three categories of location types: "headquarters," "single location," and "branch." We define a bank as having n layers of hierarchical structure if the bank has n types of locations in the family tree, where $n \in \{1, 2, 3\}$.

To give some concrete examples, Wells Fargo has all three location types and hence is classified as three hierarchical layers; North Valley Bank, with headquarters located in Corning (Ohio) and seven branches is classified as two layers; and First Place Bank, located in Warren (Ohio), with one single location, is classified as only one layer.

For each bank, we match the banks in Mergent Intellect with banks in our sample based on bank names and the city where the banks' headquarters are located (see Online Appendix D.1.1 for more details). Whereas the number of distinct "location types" in the Mergent Intellect data set can provide information on the hierarchical complexity of a bank, it is admittedly a somewhat coarse empirical measure and could underestimate the hierarchical complexity, especially for large banks.

3. Empirical Patterns of Banks' IT Spending

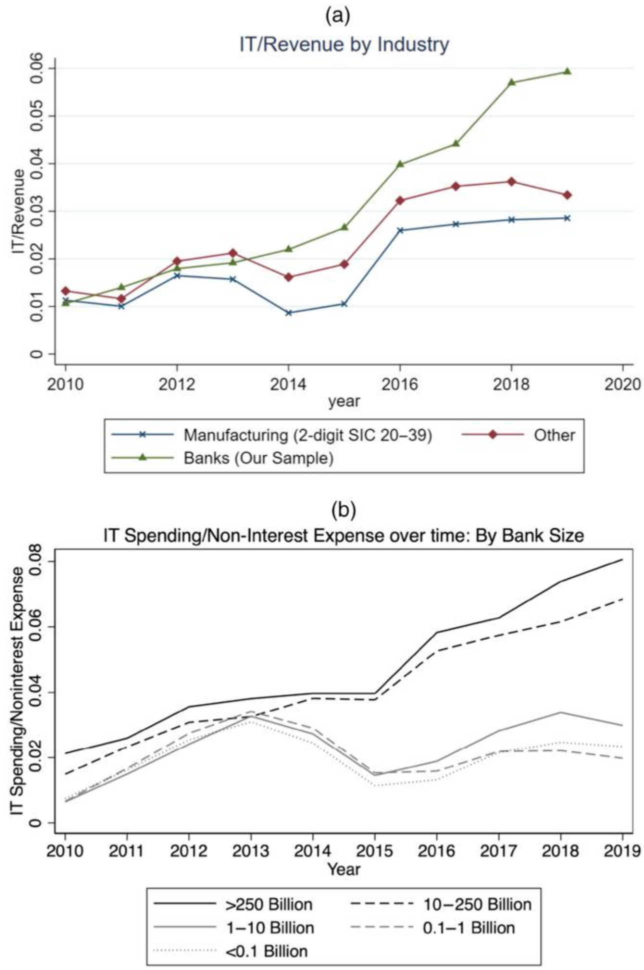
We start our analysis by reporting some basic statistics of banks' investment in IT over the last decade as well as across bank size. We further show that banks' IT investment is related to their lending activities and organization structures.

3.1. Banks' IT Investment: Trend and Cross Section

3.1.1. IT Spending in Banking: Trend and Cross Section. In Figure 1(a), we plot the evolution of IT spending as a share of total revenue of banks in our sample in the manufacturing sector (two-digit SIC: 20-39) and in all other nondepository sectors (two-digit SIC: not 60). As is evident from the figure, the IT investment in the U.S. banking sector (represented by our sample) has witnessed faster growth during the past two decades compared with other industries. Also, banks' IT spending saw faster growth starting in 2016, which could be potentially driven by the release of a white paper by the Office of the Comptroller of the Currency on March 16, 2016. This white paper set forth the regulators' perspective on supporting responsible innovation across all sizes of banks,[23] which might have pushed banks to be more aggressive in embracing technology investment as part of their strategic planning (see this article).

Banks of different sizes often behave differently in systematic ways. In Figure 1(b), we follow FDIC bank size classifications to separate banks into five size groups and present the growth trend for banks' IT investments for each group as a fraction of noninterest expenses.[24] We observe that large banks invest more in IT than their small peers do (for more detailed statistics, see Table A2 in the Online Appendix)[25] and IT

Figure 1. (Color online) IT Spending: Time Trend



Notes. (a) The evolution of IT spending as a share of total revenue of banks in our sample, the manufacturing sector, and all other industries constructed using IT budget and revenue from Harte Hanks. The "manufacturing" sector is defined as establishments with two-digit SIC code 20-39. "Other" sector is defined as all industries other than "depository institutions" (two-digit SIC code=60). "Banks (our sample)" refers to banks in our sample. These ratios are calculated by aggregating total IT spending and then scaling it against the total revenues sourced from Harte Hanks. In (b), the vertical axis is banks' total IT spending scaled by noninterest expenses. The asset size groups are categorized based on a bank's average asset size during 2010 and 2019. Noninterest expenses are calculated using banks' balance sheet item RIAD4093 in the call report.

spending in large banks (with asset size \$10–250 billion and above \$250 billion) has been steadily growing, though there is also an apparent growth in the smaller groups (with asset size below \$10 billion).[26] The study in Modi et al. (2022) also confirms the empirical pattern that larger banks tend to invest more in IT and experience higher rates of growth in IT spending. Whereas we do not have a conclusive answer for why such heterogeneity exists, our analysis of how banks (of different sizes) react to the entry of fintech in Section 5 touches on this issue directly.

Another noticeable pattern in Table A2 in the Online Appendix is that small banks tend to allocate a higher fraction of their IT budget toward communication technology than large banks do: the average communication spending over total spending decreases from 12.6% for the smallest group (below $100 million) to 6.2% for mega banks (above $250 billion). For software spending, however, there are no significant differences across bank size groups. We will come back to this contrast in Section 4, where we connect banks' IT spending categories to their lending activities that involve different ways of handling information.

3.1.2. IT Spending Categories in Banking: Trend and Cross Section.

We also document banks' adoption of different types of technologies by bank size. We focus on the Competitive Install data set, which gives a list of IT that provides installation-level data on branch-specific technologies across categories such as infrastructure, software, and communication systems. To meaningfully group these technologies, we apply a large language model–assisted reclassification using ChatGPT 4o to map granular entries into the following functional banking categories, with details (including the prompt to classify these technologies) available in Online Appendix Section B.

1. Core banking infrastructure includes foundational IT hardware, operating systems, and virtual environments that support day-to-day banking operations and secure internal workflows.
2. Customer engagement channels: technologies that interface directly with customers or facilitate real-time communication and digital service delivery.
3. Cybersecurity and access management: tools and systems dedicated to protecting sensitive data, securing networks, authenticating users, and maintaining regulatory compliance.
4. Data and analytics systems: technologies for storing, transforming, analyzing, and extracting insights from structured and unstructured data.
5. Enterprise and productivity applications: software that enhances internal operations, resource planning, compliance, and organizational efficiency.

We then examine adoption patterns by bank size group. In Figure 2, we plot the average fraction of technologies within the five assigned types by bank size group. Notably, whereas banks of all sizes have increased investment in IT to boost enterprise productivity, large banks have increased investment over all types of technologies. Besides, banks in the largest group, relative to other groups, have invested more heavily in cybersecurity and customer engagement.

3.2. Empirical Patterns of Bank IT Investment

We now present the first set of empirical results, which relate banks' IT investment to their operations, from three angles: (i) specialization in loan making, (ii) the role that a bank plays in syndicated loans, and (iii) the complexity of the bank's internal hierarchical structure.

3.2.1. Loan Specialization.

Banks provide three major types of loans: commercial and industrial loans, personal loans, and agricultural loans. Lending to different types of borrowers often involves distinct ways of dealing with borrower-specific information. Therefore, if banks specialize in different types of loans, one should expect them to differ in their IT investment profiles. Specifically, we run the following bank-level regression:

$$\frac{\text{Type S IT spending}}{\text{Revenue}}_{i,10-19} = \alpha_i + \beta \frac{\text{Type L loan}}{\text{Total loan}}_{i,10-19} + \gamma \mathbf{X}_i + \epsilon_i. \tag{1}$$

Here, the outcome variable of interest is $\frac{\text{Type S IT spending}}{\text{Revenue}}_{i,10-19}$, which is the average investment in a specific type of IT spending as a share of bank i's revenue over 2010–2019.[27] The "revenue" in the denominator of the dependent variables is the total income in the call report (RIAD4000). The main explanatory variable $\frac{\text{Type L loan}}{\text{Total loan}}_{i,10-19}$, which is the average share of a specific type of loan relative to bank i's total loan size, captures bank i's loan specialization. Control variables, which are measured over 2010–2019 at the bank level, include net income, total deposits, total equity, total salaries (all scaled by total assets), and revenue per employee. In all of our regression analyses (except for Section 5, where the main independent variable is the dummy variable indicating postentrance), we standardize the dependent variables and the regressors.

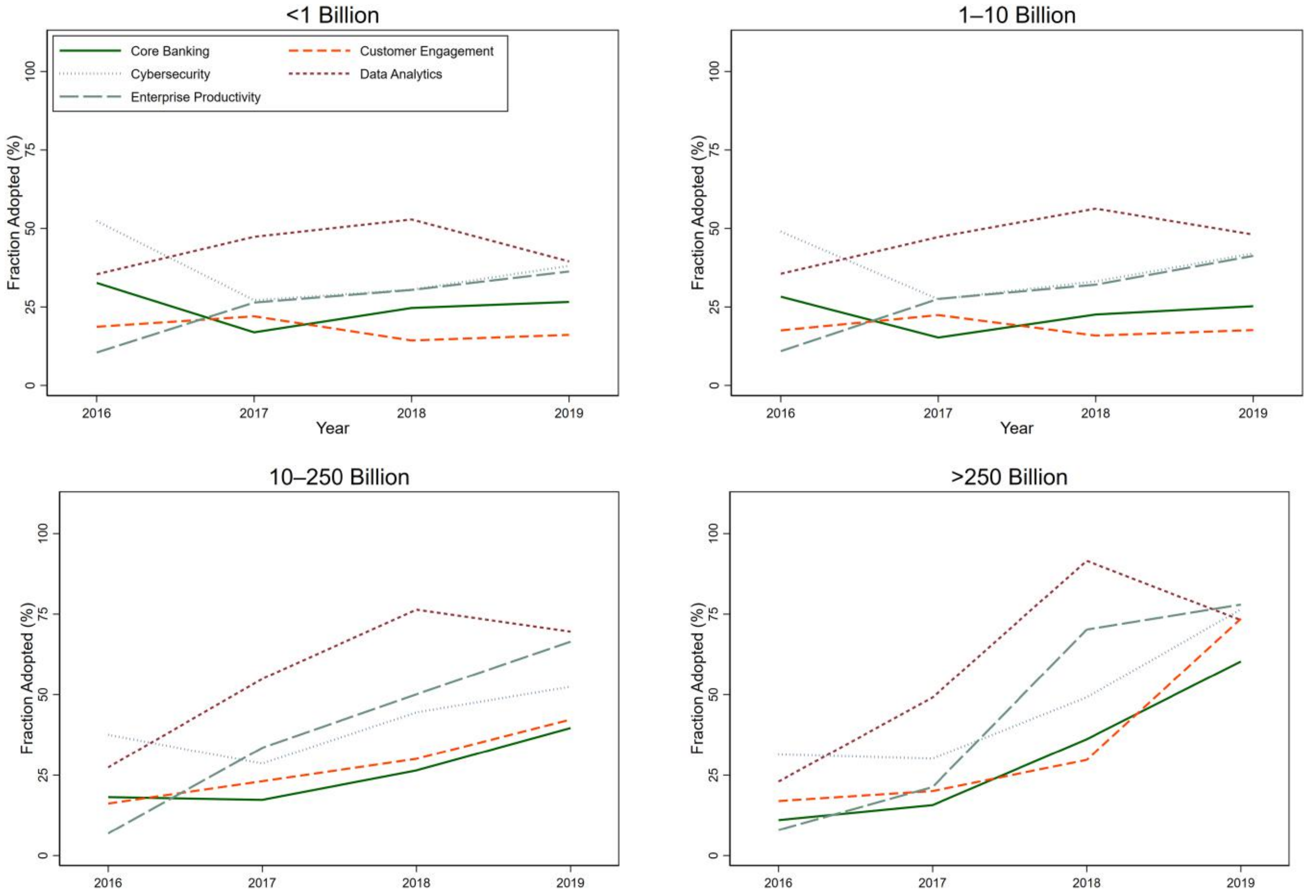
Table 3 reports the estimation results of (1) for C&I loans, together with detailed regression outcomes for control variables. We apply the same methodology for personal loans and agricultural loans. For exposition purposes, Table 4 reports key regression coefficients (i.e., those of specific IT spending shares).

