Investing in Lending Technology: IT Spending in Banking

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March 12, 2023

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 dataset combining banks' investment in information technologies (IT), this paper provides concrete empirical evidences 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, while investment in software IT helps enhance banks' hard information processing capacity. We causally show banks adapt different types of lending technology in responses to credit demand shocks with different information nature. The entry of fintech induces commercial banks (especially large banks) to increase their investment in IT, particularly in software.

Keywords: Information Technology, Small Business Lending, Mortgage Refinance, Communication Equipment, Software, Hard and Soft Information
JEL codes: G21, G51, O12, O32

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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% to 9.4% of their operating income on information technology (IT); for comparison, insurance companies and airlines only spend 3.3 percent and 2.6 percent of their income on IT, respectively. This trend has accelerated at an unprecedented pace in recent years, as industry professionals often consider top commercial banks to be more like "technology companies" than actual technology firms by virtue of their enormous IT budgets.[1] 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, 2020).

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 established banking 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, which may help researchers understand "*the consequences of consolidation in the banking industry, particularly the documented tendency for mergers to lead to declines in small business lending.*" At the same time, fast-developing technologies in recent decades provide more options for the banking sector to cope with such

[1] For instance, this article shows that IT spending by most top banks (say JP Morgan and Goldman Sachs), exceeds 17% of their total operating costs, while Amazon and Alphabet devote 12% and 20% of their operating costs respectively to IT. This article also cautions that the above-mentioned IT spending numbers do not include compensation for IT staff members.

problems.[2] 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 dataset, the Harte Hanks Market Intelligence Computer Intelligence Technology database, which has been used in the literature on the economic implications of technology in non-financial sectors (e.g., Bloom et al., 2014; Forman et al., 2012). This dataset provides detailed branch-level information on specific spending categories, and our paper offers the first comprehensive analysis of this dataset in the context of banking.

We focus on two of four major categories in banks' IT spending:[3] *software* and *communication*. *Software* IT products mainly aim to improve information processing accuracy and speed through automation, specialized programming and AI technologies, etc. *Communication* IT products facilitate smoother exchanges of information within bank branching networks, across banks, and with borrowers.[4]

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, while there was almost no growth in IT spending for the smallest banks. Another noticeable distinction between large and small banks is that smaller banks, who presumably engage in more small business lending, consistently allocate a higher share of their IT budget towards communication technology than larger banks do. As we will elaborate, this pattern points to the role communication IT plays in conducting small business lending.

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 shares in commercial and industrial (C&I) loans and agricultural loans are positively associated with the lenders' com-

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

[3]Section 2.2 explains in detail the four major categories of IT expenditure in the Harte Hanks data set—hardware, software, communication, 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.

[4]Examples include radio and TV transmitters, private branch exchanges, video conferencing, etc.

munication 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 sub-category 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 extended by lenders, we also explore how banks' IT investment is shaped by other factors affecting their business operations. Regarding the complexity of banks' internal hierarchical structure, banks with more internal layers in their hierarchical structure tend to have a higher communication spending intensity. 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 how banks' software spending reacts to their mortgage refinancing activities.[5] Finally, in the context of the syndicated lending market, we show that 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," i.e., loans that are based on a specific credit scoring system and quanti-

[5]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.

fied 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; this is because communication technologies—say, video conferencing—not only enable banks to more effectively collect soft information from entrepreneurs who often inhabit an opaque information environment, 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 find that an increase in banks' small business credit demand—due to 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.[6] A dynamic treatment effect analysis further reveals that the cross-county heterogeneity in the degree of shock exposure leads to differential growth paths in local banks' communication spending (with little effect on software spending) after the policy shock, while having no effect on the pre-policy trend for both types of IT spending.

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 payment savings of outstanding mortgages to construct a shifter to the mortgage refinance demand faced by banks across different regions.[7] We show that a one standard deviation increase in mortgage refinancing lent out by a bank (due to its local exposure to high refinance savings) leads to about 5% higher software spending relative to the sample average, without any significant impact on local banks' communication spending.

[6] We construct our instrumental variable for the shock of small business credit demand based on the "Small Business Health Care Tax Credit." As a part of the Affordable Care Act, this program was enacted between 2014 and 2015 and provided beneficial tax treatment specifically targeted at small business establishments in the US economy.

[7] 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, 2022), implying a greater mortgage refinance demand by local households.

The last part of our analysis concerns how the entry of fintech lenders into local credit markets affects banks' IT spending and their associated lending technologies. In the past decade, we have witnessed a growing penetration of fintech—as a special group of tech-intensive (potential) competitors—to the traditional banking sector. Utilizing the staggered entry of Lending Club 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 Lending Club's operation in a state, banks operating in that state saw a significant increase in their IT investment. Importantly, the growth in software spending (5.61%) is economically (as well as statistically) more significant compared with the growth in communication spending (1.9%).

Aside from the asymmetry in the IT category of banks' response to fintech entry, there is significant heterogeneity across bank size groups in their technology spending reactions. In particular, the increased IT investment intensity is predominantly observed among large banks, whereas small banks barely respond in their IT spending towards the new entry of fintech players. 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.

Related Literature

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, i.e., relationship lending and transactions lending, in the SME lending market.[8] A fundamental difference between these two types of lending is related to the role played by information as highlighted by Stein (2002), who provides an explanation as to why soft information production favors an

[8]Relatedly, Bolton et al. (2016) study the joint determination of relationship lending and transactions lending. They find that firms that rely more on relationship banking are better able to weather a crisis than firms that rely on transactions banking, suggesting a higher capital requirement for relationship banks.

organizational structure with fewer hierarchical layers.[9]

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' lending technologies, via their endogenous decisions on 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.[10]

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 development in 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 working papers show that IT adoption helps banks weather financial crisis (Pierri and Timmer, 2022) and spur entrepreneurial activities (Ahnert et al., 2021). Our paper, with the aid of detailed IT spending data, fills in the details of specific economic mechanisms that connect banks' lending technology with their IT spending.[11]

Fintech entry and banks' IT spending. The emergence of fintech is a signature result of recent developments in information technologies.[12] Our study aligns closely with studies on how the emergence of the fintech industry is affecting (or has affected) the traditional banking sector.[13]

[9]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.

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

[11]There is also a vast theoretical literature on the interactions among information technology, banking market competition and bank lending; see Freixas and Rochet (2008) for a review. For instance, Hauswald and Marquez (2003, 2006) analyze the implications of information technology on banking market competition; and more recently, Vives and Ye (2021) study how the diffusion of information technology affects competition in the bank lending market and banking sector stability.

[12]Related works include but are not limited to Jagtiani and Lemieux (2017), Buchak et al. (2018), Fuster et al. (2019), Frost et al. (2019), Hughes et al. (2019), Stulz (2019), and Di Maggio and Yao (2020).

[13]This fast-growing literature includes Lorente et al. (2018); Hornuf et al. (2018); Calebe de Roure and Thakor (2019); Tang (2019); Erel and Liebersohn (2020); Aiello et al. (2020); Gopal and Schnabl (2022); He et al. (2023), and Huang (2022).

While a common theme of this research has mostly focused on the bank-fintech competition during which traditional