3.2.1.1. Commercial and Industrial Loans.

Specialization in C&I loans is most positively associated with banks' spending in communication technology (Table 3, column (2)). A one-standard-deviation (13-percentage-point) increase in loan portfolio share allocated to C&I loans predicts a $0.16 million higher expenditure on communication per year. For detailed calculation, see Table A6 in the Online Appendix. Our economic magnitude calculation for Table 3 follows the same method.

A higher degree of specialization in C&I loans also predicts more spending on hardware (column (3)), though the magnitude is slightly smaller than that of

Figure 2. (Color online) Technology Adoption by Bank Size



Notes. This figure presents a breakdown of technology adoption by banks in different size groups using branch-level installation data from 2016 to 2019. Technologies are reclassified into five categories: core banking infrastructure, customer engagement channels, cybersecurity and access management, data and analytics systems, and enterprise and productivity applications—based on a large language model–assisted mapping. In each panel, the y-axis gives the average fraction of technologies of that type that are adopted. Online Appendix Section B gives the classification and definition.

communication spending. The coefficient of software spending, however, is insignificant (column (1)).

3.2.1.1.1. Within C&I Loans. Rows 2 and 3 of Table 4 further decompose C&I loans into "small business loans," which are measured by a bank's small business lending reported in the CRA, and "other C&I loans." Whereas the share of small business loans in a bank's portfolio is positively associated with communication spending, it is negatively related to the bank's software spending. In contrast, "other C&I loans" (e.g., loans to large firms) are positively associated with software spending, but not with communication spending. Panel A of Table 5 further shows that this positive association between small business loans and communication spending is more statistically significant for small banks.

3.2.1.2. Personal Loans. Row 4 of Table 4 reports the associations between shares in personal loans and banks' IT spending. Contrary to the pattern we observe for C&I loans, a higher share of loan portfolio allocated to personal loans appears to predict more spending on software only. Quantitatively, a one-standard-deviation increase in personal loans share (an increase of about seven percentage points) predicts a 0.0617-standard-deviation increase in software spending as a share of total revenue; in dollar terms, this amounts to an increase of $1.53 million in software spending per year. On the other hand, a higher personal loan share does not have qualitatively significant predictive power on communication, hardware, or services budgets.

3.2.1.2.1. Within Personal Loans. Paralleling our analysis of small business loans within C&I loans, we decompose personal loans into two subcategories: mortgage refinancing and everything else. It is mortgage refinancing—but not other kinds of personal loans—that positively correlates with banks' software spending. This finding motivates our study in Section 4 to pay particular attention to mortgage refinancing as a specific type of lending activity in which the processing of hard information plays a critical role.

Table 3. C&I Loans and Banks' IT Spending

	Software/Revenue (1)	*Communication/Revenue* (2)	*Hardware/Revenue* (3)	*Services/Revenue* (4)
C&I loan/Total Loan	0.027	0.053**	0.087***	0.021
	(0.028)	(0.027)	(0.027)	(0.028)
Net income/Total assets	−0.099***	−0.138***	−0.185***	−0.064**
	(0.032)	(0.030)	(0.031)	(0.032)
Deposit/Total assets	−0.062	−0.097	−0.098	−0.038
	(0.180)	(0.171)	(0.175)	(0.180)
Revenue/Employee	−0.343***	−0.493***	−0.444***	−0.381***
	(0.055)	(0.053)	(0.054)	(0.055)
Salary/Total assets	0.072	−0.142***	−0.044	0.020
	(0.045)	(0.043)	(0.044)	(0.045)
Equity/Total assets	0.136**	0.093*	0.077	0.122**
	(0.058)	(0.056)	(0.057)	(0.059)
Size group FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Adjusted R^2	0.097	0.167	0.136	0.077
N	1,434	1,434	1,434	1,434

Notes. This table presents the results of the regression of banks' C&I loans on the four major categories of banks' IT spending and a vector of control variables at bank-year level. The sample period is 2010 to 2019. $\frac{\text{Type S IT spending}}{\text{Revenue}}_{i,10-19} = \alpha + \beta \frac{\text{C\&I Loan}}{\text{Total loan}_{\text{i},10-19}} + \gamma \mathbf{X} + \epsilon_{\text{i}}$ C&I Loan/Total Loan is commercial and industrial loan of bank i scaled by total loan between 2010–2019, *Software/Revenue* is software spending scaled by total revenue, *Communication/Revenue* is communication spending scaled by total revenue, *Hardware/Revenue* is hardware spending scaled by total revenue, and *Services/Revenue* is services spending scaled by total revenue. Control variables include net income scaled by total assets, deposits scaled by total assets, revenue per employee, salaries scaled by total assets, and equity scaled by total assets. Both the left-hand-side and the right-hand-side variables are taken using the average values across 2010–2019 for each bank i. Fixed effects include bank size group and banks' headquarters state fixed effects. Standard errors are given in parentheses.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Additionally, the richness of mortgage data allows us to gain further insights by distinguishing "refinancing an existing loan" from "originating a new loan," with results reported in rows 5 and 7 of Table 4. We postpone more detailed discussion to Section 4.3.

In the end, we compare secured and unsecured personal loans. Presumably, collateral and software are complements because the presence of standardized, documentable assets makes software-based decision tools (e.g., scoring systems, automated processing) more applicable. Row 8 presents the association between IT and a measure of relative secured loan intensity, which we define as the ratio of RE loans and non-RE personal loans. Consistent with our conjecture, software IT spending increases with relative secured loan intensity, whereas for the other types of IT, the association is negligible.

3.2.1.3. *Agricultural Loans.* As shown in Row 8 of Table 4, the agriculture loan presence seems to be positively associated with all categories of IT spending, although there is no statistically significant correlation between agriculture loan proportion and a particular type of IT investment.

3.2.2. Complexity of the Hierarchical Structure. Another important factor that may affect a bank's efficacy in handling information is the internal organization structure of a bank (Stein 2002). In the first row of panel B in Table 4, we use the measure of hierarchical layers defined in Section 2.3 as our main proxy for hierarchical complexity. When the number of banks' hierarchical layers increases, banks spend more across all IT categories, especially on communication.

Increasing from one hierarchical layer to three layers implies \$0.31 million more in communication spending each year. This result is under the specification with bank-size group fixed effects included, implying that hierarchical complexity predicts higher communication spending beyond bank size.[28] For robustness, we also proxy banks' hierarchical complexity using the logarithm of the total number of offices, with qualitatively similar results reported in the second row of panel B.

As we will explain in Section 4.2.1, one can relate these findings to Stein (2002) from the perspective of within-organization transmission of information that is difficult to verify and relay. Despite a crude empirical measure of hierarchical complexity, our paper establishes a direct link between hierarchical complexity and banks' IT investment for information production and transmission.

3.2.3. Role in Syndicated Lending. Aside from specialization in different types of loans or having different levels of hierarchical complexity, banks may also differ

Table 4. Bank Characteristics and Banks' IT Spending

	Software/Revenue (1)	*Communication/Revenue* (2)	*Hardware/Revenue* (3)	*Services/Revenue* (4)
	Panel A: Loan specialization			
C&I loan/Total loan	0.027	0.053**	0.087***	0.021
	(0.028)	(0.027)	(0.027)	(0.028)
CRA/Total loan	−0.238***	0.087***	0.033	−0.012
	(0.033)	(0.032)	(0.033)	(0.034)
Other C&I loan/Total loan	0.056**	0.044	0.084***	0.024
	(0.028)	(0.027)	(0.027)	(0.028)
Personal loan	0.062**	0.051*	0.016	−0.001
	(0.029)	(0.029)	(0.029)	(0.030)
Refinance/Total loan	0.076***	0.037	0.047	−0.001
	(0.031)	(0.031)	(0.031)	(0.031)
Other personal loan/Total loan	0.053*	0.052*	0.010	0.002
	(0.029)	(0.029)	(0.029)	(0.030)
Refinance/Origination	0.068**	0.026	0.048	0.044
	(0.033)	(0.032)	(0.032)	(0.034)
RE loan/Non-RE loan	0.064**	0.005	0.003	−0.012
	(0.029)	(0.028)	(0.029)	(0.030)
Agriculture loan/Total loan	0.024	0.050	0.004	0.015
	(0.034)	(0.033)	(0.034)	(0.034)
	Panel B: Hierarchical complexity and IT spending			
Hierarchical layer	0.024	0.072**	0.033	0.037
	(0.035)	(0.034)	(0.035)	(0.035)
ln*(num of offices)*	0.052	0.084**	0.028	0.048
	(0.041)	(0.039)	(0.041)	(0.041)
	Panel C: Banks' role in syndicated lending			
% Lead bank/Total syndicate	0.075	0.093**	0.048	0.016
	(0.047)	(0.045)	(0.047)	(0.047)

Notes. This table presents the results of correlation between banks' IT spending and banks' characteristics. The regression specification is as follows.

$$\frac{\text{Type S IT spending}}{\text{Revenue}}_{i,10-19} = \alpha + \beta \frac{\text{Type L loan}}{\text{Total loan}}_{i,10-19} \text{ or } (\text{Bank Char}) + \gamma \mathbf{X} + \epsilon_i$$

Panel A shows how the banks' loan specialization correlates with banks' IT spending. *Type L loan/Total Loan* is the average of a specific type of loan scaled by total loan. Among them, *Personal loan/Total Loan* is the sum of personal loans and real estate loans to one to four family units scaled by total loan, *Agriculture/Total loan* is the agricultural loan scaled by total loan, *CRA/Total loan* is the sum of small business loans reported in CRA scaled by total loan, *Other C&I/Total loan* is the total C&I loan minus small business loans reported in CRA scaled by total loan, *Mortgage refinance* is the total amount of mortgage refinance reported in HMDA scaled by the bank's total loan, and *Other personal loans* is the deduction of mortgage refinance from *Personal* and *Mortgage loans*. *RE loans* is the volume of real estate loans. *Non-RE loans* is the personal loans excluding real estate loans. *Refinance/Origination* is the dollar amount of mortgage refinance scaled by dollar amount mortgage origination of a bank. *Software/Revenue*, *Communication/Revenue*, *Hardware/Revenue*, and *Services/Revenue* are, respectively, spending on software, communication, hardware, and services scaled by total revenue. Panel B shows how a bank's hierarchical structure correlates with its IT spending. *Hierarchical layer* is the number of types of its locations as defined in Section 2.3. *ln(num offices)* is the logarithm of the total number of offices. Control variables include net income scaled by total assets, deposits scaled by total assets, revenue per employee, salaries scaled by total assets, and equity scaled by total assets. Fixed effects include bank size group and banks' headquarter state fixed effects. Panel C shows how a bank's role in the syndicated loan market correlates with its IT spending. %Lead bank is the frequency of a bank's showing up as a lead bank in the syndicated loan market as a share of total number of syndicated loans lent out. All of the loan profile variables are calculated as the average of the loan profile of a bank between 2010 and 2019.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

in the role they play in dealing with information when conducting lending. For instance, in the context of syndicated lending, lead lenders and participant lenders perform drastically different tasks.

Panel C of Table 4 presents the regression of IT spending on "%Lead bank/Total syndicate," defined as the percentage frequency that a bank shows up as lead bank in the syndicated loan market. We find that communication, hardware, and services show a strong positive correlation with changes in lead bank frequency in the syndicated loan market, with communication spending having the largest magnitude. A one-standard-deviation increase in the lead bank frequency is associated with \$0.27 million more in the bank's annual communication budget. These findings, as we will elaborate in Section 4.2, can be attributed to the

Table 5. Bank Characteristics and Banks' IT Spending: Size and Hierarchical Dependence

	Software/Revenue (1)	*Communication/Revenue* (2)
Panel A: Bank size and IT spending		
Refinance/Total loan	0.082*	
	(0.043)	
Small × *Refinance/Total loan*	0.032	
	(0.054)	
CRA/Total loan		0.028
		(0.041)
Small × *CRA/Total loan*		0.162**
		(0.070)
Small	−0.031	−0.286***
	(0.082)	(0.089)
Size group FE	Y	Y
State group FE	Y	Y
R^2	0.103	0.133
N	1,432	1,432
Panel B: Bank hierarchical structure and IT spending		
Refinance/Total loan	0.041	
	(0.036)	
High layer × *Refinance/Total loan*	0.084	
	(0.052)	
CRA/Total loan		0.301**
		(0.121)
High layer × *CRA/Total loan*		0.087*
		(0.052)
High layer	0.053	0.024
	(0.052)	(0.051)
Size group FE	Y	Y
State group FE	Y	Y
R^2	0.089	0.127
N	1,426	1,426

Notes. This table presents the results of the dependence of correlation between banks' IT spending with their lending activities on the size and hierarchical complexity of banks. The regression specification is as follows.

$$\frac{\text{Type S IT spending}}{\text{Revenue}}_{i,10-19} = \alpha + \beta \times (\text{Bank Char.}) \times \left(\frac{\text{CRA}}{\text{Total loan}_{i,10-19}} \text{ or } \frac{\text{Refinance}}{\text{Total loan}_{i,10-19}}\right) + \gamma \mathbf{X} + \epsilon_i$$

In panel A, small (large) banks are defined as the banks with asset size below (above) median asset size in our sample. In panel B, *High layer* is defined as equal to one if a bank has two or three hierarchical layers. The number of types of its locations as defined in Section 2.3. "Size group FE" refers to the fixed effects of the five bank asset groups defined in Section 3.1 or Table 1. Control variables include net income scaled by total assets, deposits scaled by total assets, revenue per employee, salaries scaled by total assets, and equity scaled by total assets.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

distinct responsibilities for handling information assumed by lead and participant banks.

4. Economics of Banks' IT Investment

Having demonstrated the basic patterns of IT investment in the U.S. banking sector and its interaction with various banking business operations, we now move on to our central question: What are the economics behind banks' IT spending decisions, and how do they relate to—and contribute to—the development of banks' lending technology? We start with a conceptual discussion of lending technologies based on the nature of information handling. By mapping different types of IT investment onto various dimensions of lending technology, this framework helps us understand various empirical patterns shown in Section 3. We then study two credit demand shocks that involve different kinds of information handling and establish their causal impact on banks' lending technology adoption behaviors.

4.1. Lending Technology, Information Handling, and IT Spending

We view a bank's lending technology as its ability to deal with borrower-specific information throughout the lending process.

Broadly speaking, banks engage in two types/stages of activities in loan making: information *production/transmission* and information *processing*. More specifically, information *production/transmission*—broadly related to *soft* information in Stein (2002)—refers to the stage in which information on borrowers is gathered and then relayed to those who make decisions later. On the other hand, information *processing*—broadly related to *hard* information—is more about the stage in which lenders assemble and examine existing information on borrowers for better decision making.

4.1.1. Communication IT and Soft Information Production/Transmission.

When facing borrowers with whom lenders have never dealt or whose information is relatively opaque, for effective information gathering, bankers often need to communicate with their borrowers, either through face-to-face meetings or seeing borrowers' projects for themselves. Once this first-hand information has been gathered, which often can be subjective and thus difficult to convey to others, effective transmission of such information within the organization can also affect banks' lending efficiency.

One concrete example of how communication technology can help in the two aforementioned dimensions is video conferencing, which has become an important means for loan officers to interact with customers and colleagues during the past decade. In the past, banks opened new checking accounts and originated loans only through brick-and-mortar branches and in-person visits; now, they also use video conferencing, as it makes the direct—yet virtual—contact between loan officers and borrowers more efficient.[29] Moreover, video conferencing within an institution has also been welcomed by the banking sector for its advantages in facilitating effective internal communication and collaboration among employees.[30]

4.1.2. Software IT and Hard Information Processing.

Once information has been produced (by the lender itself) or is readily accessible (via a third party), the next concern for the lender is how to use this information. In the context of credit allocation, banks need to properly evaluate the borrowers' creditworthiness to determine loan amounts and rates. For borrowers who bankers already know from previous interactions or with transparent information, lending decisions simply boil down to efficient processing of the existing information.

Accurate evaluations of borrowers' credit risk often require complicated modeling and simulations, which are impossible without modern software tools. Nowadays, banks have actively adopted new software-based technologies to store, organize, and analyze large chunks of loan applicants' data.[31]

One popular form of software technology product is credit scoring software for banks making *refinancing* decisions,[32] which primarily involve the processing and assessment of *existing* information that lenders already possess through past interactions. In fact, the recent penetration of fintech companies, which specialize in utilizing software and algorithm-driven lending approaches, has been particularly pronounced in the mortgage refinancing market (Buchak et al. 2018, Fuster et al. 2019).

In the next two sections, we will explore in detail the lending technology adoption along two dimensions—those targeting the production and transmission of soft information (Section 4.2) and those targeting hard information processing (Section 4.3). In short, communication devices facilitate the gathering and dissemination of soft information, whereas software is for efficiently utilizing hard information. From this point on, we focus on two particular categories—*communication* and *software*—when examining banks' IT investment behavior.[33]

4.2. Bank IT Spending and Soft Information

4.2.1. Soft Information Production/Transmission in Bank Lending

4.2.1.1. Small Business Lending.

Lending to small business borrowers is one concrete example in which the efficient production and transmission of soft information is essential. Sahar and Anis (2016) document that in the context of lending to small- and medium-size enterprises, direct contact with borrowers and frequent visits to their work sites allow loan officers to collect and produce soft information. Agarwal et al. (2011) highlight that soft information, such as what the borrower plans to do with the loan proceeds, is always the product of multiple rounds of lender-borrower interactions.

That small business lending involves intensive soft information production and transmission is consistent with Section 3.2.1, where we show that banks specializing in small business lending (as measured by small business loans over total loans) incur more spending on communication IT. As smaller banks generally extend more loans to small businesses (Berger and Udell 2006, Chen et al. 2017), this helps explain the robust pattern that smaller banks have higher fractions of communication IT spending, shown in Table A2 in the Online Appendix. Indeed, Table 5 shows that small banks' communication spending is significantly more associated with their small business loans compared with large banks.[34] The finding that smaller banks focus more on communication technology aligns with the mechanism in Chen et al. (2017), which argues that large banks' efforts to scale SME lending via automated, score-based methods before the financial crisis ultimately failed because of rising defaults and disadvantages to process soft information, prompting a postcrisis retreat from the market.

4.2.1.2. Hierarchical Complexity. Recall that in Section 3.2.2, we find banks with a more complex hierarchical structure tend to have higher communication IT spending. This is in line with Stein (2002), who argues that a low hierarchical complexity facilitates the within-organization transmission of soft information, making it easier to issue loans requiring soft information (e.g., small business loans). Digging one step further, panel B of Table 5 shows that, given the same percentage increase in small business loans, banks with a more complex hierarchical structure respond with a greater increase in their communication spending. This is consistent with "hierarchical frictions" in soft information transmission: when banks face a need (or choose) to make more small business loans, which implies a demand for improving their soft information handling capability, those with a more complex internal hierarchical structure have to spend more on communication IT so as to overcome such frictions.[35]

Finally, as a placebo test, one should expect no systematic impact of banks' hierarchical complexity on the correlation between their software spending and mortgage refinancing activities, which is indeed confirmed in panel B of Table 5. Overall, our empirical findings on banks' hierarchical complexity corroborate previous works studying banking organization structure and information production (Degryse et al. 2008, Skrastins and Vig 2018, Levine et al. 2020), and more research needs to be done on this topic.

4.2.1.3. Lead Lender in Syndicated Loans. The syndicated loan market also provides a special environment to explore the relationship between communication technology and soft information production/transmission. In syndicated lending, the nature of interactions between lenders and borrowers depends crucially on whether the lender is a lead bank or a participant bank (Sufi 2007). Compared with participant banks, the lead bank is mandated by borrowers to organize other lending participants, conduct compliance reports, and negotiate loan terms. After the loan is issued, it also has the responsibility to conduct monitoring, distribute repayments, and provide overall reporting among all lenders within the deal.[36] In this regard, performing the job of lead bank involves significantly heavier effort in information generation and sharing as well as coordinating negotiations, during which effective communication plays a central role. These differences between lead and participant banks are empirically verified in Section 3.2.1: there is a strong correlation between the frequency of a bank serving as a lead arranger in syndicated loans and its communication IT spending (Table 4, row 4).

4.2.2. Banks' IT Spending and Demand Shock on Small Business Loans. We now present the first piece of causal evidence on banks' adaptation of their lending technology by studying their IT investment responses when hit by a positive demand shock in small business loans. As small business lending is associated with intensive soft information production/transmission, we predict that banks will increase their spending on communication technology (soft information), but not on software (hard information).

Our identification strategy relies on a policy shock that affected small businesses' credit demand, which hit the U.S. banking sector heterogeneously across different regions. The Small Business Healthcare Tax Credit was initially enacted in 2010 as part of the Affordable Care Act. The program, whose details are available here, offers a tax credit to small business employers who pay health insurance premiums on behalf of employees. From 2010–2013 (the first phase), the tax credit was up to 35% for qualified small businesses (QSBs), and in 2014, the tax credit increased from the 35%–50% for QSBs (the second phase). To qualify, the employer needed to (i) have 25 or fewer employees, (ii) pay average wages less than $50,000 a year per full-time equivalent, (iii) pay at least 50% of its full-time employees' premium costs, and finally, (iv) have provided a health plan to employees that is qualified under Small Business Health Options Program (SHOP) requirements.

In addition to raising the tax credit from 35% to 50%, in 2014, the government also launched the SHOP Marketplace to offer small business owners a transparent and convenient platform/exchange to compare and shop for insurance packages. Qualified employers were required to purchase insurance packages via the marketplace, which directly lists health plan choices certified for the tax credit in which the employers could enroll their employees. The marketplace was initially planned to be launched at the end of 2013; however, there was a delay in the launch of the marketplace until November of 2014 so that the tax credit could be applied to coverage starting from 2015.[37]

We utilize the tax credit hike in 2014 (i.e., the second phase) to identify the impact of soft information demand on banks' technology adoption. Because 2010 is right after the implementation of the Recovery Act in 2009, during which numerous other stimulus policies were launched to aid in postrecession economic recovery, this proximity in timing may contaminate the identification. Perhaps more importantly, several surveys revealed that the first phase of the tax credit was not well implemented; some small businesses think the tax credit in the first phase is not high enough or were not even aware of the policy after its implementation.[38] On the other hand, after the tax credit hike and launch of the SHOP Marketplace in 2014, there is a significant decrease in the number of uninsured small business employees.[39]

There are many channels through which this program could boost credit demand from small businesses. First of all, the policy is economically significant: the increased tax credit on average can induce a 14% of savings in terms of total net profit.[40] Thanks to the increased program subsidy, some small business owners who previously could not afford employee health coverage were now likely to provide it, and some may even have chosen to expand their businesses by hiring more employees given the lower effective labor cost.[41]

More importantly, the nature of the timing for the tax "rebate" incentivizes small businesses to apply for extra business loans, as all business owners would need to borrow in advance to cover employee health packages and then repay the loan once they have claimed the credit the following year. In turn, banks would be handling additional soft information, such as the employee hiring and health plans, to screen for genuinely credit-worthy borrowers.

The key to our identification is that the fraction of total establishments that are qualified for the tax policy right before the program launch date varies substantially across different counties. Because the qualified small business share is a key determinant for credit demand from local small businesses, such variation thus helps us identify the impact of the small business credit demand shock on local banks' behavior. As the policy only explicitly targets small businesses, its impact on other types of local credit demand would be indirect or limited.

4.2.2.1. Empirical Design: 2SLS Regression. We run the following two-stage least squares (2SLS) regression:

$$\Delta \ln(\mathrm{CRA})_{i,c,post} = \tilde{\alpha}_i + \mu_1 \left(\frac{\#\,\text{Qualified small business est}}{\text{Total}\,\#\,\text{of establishments}} \right)_{c,pre} + \mu_2 \mathbf{X}_{i,c} + \epsilon_{i,c}$$

$$\Delta \ln \mathrm{IT}_{i,c,post} = \alpha_i + \beta \Delta \ln \widehat{(\mathrm{CRA})}_{i,c,post} + \gamma \mathbf{X}_{i,c} + \epsilon_{i,c}. \qquad (2)$$

In the first-stage regression, the outcome variable $\Delta\ln(\mathrm{CRA}_{i,c,post})$ is the change in the logarithm of bank i's small business loans in county c in the three-year time window before and after the policy change in 2014. The instrumental variable (IV) $\frac{\#\,\text{Qualified small business est}}{\text{Total}\,\#\,\text{of establishments}}\Big|_{c,pre}$ is the proportion of total business establishments that have fewer than or equal to 20 employees, averaged between 2011 and 2013 before the shock.[42]

In the second stage, we regress $\Delta\ln \mathrm{IT}_{i,c,post}$, which is the change in logarithm of a specific type of IT spending of bank i in county c during 2014–2017 compared with the period of 2011–2013, on the fitted value from the first stage.[43]

The instrument in (2), that is, the QSB share before the policy shock, is a slow-moving object that reflects the status of the local economy. Our identification assumption is that, conditional on the control variables, the QSB share affects the cross-county growth rate in banks' IT spending around the policy shock only through affecting the small business loans extended in the local economy. Table A8 in the Online Appendix shows that the growth in small business around the policy year was mostly concentrated in those businesses that were qualified for the tax policy, which corroborates our first-stage results that counties with a higher "QSB share" experienced faster growth in small business credit around 2014. Finally, the parallel trend assumption requires that heterogeneity in the qualified small business share explains divergent paths in local banks' IT spending only after the policy, which we empirically verify shortly.

We have included a rich set of preshock control variables in Regression (2). Bank fixed effects absorb any unobserved heterogeneity that may also induce banks in areas with more qualified small businesses to be on a higher IT spending growth path. Revenue per employee at the bank-county level proxies for investment opportunity of a bank in the local economy. We also add a set of county-level economic characteristics, which include county size (proxied by the logarithm of total number of establishments) and local economic situation (proxied by population growth rate, changes in unemployment, labor force participation ratio, the share of nontradable sector business establishments, and real GDP per capita).

Besides adding controls and fixed effects, we also perform several placebo tests along various dimensions. In Online Appendix Table A11, we hypothetically postulate the tax policy event to take place in year 2018 and then examine the effect of QSB share on the dynamics of small business credit around these pseudo–event years. In Online Appendix Table A12, we test whether the variation in the QSB share also drives differences in the growth rate in other types of credit (e.g., mortgage origination or refinancing) around the tax policy time. In either test, we find little effect from the variation in QSB share, in contrast to its significant impact on the small business credit growth around the policy year of 2014.

4.2.2.2. Estimation Results. We report the estimation results of (2) in the first three columns of Table 6. Standard errors are clustered at the county level. Column (1) shows the regression estimates in the first-stage regression with a strong first-stage result: the F-statistic of 13.71 is above the conventional threshold for weak instruments (Stock and Yogo 2005).

We find a positive and statistically significant response in banks' communication investment across

Table 6. Soft Information and Banks' IT Spending

	First stage (1)	ln(Software) (2)	ln(Communication) (3)	ln(Software) (OLS) (4)	ln(Communication) (OLS) (5)
$\left(\frac{\text{Qualified small businesses establishments}}{\text{Total establishments}}\right)_{c,pre}$	1.032***				
	(0.251)				
$\Delta\ln(\widehat{CRA})$		−0.057	0.670**		
		(0.305)	(0.328)		
$\Delta\ln(CRA)$				0.004	0.019*
				(0.010)	(0.011)
Bank FE	Y	Y	Y	Y	Y
Clustered	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
F-statistic	13.708				
Adjusted R^2	0.427	−0.179	−0.522	0.120	0.102
N	19,848	19,848	19,848	19,848	19,848

Notes. This table presents the results of 2SLS and OLS discussed in Section 4.2.2. The first three columns show the results for the following specification.

$$\Delta\ln(\text{CRA})_{i,c,post} = \tilde{\alpha}_i + \mu_1 \times \left(\frac{\#\text{ Qualified small business est}}{\text{Total \# of establishments}}\right)_{c,pre} + \mu_2\mathbf{X}_{i,c} + \epsilon_{i,c}$$

$$\Delta\ln(\text{IT})_{i,c,post} = \alpha_i + \beta \times \Delta\ln(\widehat{\text{CRA}})_{i,c,post} + \gamma\mathbf{X}_{i,c} + \epsilon_{i,c}$$

Column (4) and column (5) show the following OLS specification.

$$\Delta\ln(\text{IT})_{i,c,post} = \alpha_i + \beta \times \Delta\ln(\text{CRA})_{i,c,post} + \mu_c + \gamma\mathbf{X}_{i,c} + \epsilon_{i,c}$$

$\Delta\ln\,(\text{CRA})_{i,c,post}$ is the change in average natural log of small business loans reported in CRA of bank i at county c during the years 2014–2017 compared with 2011–2013. Bank control variables include preshock revenue per employee of the bank in a county. County-level control variables include the preshock unemployment growth rate, labor force participation rate, population growth rate, logarithm of total number of establishments, share of nontradable sector small business establishments, and GDP per capita. Fixed effects include bank fixed effects. Standard errors are clustered at the county level.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

counties in the second stage. In particular, banks that were facing a one-standard-deviation-higher growth in their small business loan making—because of a higher policy exposure captured by QSB share—experienced a 0.67-standard-deviation-higher growth in their communication spending; in dollar terms, this translates into an increase of $40,298 in communication IT spending.[44]

On the other hand, one-standard-deviation higher growth in small business loans leads to 0.057-standard-deviation-slower growth in software spending and is statistically insignificant, suggesting that banks did not respond in increasing their software spending (which is more pertinent to dealing with ready-to-use hard information). Note that by including bank fixed effects, our results come from "within-bank but cross-county" variations. Overall, this asymmetric impact on banks' IT adoption behavior is consistent with our hypothesis that small business lending relies more on soft information handling than on processing hard information.

4.2.2.3. Bank Responses and "Young Firm Share." With the premise that young small businesses often lack credit records and thus need extra interaction for loan officers to gather relevant soft information, we test whether the tax policy leads to a larger impact on banks' IT spending response in counties with more young small business borrowers. Specifically, we expand the 2SLS regression in Equation (2) by introducing an interaction term $\Delta\ln(\text{CRA})_{i,c,post} \times$ High young, where the dummy *High young* takes value one for counties whose proportion of small businesses younger than one year was above median among all counties in 2013. Table 7 shows that communication spending for banks in the *High young share* counties is the main driver of the overall positive causal impact, whereas the response of banks in *Low young share* counties is statistically insignificant.

4.2.2.4. Dynamic Treatment Effects. We now study the dynamics of bank IT spending responses to the policy shock; this also helps us evaluate the validity of the IV by examining the pretrend patterns of banks' IT spending. We run the following regression with observations of bank i at county c in year t:

$$\ln IT_{i,c,t} = \alpha_{i,t} + \alpha_{i,c} + \sum_{s\in[-3,3],\, s\neq -1} \beta_s \times \mathbb{1}_{\{t-2014=s\}} \times \text{High QSB exposure}_{pre} + \mathbf{\Pi}_t \times \mathbf{X}_{i,c,t} + \epsilon_{i,c,t},$$

where $\alpha_{i,t}$ and $\alpha_{i,c}$ are bank-year and bank-county fixed effects, and *High QSB exposure* is an indicator variable that

Table 7. Dependence of Banks' Shock Response on Young Firm Share

	First stage $\Delta\ln(\text{CRA})$	First stage $\Delta\ln(\text{CRA}) \times$ *High young*	Second stage *ln(Software)*	Second stage *ln(Communication)*	OLS *ln(Software)*	OLS *ln(Communication)*
	(1)	(2)	(3)	(4)	(5)	(6)
$\%QSB_{pre}$	0.024*	0.028**				
	(0.012)	(0.014)				
$\%QSB_{pre} \times$ High young	−0.021**	0.025**				
	(0.010)	(0.010)				
$\Delta\ln(\widehat{\text{CRA}})$			−0.429	−0.321		
			(0.617)	(0.685)		
$\Delta\ln(\widehat{\text{CRA}}) \times$ High young			0.687	1.534*		
			(0.844)	(0.928)		
High young			0.017	0.025	−0.042*	−0.056**
			(0.070)	(0.075)	(0.023)	(0.022)
$\Delta\ln(\text{CRA})$					0.003	0.017
					(0.014)	(0.016)
$\Delta\ln(\text{CRA}) \times$ High young					0.004	0.019
					(0.021)	(0.021)
Bank FE	Y	Y	Y	Y	Y	Y
Clustered	Y	Y	Y	Y	Y	Y
F-statistic	12.350	12.350				
Adjusted R^2	0.321	0.291	−0.330	−1.289	−0.179	−0.178
N	19,234	19,234	19,234	19,233	19,234	19,233

Notes. This table presents the impact of soft information demand and banks' IT spending for counties with a differential share of younger small businesses. The 2SLS regression specifications are as follows.

$$\Delta\ln(\text{CRA})_{i,c,post} = \widehat{\alpha_i} + \eta_1 \times \left(\frac{\#\text{ Qualified small business est}}{\text{Total \# of establishments}}\right)_{c,pre} + \eta_2 \mathbf{X}_{i,c} + \epsilon_{i,c}$$

$$\Delta\ln(\text{CRA})_{i,c,post} \times \text{High young} = \tilde{\alpha}_i + \mu_1 \times \left(\frac{\#\text{ Qualified small business est}}{\text{Total \# of establishments}}\right)_{c,pre} + \mu_2 \mathbf{X}_{i,c} + \epsilon_{i,c}$$

$$\Delta\ln(\text{IT})_{i,c,post} = \alpha_i + \beta \times \Delta\ln(\widehat{\text{CRA}})_{i,c,post} + \beta_1 \times \widehat{\Delta\ln(\text{CRA})_{i,c,post} \times} \text{High young} + \beta_2 \text{High young} + \gamma \mathbf{X}_{i,c} + \epsilon_{i,c}$$

$\Delta\ln(\text{CRA})_{i,c,post}$ is the change in average natural log of small business loans reported in CRA of bank i at county c during the years 2014–2017 compared with 2011–2013. Bank control variables include preshock revenue per employee. *High young* counties are defined as counties whose proportion of small businesses younger than one year old was above median among all counties in 2013. County-level control variables include the preshock unemployment growth rate, labor force participation rate, population growth rate, log of total number of establishments, share of nontradable sector small business establishments, and GDP per capita. Fixed effects include bank fixed effects. Standard errors are clustered at the county level and are given in parentheses.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

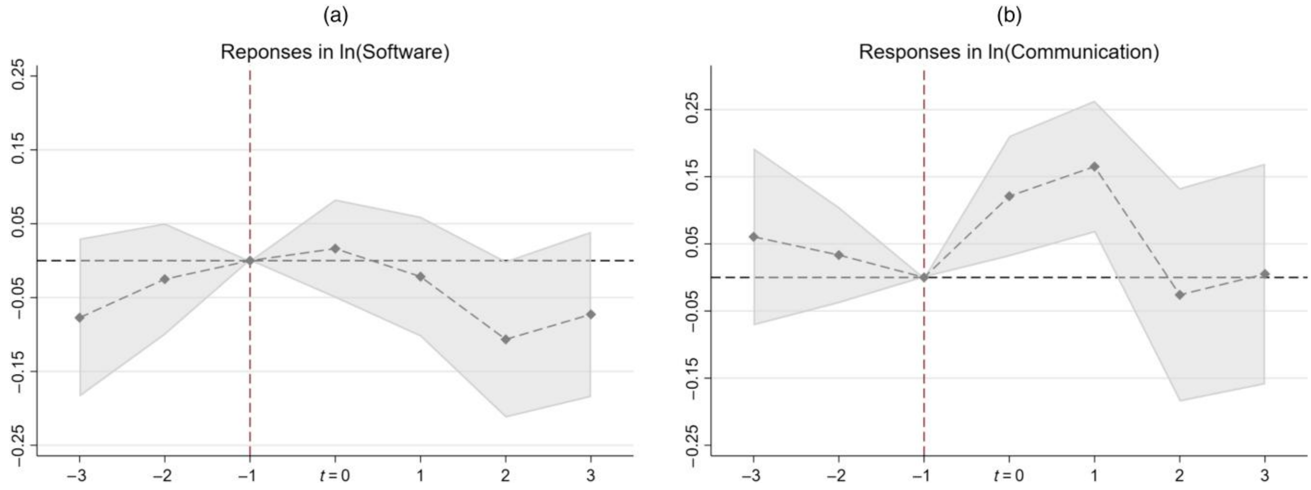
equals one (zero) if the average $\frac{\#\text{ Qualified small business est}}{\text{Total \# of establishments}}_{c,pre}$ between 2011 and 2013 sits in the top (bottom) tercile. Note that here, we allow the coefficients on control variables to be time varying.

Figure 3 plots the set of estimated coefficients $\{\widehat{\beta}_s\}$, which measures the intent-to-treat (ITT) effects of the policy change on $\ln IT_{i,c,t}$ through heterogeneous exposure as captured by QSB share, with the base year as 2013. Prior to the policy shock, the time trends of both types of IT spending display no significant differences for banks located in high-exposure counties versus those in low-exposure counties. Because of the tax credit hike in 2014, the communication spending of banks located in high-exposure counties sees a continuous growth for two consecutive years (Figure 3(a)), whereas the software spending of banks (Figure 3(b)) in high-exposure counties and low-exposure counties demonstrates no difference before 2014 and remains similar after. Finally, $\{\widehat{\beta}_s\}$ for communication, IT spending (Figure 3(a)) starts to decrease around 2016; this might be because of the "capital" nature of IT investment.[45]

4.2.2.5. Comparison: OLS Estimates. We report the OLS estimates in columns (4) and (5) of Table 6.

Qualitatively, OLS estimates are similar to those obtained from the 2SLS method, but in terms of magnitude, they are significantly smaller. One explanation for such a downward bias in OLS estimators could be a potential "omitted variable" problem, in which counties experiencing faster growth in small business loans are those with even faster growth in some unobservable economic variables—say, mortgage refinancing

Figure 3. (Color online) Bank IT Spending Around Small Business Tax Credit Policy



Notes. This figure reports the event studies of IT spending around the small business tax credit event. The specification is

$$\ln IT_{i,c,t} = \alpha_{i,t} + \alpha_{i,c} + \sum_{s\in[-3,3],\, s\neq -1} \beta_s \times \mathbb{1}_{\{t-2014=s\}} \times \text{High QSB exposure}_{pre} + \mathbf{\Pi}_t \times \mathbf{X}_{i,c,t} + \epsilon_{i,c,t},$$

where, for bank i at county c in year t, $\alpha_{i,t}$ are the bank-year fixed effects, and $\alpha_{i,c}$ are the bank-county fixed effects. $1_{\{t-2014=s\}}$ is a dummy variable that is equal to one if the distance between year t and the event year (2014) is s. High exposure$_{pre}$ is equal to one if the average $\left(\frac{\text{\# Qualified small business est}}{\text{Total \# of establishments}}\right)_{c,pre}$ is within the top tercile between 2011 and 2013, and *High exposure* is equal to zero if the average $\left(\frac{\text{\# Qualified small business est}}{\text{Total \# of establishments}}\right)_{c,pre}$ in the bottom tercile between 2011 and 2013. Bank control variables include banks' revenue per employee of the bank in a county. County control variables include unemployment rate, labor force participation rate, population growth rate, logarithm of total number of establishments, share of small businesses in nontradable sector, and GDP per capita. Shaded regions are the 95% confidence interval of the estimated β_s. Standard errors are clustered at the county level.

demand—that drive local banks to spend less on communication, leading the OLS estimator to be downward biased.

4.3. Bank IT Spending and Hard Information

4.3.1. Hard Information Processing in Bank Lending: Mortgage Refinancing. Unlike the lending activities analyzed in Section 4.2, where soft information handling is key, in other situations, banks' ability to extend profitable credit is determined by how efficiently they can deal with hard information. As mentioned earlier, mortgage refinancing is the stereotypical type of loan that relies heavily on efficient processing of readily accessible hard information. The discussion in Section 4.1 suggests that banks' software spending should be positively correlated with mortgage refinancing, an empirical fact that we have shown in Table 4, row 5, in Section 3.2.1.

We move one step further and conduct a similar analysis within the mortgage lending business by splitting it into mortgage origination and mortgage refinancing. For each bank, we construct *Refinance/Origination* over the period 2010–2019, and row 7 of Table 4 shows that banks with a greater *Refinance/Origination* spend more on software, whereas there is no significant effect on communication spending.

The close linkages between banks' software spending and their engagement in mortgage refinancing are also consistent with a recent strand of literature studying fintech lenders' penetration into credit markets. As documented in Fuster et al. (2019), the expansion of fintech lenders—who often serve as the suppliers of new banking software products and typically rely on readily available hard information—is particularly pronounced in the refinancing segment of the mortgage, auto loans, and student loan markets. Later in Section 5, we confirm that software indeed stands out as the major category of IT spending in which commercial banks respond to the entry of fintech lenders.

4.3.2. Bank IT Spending and Demand Shock on Mortgage Refinancing. Paralleling Section 4.2.2, we ask: How would banks respond when hit by credit demand shocks that mostly involve processing hard information, say, mortgage refinancing? We expect banks to increase their spending on software (hard information), but not on communication (soft information).

For exogenous sources of cross-sectional variation in mortgage refinance demand, following Di Maggio et al. (2017) and Eichenbaum et al. (2022), we construct an IV for county-level refinancing propensity by utilizing the postcrisis low-interest-rate period. The nationwide mortgage rate decrease prompted existing homeowners to refinance their mortgages, and an important determinant of homeowners' refinancing propensity was the precrisis mortgage characteristics in place before the low-interest episode kicked in.[46]

We consider two ways to construct the instrumental variable. The first follows Eichenbaum et al. (2022) by constructing the IV as the *dollar amount difference*. Specifically, for each loan j in county c with unmatured balance in year t between 2011 and 2016, we calculate the interest savings under the new mortgage rate compared with the old mortgage rate:

$$\begin{aligned}\Delta\text{Payment}_{j,c,t} &= (\text{Total Interest Payment}|\text{mortgage rate}_j)\\ &\quad - (\text{Total Interest Payment}|\text{new mortgage}\\ &\qquad \text{rate}_t^{\text{FICO, maturity, zip}}),\end{aligned}$$

where the total interest payments are calculated from the amortization schedule with the remaining loan balance as principal. The new mortgage rates are constructed by the bucket of "zip × maturity × FICO" based on new origination in year t and then matched to each loan j. We then calculate the average $\Delta\text{Payment}_c$ by taking the average of all savings of unmatured loans j and over years 2011–2016.[47] In words, we calculate the average total remaining mortgage savings under old versus new interest rates at the county level.[48] The variation in local homeowners' refinancing savings thus serves as an exogenous shifter on the mortgage refinance demand faced by local banks.

Though frequently utilized by the previous literature, $\Delta\text{Payments}_c$ is likely correlated with the remaining loan balances of a county, which are, in turn, correlated with the average loan size or house price level of a county. Therefore, $\Delta\text{Payments}_c$ may correlate with local banks' IT spending because of other channels beyond mortgage refinance demand. As an alternative IV, we construct the average mortgage rate gap between the rates at origination and the current rate for the unmatured existing mortgages in a county c:

$$\begin{aligned}\Delta\text{Mortgage rate}_{c,t} &= \sum_j (\text{mortgage rate}_{j,c}\\ &\qquad - \text{new mortgage rate}_t^{(\text{FICO, maturity, zip})})\\ &\quad \times \frac{\text{Total loan amount}_{j,c}}{\text{Total loan amount during 1999–2010}_c}.\end{aligned}$$

We then take the average of $\Delta\text{Mortgage rate}_{c,t}$, which captures the average mortgage *rate* savings instead of *dollars* at year t for mortgage borrowers across years 2011–2016. In words, for a given county, we compute the weighted average of mortgage interest rate gaps, with weights as the loan volume at the initiation.

4.3.2.1. Empirical Design and Estimation Results. We aim to identify whether banks' software investment increases given a greater mortgage refinance demand compared with mortgage origination, with the following standard 2SLS specification:

$$\begin{aligned}&\ln(\text{Refinance/Origination})_{i,c}\\ &\quad = \tilde{\alpha}_i + \mu_1 \Delta\text{Payments}_c/\Delta\text{Mortgage rate}_c + \mu_2 \mathbf{X}_{i,c} + \tilde{\epsilon}_{i,c},\\ &\ln(\text{Software})_{i,c} \text{ or } \ln(\text{Communication})_{i,c}\\ &\quad = \alpha_i + \beta \ln(\widehat{\text{Refinance/Origination}})_{i,c} + \gamma \mathbf{X}_{i,c} + \epsilon_{i,c}.\end{aligned} \tag{3}$$

Similar to before, our control variables include banks' revenue per employee and deposit market share of the bank in a county. County-level control variables include the unemployment rate, labor force participation rate, population growth rate, logarithm of number of establishments, and logarithm of small business loans. We include bank fixed effects and cluster standard error at the county level.

Table 8 reports our estimation results. In the first stage of column (1), the instrumental variable $\Delta\text{Mortgage rate}_c$ predicts mortgage refinancing activities quite well, with a high *F*-statistic (10.81). For the second stage, columns (2) and (3) show that a one-standard-deviation increase in mortgage refinancing relative to mortgage origination—driven by its local exposure to high refinance interest savings—leads to a 0.310-standard-deviation increase in software spending. In dollar terms, this translates to an increased software spending of $133,260. This increase is of a similar magnitude, though smaller than the corresponding $455,500 revenue increase from mortgage refinancing,[49] and it is worth emphasizing that our current data does not provide a comprehensive estimate of costs across other dimensions.

Columns (4)–(6) show the results using $\Delta\text{Payment}_c$ as the instrumental variable. Note that whereas the difference between coefficient estimates with these two IVs is statistically insignificant (consistent with the premise that both IVs give us unbiased estimates), we believe $\Delta\text{Mortgage rate}_c$ satisfies the exclusion restriction condition better. In Online Appendix Table A15, we tabulate the correlations between $\Delta\text{Payment}_c$ and $\Delta\text{Mortgage rate}_c$ with major county-level economic variables. As shown, $\Delta\text{Mortgage rate}_c$ exhibits statistically and economically insignificant correlations with most of the county characteristic variables, whereas $\Delta\text{Payment}_c$ has positive correlations with some of them (though of relatively small magnitude).

Finally, by including bank fixed effects, our result is identified from within-bank, cross-county variations. In addition, communication spending does not

Table 8. Hard Information and Banks' IT Spending

	2SLS			2SLS			OLS	
	First stage (1)	ln(Software) (2)	ln(Comm) (3)	First stage (4)	ln(Software) (5)	ln(Comm) (6)	ln(Software) (7)	ln(Commu) (8)
ΔMortgage rate$_c$	1.824*** (0.622)							
ΔPayment$_c$				0.819*** (0.237)				
$\ln\widehat{\text{Refinance/Origination}}$		0.315* (0.167)	0.239 (0.150)		0.373* (0.225)	0.296 (0.211)		
ln(Refinance/Origination)							0.024*** (0.006)	0.025*** (0.006)
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Clustered	Y	Y	Y	Y	Y	Y	Y	Y
F-statistic	10.81			13.82				
Adjusted R^2	0.356	−0.349	0.072	0.423	0.447	0.576	0.449	0.423
N	14,626	14,626	14,626	14,626	14,626	14,626	14,626	14,626

Notes. This table presents the results of the regressions discussed in Section 4.3.2. The first six columns show the results for the 2SLS specification below.

$$\ln(\text{Refinance/Origination})_{i,c} = \tilde{\alpha}_i + \mu_1 \times \Delta\text{Mortgage rate}_c(\text{or } \Delta\text{Payments}_c) + \mu_2 \mathbf{X}_{i,c} + \epsilon_{i,c}$$
$$\ln(\text{Type S Spending})_{i,c} = \alpha_i + \beta \times \ln(\widehat{\text{Refinance/Origination}})_{i,c} + \gamma \mathbf{X}_{i,c} + \epsilon_{i,c}$$

Columns (7) and (8) show the results of the OLS specification below.

$$\ln(\text{Type S Spending})_{i,c} = \alpha_i + \beta \times \ln(\text{Refinance})_{i,c} + \gamma \mathbf{X}_{i,c} + \epsilon_{i,c}.$$

$\ln(\text{Type S Spending})_{i,c}$ is the average logarithm of banks' IT spending during 2011 and 2016. $ln(\text{Refinance/Origination})_{i,c}$ is the average logarithm of amount of mortgage refinance loan relative to mortgage origination issued by bank *i* in county *c* during 2011 and 2016. $\Delta\text{Payments}_c$ is the hypothetical amount of interest payments that could be saved because of the interest rate decrease if local households chose to refinance their mortgages during the year of 2011 and 2016. $\Delta\text{Mortgage rate}_c$ is the average differences of mortgage rate of unmatured loans in 2011–2016 and the prevailing mortgage rates of newly issued mortgages in a county *c*. Bank control variables include banks' revenue per employee of the bank in a county. County-level control variables include unemployment growth rate, labor force participation rate, population growth rate, logarithm of total number of establishments, logarithm of total small business loan, share of nontradable sector establishments, and GDP per capita. Fixed effects include bank fixed effects. Standard errors are clustered at the county level.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

demonstrate statistically significant changes in response to the refinancing demand shocks, which supports our premise that mortgage refinancing is a stereotypical lending activity that hinges on efficient processing of readily accessible hard information instead of producing new information.

4.3.2.2. Comparison: IV Estimates and OLS Estimates. We conduct the OLS version of the 2SLS regression in Equation (3) and report the results in the last two columns of Table 8, with quantitatively smaller OLS estimators.[50] Similar to our analysis of small business credit demand in Section 4.2.2, an omitted variable issue can explain such downward biases in OLS estimators. Here, counties seeing more mortgage refinances issued by local banks might also have other loan demands that recovered more significantly during the postcrisis period (say, small business loans), which might then tilt local banks' IT budget toward other types of IT spending (say, communication, as shown in Section 4.2), lowering their spending on software. Our instrumental variable used in the 2SLS method addresses this issue.

5. Bank IT Spending and Fintech Entry

In recent years, the emergence and expansion of fintech lenders have drawn heightened public attention to the competition between fintech lenders and traditional banks. Via the angle of examining commercial banks' IT spending, we aim to study a widely debated question: Has the traditional banking sector started reacting to the fast-growing fintech industry? If yes, how?

5.1. How Should Banks React to Fintech Entry?

Existing studies suggest that fintech lenders' services involve better use of technology and little human interaction. This tech-intensive feature improves customer experience and likely reduces lending-associated costs (Buchak et al. 2018, Fuster et al. 2019).

Whereas fintech lenders have been quickly gaining market share in various markets over the past decade, it remains unclear how the incumbent commercial banks should react. For instance, when banks and nonbank lenders offer complementary services, it is possible for banks to strategically shift investment toward areas with fewer activities from fintech lenders. Furthermore, from an information channel, the emergence of fintech lenders that have comparative advantages in information handling in certain markets would render traditional bank lenders more adversely selected in these markets. Both would imply a "falling back" of traditional banks from the markets with fintech entry and a lowered investment in the IT category in which fintech lenders have comparative advantages.

On the other hand, incumbent banks might instead choose to protect their market share and compete against these new fintech entrants, suggesting a potential catching-up behavior of the traditional banking sector. Which economic force dominates is an empirical question that we now aim to answer.

5.2. Entry of LendingClub and Local Bank IT Investment

To causally identify banks' response in their IT spending toward the increasing presence of fintech lenders, we employ a difference-in-difference strategy that relies on the staggered entrance of LendingClub into different states.

5.2.1. Staggered Entry of LendingClub. As one of the leading players in the fintech industry, LendingClub launched its platform in 2007. Since 2008, LendingClub has been pursuing regulatory approval to conduct peer-to-peer lending in all 50 states. By October 2008, 41 states moved relatively fast to approve its entry, and between 2010 and 2016, another nine states approved LendingClub's entrance at different times.[51] Table 9 summarizes the timing of LendingClub's staggered entrance into different states.

Following Kim and Stähler (2020) and Wang and Overby (2022), we first drop the 41 states that approved LendingClub's entry in 2008.[52] For Kansas and North Carolina, the actual approval was in 2010 Q4. Because 2010 is the starting year of our Harte Hanks data set, 2010 as a pretreatment period is contaminated for these two states. We hence also exclude these two states, leaving us with a total of seven states for our staggered entrance analysis.

Table 9. Staggered Entry of LendingClub to Nine States After 2010

State	Approval year
All states, except the states listed below	2008
Kansas	2010 Q4
North Carolina	2010 Q4
Indiana	2012 Q4
Tennessee	2013 Q1
Mississippi	2014 Q2
Nebraska	2015 Q2
North Dakota	2015 Q2
Maine	2015 Q3
Idaho	2016 Q1
Iowa	Not approved as of 2022 Q1

Importantly for our identification purpose, the variation in the approval time since 2010—presumably because of variations in administrative efficiency and potential political issues across states—allows us to get around several major endogeneity concerns regarding the entry of LendingClub. For instance, if LendingClub were to chose to enter the local markets with rising credit demand, then any observed change in local commercial banks' IT investment behavior could not have been convincingly attributed to the entry of their fintech challenger.

For the states in our sample, after its entrance, the personal loan issuance market share of LendingClub across states has a median of 4.85%, with 1.79% (10.29%) being its 25th (75th) percentile (Online Appendix Table A17).

These statistics suggest that (i) at the state level, LendingClub's presence in the personal loan market features significant variations; and (ii) in states where LendingClub actively operates, it makes a nontrivial contribution to the local personal loan market. Both of these two facts are important for our empirical identification, in which the key variation (driven by differences in approval time) operates at the state level.

From the perspective of incumbent banks, Table A19 in the Online Appendix shows that personal loans represent a significant portion of banks' interest income among all categories of loans, especially for larger banks (banks with more than $10 billion in assets): around 20% of interest income comes from personal loans. This indicates that banks have a compelling reason to react when fintech lenders emerge in one of their most profit-generating loan segments.

5.2.2. Empirical Design and Results. Our empirical method follows the staggered difference-in-difference design as in Wang and Overby (2022). The regression specification is

$$\ln(\text{IT Spending})_{i,c,t} = \alpha_{i,t} + \alpha_c + \beta \times \text{LC}_{i,c,t} + \mu_t X_{i,t} + \epsilon_{i,c,t}, \tag{4}$$

where IT Spending $\in$ {Software, Communication}. We include the bank-year and county fixed effects, denoted by $\alpha_{i,t}$ and α_c respectively, and controls $X_{i,t}$ are in the caption of Table 10. $\text{LC}_{i,c,t}$ is a dummy variable that is equal to one if LendingClub entered the state where county c is located in year t for bank i; β hence measures the average treatment effect of LendingClub entry on bank technology spending. Estimations are weighted by LendingClub loan volume after entry, and the standard error is clustered at the county level.

Columns (1) and (2) in panel A of Table 10 report the results for software and communication spending, respectively. Consistent with the catching-up story, column (1) shows that after LendingClub entered country

Table 10. Fintech Entry and Banks' Lending Technology Adoption

	Baseline		Callaway and Sant'Anna (2021)	
	ln(Software) (1)	ln(Communication) (2)	ln(Software) (3)	ln(Communication) (4)
Panel A: Baseline results				
After	0.076***	0.001	0.080**	0.007
	(0.023)	(0.018)	(0.042)	(0.040)
Fixed effects	Bank × county, year, size group			
Adjusted R^2	0.808	0.790		
N	13,406	13,406		
Panel B: Effects by bank size				
After	0.051	0.037	0.043	0.090
	(0.032)	(0.030)	(0.048)	(0.052)
After× Large	0.062*	−0.058*	0.097***	−0.167***
	(0.032)	(0.035)	(0.040)	(0.061)
Fixed effects	Bank × county, year, size group			
Clustered	Y	Y		
Adjusted R^2	0.777	0.96		
N	13,406	13,406		
Panel C: Effects by personal loan share				
After	0.054**	0.007	0.058	0.050
	(0.026)	(0.023)	(0.050)	(0.052)
After×High personal loan	0.055**	−0.002	0.078**	−0.041
	(0.025)	(0.026)	(0.043)	(0.054)
Fixed effects	Bank × county, year, size group			
Clustered	Y	Y		
Adjusted R^2	0.837	0.774		
N	13,406	13,406		

Notes. This table presents the effect of LendingClub's entrance on local banks' IT spending. The regression equation is as follows.

$$\ln(\text{ITSpending})_{i,c,t} = \alpha_{i,c} + \alpha_t + \beta \times \text{LC}_{i,c,t} + \gamma_t \mathbf{X}_{i,t} + \epsilon_{i,c,t},$$

where $\alpha_{i,c}$ and α_t are the bank-county and year FE, respectively. Columns (1) and (2) of panel A show the baseline results. Bank control variables include banks' revenue per employee of the bank in a county. County-level control variables include unemployment growth rate, labor force participation rate, population growth rate, logarithm of total number of establishments, share of nontradable sector establishments, and GDP per capita. Standard errors are based on 50 bootstrapped samples. Panel B presents the differential responses to fintech entrance of banks with different sizes. *Large banks* are defined as banks with asset size above median of all the asset sizes in the sample. Panel C presents the differential responses to Fintech entrance of banks with different personal loan share. *High personal loan* banks are defined as banks for which the personal loan as a share of total loan is above median among all banks in the sample. The estimations in column (3) and column (4) of the three panels are based on the interacted TWFE method as in Callaway and Sant'Anna (2021). Standard errors are in the parentheses and are clustered at the county level.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

c, banks on average increase their software IT spending in county c by around 7.6 percentage points, and this estimate is statistically significant. In contrast, communication spending right after LendingClub's entry displays no statistically significant changes compared with pre-entrance.

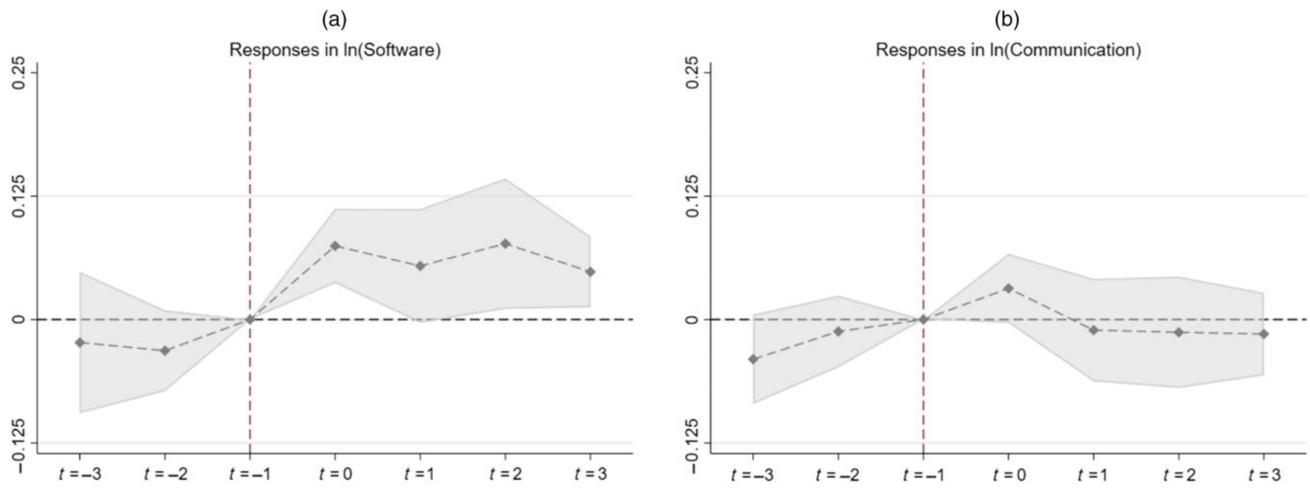
Figure 4 graphically explores the dynamics of banks' IT spending within the three-year time window around the fintech entrance year from the following estimation:

$$\ln \text{IT}_{i,c,t} = \alpha_{i,c} + \mu_t + \sum_{s\in[-3,3],\, s\neq -1} \beta_s \times \mathbb{1}_{s=t-\text{entrance year}} + \mathbf{\Pi}_t \mathbf{X}_{i,c,t} + \epsilon_{i,c,t},$$

where fixed effects and controls are the same as in Equation (4), and the coefficients on the controls are allowed to be time varying. The estimated $\{\widehat{\beta}_s\}$ and the 95% confidence intervals are plotted. Importantly for our identification, there is no statistically significant pretrend in either type of IT spending before the fintech entrance, which allows us to plausibly attribute changes in banks' IT spending to the penetration of fintech into the local economy. Consistent with Table 10, a bank's software spending displayed a significantly sharper increase than communication IT spending after the fintech entry.

Recent literature points out the bias in a staggered two-way fixed effects (TWFE) setting, even if the assumption of parallel trends holds. For robustness, we use the interacted TWFE design as in Callaway and Sant'Anna (2021).[53] As shown in columns (4) and (5) of Table 10, the estimates are similar to, albeit a little larger than, those in columns (1) and (2).

Figure 4. (Color online) Bank IT Spending Around Fintech Entrance



Notes. This figure reports the event studies of IT spending around the entrance of LendingClub. The specification is

$$\ln IT_{i,c,t} = \alpha_{i,c} + \mu_t + \sum_{s\in[-3,3],\, s\neq -1} \beta_s \times \mathbb{1}_{t-\text{entrance year}=s} + \mathbf{\Pi}_t \mathbf{X}_{i,c,t} + \epsilon_{i,c,t},$$

where, for bank i at county c in year t, $\alpha_{i,c}$ are the bank-county fixed effects, and μ_t are the year fixed effects. $\mathbb{1}_{t-\text{entrance year}=s}$ is a dummy variable that is equal to one if the number of years between the observation year t and the fintech entrance year into the state where county c is located is s. For (a), the left-hand-side variable is logarithmic spending on software IT. For (b), the left-hand-side variable is logarithmic spending on communication IT. Bank control variables include banks' revenue per employee of the bank in a county. County control variables include unemployment rate, labor force participation rate, population growth rate, logarithm of total number of establishments, share of small businesses in the nontradable sector, and GDP per capita. Shaded regions are the 95% confidence interval of the estimated β_s. Standard errors are clustered at the county level.

5.2.3. Heterogeneity in Responses Across Bank Sizes. In panel B of Table 10, we explore whether banks of different sizes respond differently to fintech entry. Similar to our specification in Table 5, large (small) banks are defined as lenders with asset size above (below) the median size in our sample. We find that large banks increased software spending by 6.2 percentage points more compared with small banks after LendingClub's entry, and the difference is statistically significant. On the other hand, large banks cut their communication spending by 5.8 percentage points compared with small banks following the fintech entry, which is statistically significant. Note that via a different instrument variable, Modi et al. (2022) also document that large banks increase their IT spending when facing competition from fintech lenders, but our data allow us to speak to the underlying mechanism of such response by separating different categories of IT spending, showing that it is mainly driven by hard information considerations.

The asymmetric impact on the IT spending reactions by different-sized banks is intriguing and suggests that the specialty (regarding information handling) of the newly entered fintech is more relevant for the market segments served by large banks. This is consistent with Balyuk et al. (2020), who find that fintech lending often substitutes lending made by large banks rather than small banks. Given that small banks engage more in relationship-based small business lending, the entry of LendingClub—which is equipped with superior hard information processing capacity—will not strongly affect these banks' profit making. Furthermore, that large banks cut their communication spending is also consistent with the recent literature studying how fintech entry affects credit market outcomes. For instance, as documented by Balyuk et al. (2020), credit extended by fintech entrants often substitutes for loans from out-of-market banks (which are often large ones), as opposed to those by small/in-market banks. As a consequence of large banks' retracted engagement in out-of-market lending, which often relies on the support of communication IT, one should naturally expect them to reduce their communication IT spending.

That banks' IT spending responses are size dependent is also consistent with the notion that the entry of fintech lenders helps convert soft information to hard information.[54] Linking this "hardening soft information" effect to our analysis where the focus is placed on bank lenders' decision making, one should expect large banks, rather than small ones who specialize more in relationship-based soft information handling, to reallocate their investment away from communication to software because of a decreased (increased) need of dealing with soft (hard) information.

Finally, recall that in Section 3.2.1, we document a strong correlation between banks' software IT spending and their specialization in the personal loan lending, which is what LendingClub mainly focuses on.

Consistent with this, panel C of Table 10 shows that banks with higher personal loan shares respond more significantly to the entry of LendingClub.

Altogether with Table 4, which shows that real estate loans are more strongly associated with software IT than non–real estate loans, we highlight the following comparison: in contrast with SME loans that map with communication technology, personal lending, including credit card and similar products, relies heavily on hard, automatable information. Thus, facing competition in this domain, banks ramp up software technologies to stay competitive. Whereas within personal loans, secured lending (e.g., mortgages) tends to rely more on software IT because the presence of standardized, documentable assets makes software-based decision tools (e.g., scoring systems, automated processing) more applicable.

5.2.4. Summary and Discussion. We find that the fintech entry induces banks—especially large ones—to "catch up" and invest to adapt their lending technology. To the best of our knowledge, this is the first piece of direct evidence that the entry of fintech lenders spurs incumbent banks to invest more in their technology to catch up. Furthermore, consistent with existing literature (say, Berg et al. 2022) that highlights the comparative advantage of fintech lenders in processing hard information and making prompt decisions, we show that most "catching up" from traditional banks takes the form of ramping up their *software* IT spending.

We have discussed in Section 5.1 the potential channels through which the entry of fintech lenders affects local commercial banks' IT investment decisions. Our empirical findings support a competition story that, following fintech entry, large banks respond by increasing their IT spending in the relevant categories, presumably to protect their market share. Behind this increased investment in IT could be a "winner's curse" channel that banks need to upgrade their lending technology for fear of being adversely selected by the newly entered fintech competitors once they have decided to continue operating in the same market segment. However, to fully assess this channel, one would need to investigate the composition change of banks' customers induced by the entry of fintech lenders, as well as the dynamics of market share composition. We leave these endeavors to future research.

A related question is whether the catching up of IT has increased those banks' market shares. The staggered approval of LendingClub across U.S. states offers a plausible exogenous shock to competition in the personal loan segment—one that directly threatens incumbent banks' lending business. Accordingly, we leverage this setting to investigate whether banks' IT investments help preserve their market share.

As banks' personal loan amounts are not available locally, we construct a measure of bank-county-year personal loan volume based on banks' total personal loan amount and within-bank shares of deposit share. Specifically, we first calculate each bank's total personal loans p_{it} from call reports. We then compute each bank's deposit share in each county-year d_{ict} from FDIC Summary of Deposits data. Then, we calculate county-level personal loan amounts as $p_{ict} = p_{it} \times d_{ict}$. Personal loan market shares are then calculated based on p_{ict}.

The results, summarized in Table A18 in the Online Appendix, show no statistically significant changes in market share following fintech entry, either on average (columns (1) and (4)) or conditional on bank size or initial personal loan orientation (columns (2)–(3) and (5)–(6)). We interpret this null result as consistent with an equilibrium response: banks do respond to fintech entry by increasing IT spending, as we document, but this investment may only mitigate losses rather than expand market presence. Meanwhile, these empirical results are cross sectional in their nature, and typically do not directly speak to the time-series trend, say, banks' declining market shares of SME lending over the last decade.

6. Conclusion

Development of information technologies over the past several decades has dramatically revolutionized the way lending is conducted by the banking sector. In this paper, we provide the first comprehensive study of banks' IT spending, which we view as banks' investment to improve their lending technology, especially their ability to deal with soft information and hard information.

The detailed IT spending profiles available in our unique data set enable us to uncover several novel findings. First, at the aggregate level, we document an overall fast-growing trend in banks' IT spending in the last decade. Second, as a key step in linking banks' IT spending to the development of their lending technology, we show that different types of information technology are closely related to the nature of information embedded in different types of lending activities. More specifically, the production and transmission of soft information, which plays a crucial role in conducting small business lending or performing the role of a "lead" bank in syndicated lending, is strongly associated with banks' communication spending. By contrast, hard information processing, which is most relevant for conducting mortgage refinancing, is strongly associated with banks' software spending.

We conduct a set of event-based analyses whose answers inform us of how banks adapt their lending technologies in response to economic shocks in their operating environment, including credit demand shocks and the entry of fintech. These causal analyses, to the best of our knowledge, provide the first piece of evidence on endogenous lending technology adoption in the banking literature.

Our findings open up several important follow-up questions. How does endogenous technology adoption in the banking sector transform the banking/credit market structure? How do technology upgrades in the banking sector affect banks' deposit-taking activities, loan outcomes, properties of the credit cycle, and monetary policy transmission? We leave these questions to future research.

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Endnotes

[1] For instance, First Citizens National Bank implemented its employee intranet to strengthen internal communications in February 2019. For details, see this article.

[2] Section 2.2 explains in detail the four major categories of IT expenditure in the Harte Hanks data set—hardware, software, communication, and services—in the context of the banking industry. Representative examples of software include desktop applications (e.g., Microsoft Office), information management software, and risk and payment management software. Examples of communication technology include radio and TV transmitters, private branch exchanges, and video conferencing.

[3] This asymmetric pattern is consistent with the notion of hierarchical friction in Stein (2002): a lower level of hierarchical complexity helps facilitate the within-organization transmission of soft information, which is more relevant for small business lending than mortgage refinancing.

[4] Our empirical identification is based on the Small Business Health Care Tax Credit, which was introduced in 2010 and then experienced a significant policy change in 2014. We construct the instrumental variable using counties' exposure to policy change in 2014, with details explained in Section 4.2.2.

[5] We take advantage of the low-interest episode from 2011 to 2015, during which nationwide average mortgage interest rates decreased from 6.5% to 3.5%. When interest rates drop, the mortgage prepayment option is in the money (Eichenbaum et al. 2022, He and Song 2025), implying a greater mortgage refinance demand by local households. In addition to mortgage repayment savings, we also consider an alternative instrumental variable (IV) constructed as the weighted mortgage rate gap for outstanding mortgages in a given county.

[6] Note that previous literature documents a decline of large banks' loan extension to small businesses, for example, Chen et al. (2017). Whereas we do not find an increase in IT associates with increasing market share, this is because our approaches are largely cross sectional in nature and therefore do not directly speak to longer-run time-series trends, such as this steady decline in banks' SME lending market share over the past decade.

[7] Relatedly, consistent with large banks' dominance in the personal loan lending market, we also find that the response to LendingClub's entry is particularly pronounced for banks more specialized in personal loan lending.

[8] Along these lines, Liberti and Mian (2009) find empirically that greater hierarchical distance leads to less reliance on subjective information and more on objective information. Paravisini and Schoar (2016) document that credit scores, which serve as hard information, improve the productivity of credit committees, reduce managerial involvement in the loan approval process, and increase the profitability of lending.

[9] Previous literature has shown that credit supply positively affects nonfinancial firms' technology adoption or innovation (Amore et al. 2013, Chava et al. 2013, Bircan and De Haas 2019).

[10] There is also a vast theoretical literature (Hauswald and Marquez 2003, 2006; Vives and Ye 2022) on the interactions among information technology and credit market competition; see Freixas and Rochet (2008) for a review. For instance, in the framework of credit market competition where the specialized lender acquires additional "soft" information, He et al. (2024) study the role of information span where loan quality is determined by multidimensional characteristics, and Blickle et al. (2025) provide a model that delivers the negative interest rate wedge observed in the data (that is, loans granted by specialized lenders are with lower ex ante rate and better ex post performance).

[11] Related works include, but are not limited to, Jagtiani and Lemieux (2018), Buchak et al. (2018), Frost et al. (2019), Fuster et al. (2019), Hughes et al. (2019), Stulz (2019), and Di Maggio and Yao (2020).

[12] This fast-growing literature includes Hornuf et al. (2021a), Lorente et al. (2018), Calebe de Roure and Thakor (2019), Tang (2019), Aiello et al. (2023), Erel and Liebersohn (2022), Gopal and Schnabl (2022), Huang (2022), and He et al. (2023).

[13] Whereas we use detailed IT "budget" data from Harte Hanks, several papers use its IT "installment" data that report firm-level IT product installment; see Section 2.1 for details of the differences between these two data sets. For instance, Charoenwong et al. (2022) study installment of IT products catering to compliance requirements, and Pierri and Timmer (2022b) investigate whether banks installed with more PCs per employee can better survive a financial crisis. We use the budget data that report detailed dollar amounts for various IT categories, which are crucial for our study.

[14] The Harte Hanks data set has been utilized by a broad literature of economic studies. For instance, Forman et al. (2012) investigate firms' IT adoption and regional wage inequality, Bloom et al. (2014) study the impact of information communication technology on firms' internal control, and Tuzel and Zhang (2021) study labor-technology substitution at the establishment level, based on this data set.

[15] An important feature of the regulatory Y-9C and call report data is that the reporting of banks' IT expenses is censored at a certain threshold; that is, IT expenses below that threshold are often reported as zero or missing values. This contributes to a higher IT spending measure in our sample than either Kovner et al. (2014) or Modi et al. (2022). More details regarding the reporting rules of these regulatory data are provided in Data Appendix C.2.1.

[16] It is worth noting that our IT expense measure, which aligns well (in dollar amounts) with the aggregated IT spending in Y-9C following the method in Kovner et al. (2014), is systemically higher than that in Modi et al. (2022). This is because Kovner et al. (2014)

sum the two standardized "other noninterest expenses" and unstandardized write-in items, whereas Modi et al. (2022) only account for the unstandardized write-in items of "other noninterest expenses." Furthermore, the censored reporting in the call report (and in Y-9C) also contributes to a smaller IT expense measure in Modi et al. (2022) compared to the measure offered by Harte Hanks.

[17] These comparisons include (i) the industry-level Bureau of Economic Analysis (BEA) data, with a focus on the detailed composition of banks' IT spending; and (ii) the data storage cost in Feyen et al. (2021).

[18] The Harte Hanks data set has two major parts—the "IT installment" data, which contain information on whether a firm installs a certain IT product and the earliest installment date, and the IT budget data, which contain information on the dollar amounts of detailed categories of IT investment. Whereas the data vendor gets some of the installment information using algorithms extracting installment information from firms' public reports, job postings, etc., the IT budget data are based primarily on surveys. Our analysis in this paper only uses the IT budget data by Harte Hanks.

[19] These software products are easy to grasp by bank employees who are then able to conduct basic calculations and visualizations of data associated with lending businesses. For example, on Mendeley.com, the job postings for loan officers or project managers by many banks require applicants to be proficient in Microsoft Office.

[20] Examples of processing software include Trapeze Mortgage Analytics, Treeno Software, and Kofax. These software products feature document assembly enhancement, digitization, and information classification.

[21] These software products, for example, Actico, ZenGRC, Equifax, and Oracle ERP, allow banks to better monitor loans in progress. Other software products include security trading systems and operating systems that are typically bundled with the specific software products.

[22] Huvaj and Johnson (2019) use this database to study the impact of firms' organizational structure on their innovation activities.

[23] In this white paper, the Office of the Comptroller of the Currency defines "responsible innovation" as "the use of new or improved financial products, services, and processes to meet the evolving needs of consumers, businesses, and communities in a manner that is consistent with sound risk management and is aligned with the bank's overall business strategy."

[24] The magnitude of IT budget as a share of noninterest expenses in this figure is also in line with Hitt et al. (1999), who report banks' IT spending could be as high as 15% of noninterest expenses in their survey. The trend of IT spending as a share of total revenue, as shown by the solid line in Figure 1, shares a consistent pattern with IT spending as a share of noninterest expenses.

[25] Table A2 in the Online Appendix shows a robust cross-sectional pattern that IT spending (say, scaled by noninterest income) increases with bank size. This could be due to the fact that small banks often cannot afford IT purchases with significant lump-sum costs.

[26] Medium- and smaller-size banks (asset size bins bellow $10 billion) saw growth from 2010 to 2013, slowed down in 2015, and then have picked up again since 2016. One possible explanation for the temporary slowdown in IT spending in 2015 is that banks chose to "wait and see" in 2015 before the release of the white paper in 2016 (see the first paragraph in Section 3.1).

[27] For robustness, we also conduct analyses with an alternative measure of banks' IT spending intensity scaled by banks' deposits, with qualitatively similar results (Table A3 in the Online Appendix).

[28] Recall that in Section 3.1, we show that smaller banks tend to allocate a larger portion of their IT budget to communication spending. Our finding therefore suggests that despite its high correlation with bank size, the complexity of a bank's internal hierarchical structure has an additional impact on its IT spending on top of the bank size effect. Put differently, one cannot simply use the size of a bank as an empirical proxy for its hierarchical complexity.

[29] See "Liveoak" for a real-world example of a communication tool designed for banking services.

[30] See this article from Bankingdive (Bhattacharyya 2020) for a detailed description of how video conferencing helps within-bank communication.

[31] For example, nCino is an operating system software that allows financial institutions to replace manual collection of loan/account applications with automated and AI-based solutions. Finaxtra and Turnkey are both comprehensive loan origination systems that offer solutions for the whole lending process.

[32] Some concrete examples of credit scoring software include SAS Credit Scoring, GinieMachine, and RNDPoint. To use such software, banks usually just need to import borrowers' demographic and historical data, based on which the software calculates credit scores and conducts statistical tests using AI and machine learning methodologies, saving banks from tedious manual work and expediting the processing.

[33] We will shortly show in Sections 4.2 and 4.3 that these two categories of banks' IT spending have a more direct link to banks' dealing with different types of borrower-specific information, a fact already hinted at by the empirical patterns of bank IT spending documented in Section 3.2.

[34] The relatively lower communication spending by large banks is also consistent with recent empirical findings that large banks, which have deeper pockets than small banks, more frequently invest in or acquire fintech startups (Hornuf et al. 2021b, Cornelli et al. 2022). As fintech businesses specialize in transforming the soft information embedded in the alternative data of consumers into credit scores (a form of hard information), large banks' reliance on communication technology in small business lending is lower.

[35] Our finding echoes previous work on credit decision making. For instance, Paravisini and Schoar (2016) document that business loan decisions are often made by committee; when decisions cannot be made after committee discussions, the committee will refer to managers in an upper layer, say, regional managers. The greater the hierarchical complexity, the higher the "transaction cost" involved for loan decisions.

[36] Because of the vast reporting and coordination efforts, lead banks often charge an initiation fee, which can be as high as 10% (Ivashina 2009).

[37] See the IRS's FAQ regarding the tax claim rules, and see this report for the delay of the marketplace.

[38] This summary explains the low participation of small businesses in the first few years after 2010: "SHOP programs were operational nationwide, but many features were not initially available, and enrollment had been lower than anticipated. Many small businesses did not enroll because they were apprehensive about joining an unestablished program." Relatedly, the 2012 GAO report summarized that "the small employers do not likely view the credit as a big enough incentive to begin offering health insurance and to make a credit claim." Regarding small businesses' awareness of the policy, this survey posted in 2011 summarized small businesses' unfamiliarity with the policy.

[39] This report finds that uninsured small business employees decreased by around 30% during 2014–2016 compared to 2013.

[40] We provide further evidence for the positive impact of the tax credit hike on QSBs by studying their growth in the number of both

establishments and employees after the tax policy. The details of these analyses on the mechanism and economic magnitude of the policy impact are provided in Online Appendix Tables A7, A8, and A9.

[41] Similar expansion of factor input is also documented in Agrawal et al. (2020), who show that following an R&D tax credit to small businesses, which resembles the health insurance tax credit in our paper, firms responded by increasing their R&D spending significantly. Further, Gao et al. (2023) show that following insurance premium increase, firms reduce employment. More broadly, for reactions from small businesses after the implementation of corporate tax cuts or the launch of subsidies, see Cerqua and Pellegrini (2014), Rotemberg (2019), and Ivanov et al. (2021).

[42] Recall that only employers with 25 or fewer employees are qualified for this program. However, the County Business Pattern database provides categorization of small business sizes (number of employees) based on the following cutoffs: ≤5, 5–9, 10–19, 20–49, 50–99, 100–249, 250–499, 500–1,000, and ≥1,000. Because of this data limitation, we chose the closest cutoff, which is "fewer than or equal to 20."

[43] We make two points. First, the QSB share, together with the growth rate of bank IT spending and local small business loans, is independent of scale; this helps alleviate the concern that the heterogeneity in policy exposure might be correlated with the size of the local economy. Second, we use ln(Spending) and ln(Loan) in all of our regression analyses by removing all observations with zero budget or zero lending. Because we aggregate branch-level observations to bank-county level, the occurrence of zero budget/lending is low—the total amount of observations with zero budget/lending is only 0.6% in our sample. One could use $\ln(1+x)$ instead of $\ln(x)$ to include observations with zeros, but because the aggregated IT spending (quoted in USD) and CRA loans (quoted in 1,000 USD) range from a couple of thousands to millions (software spending and CRA lending have medians of 25,000 and 1,400, respectively), which are much larger than one, $\ln(1+x)$ and $\ln(x)$ are close to each other. Indeed, these two specifications yield quantitatively similar results (in the second stage, we get 0.67 as opposed to 0.76.)

[44] For detailed calculations, see Online Appendix Table A6. To put this number into perspective, according to our estimation, banks can earn around $167,000 extra revenue (given the $8.366 million extra increase in CRA loans from the first stage), which makes the increased communication IT spending seemingly small. This is expected because soft information relies not only on IT products but also on loan officers who gather and transmit information using the communication IT. Accompanying the communication IT spending, banks will also need to hire extra loan officers (or compensate more hours) when they increase their labor input to deal with the increased small business lending. Because our data do not contain compensation to employees, our calculation only provides a lower bound of the estimation of banks' expenses in response to small business lending growth.

[45] That is, having built up their "IT capital" stock after two years of high "flow" spending right after the policy shock, bank branches no longer need to install more IT equipment, even if the demand for small business credit remains high in these high-exposure regions. This would then translate into a reduction in the flow of IT spending.

[46] Berger et al. (2022) show that effectiveness of monetary policy is crucially dependent upon the previous levels of mortgage rates.

[47] We construct the payment savings based on the 2011–2016 sample because the federal funds rate and mortgage rate remained at the low level until 2016 (Figure A2 in the Online Appendix).

[48] We remove loans that were defaulted on or prepaid to ensure that the measure captures only refinance propensity from local households with outstanding loans.

[49] This increase in revenue is implied by a one-standard-deviation increase in ln(Refinance/Origination); a detailed calculation is provided in Online Appendix Table A6.

[50] Table A4 in the Online Appendix shows the results of the same OLS specification with bank, year, and county fixed effects and bank×year and county fixed effects.

[51] As explained by Wang and Overby (2022), LendingClub launched its platform in 2007. In April 2008, LendingClub entered a "quiet" period in which it suspended peer-to-peer lending until it registered with federal and state regulators as a licensed lender (or loan broker). During this quiet period, LendingClub funded some loans with its own money and pursued regulatory approval to resume peer-to-peer lending in all 50 states. Six months later, it had received approval in 40 states plus the District of Columbia by October 2008. For nine states, it received approval at different times between 2010 and 2016. For one state (Iowa), it had not received approval as of February 2021.

[52] Given that a majority of states approved LendingClub around the same time period (2008 Q4), a potential concern of endogeneity arises: as these approvals occurred shortly after applications by LendingClub, which might have seen a rising opportunity from entering, these approvals might coincide with some unobserved changes in economic conditions happening during the same time.

[53] In this method, we run separate regressions in (4) for each group of states, which are treated at the same year, with the not-yet treated as the comparison group and then aggregate β to form the aggregated average treatment effect of the treated (ATT). For aggregation, we weight the cohort-specific treatment effect by the total volume of loans made through LendingClub within the three years after LendingClub's entry. Standard errors are based on bootstrapping with 50 draws.

[54] For instance, Beaumont et al. (2025) show that borrowers with better fintech access are more likely to purchase and pledge hard information–heavy assets as collateral to obtain new bank credit.

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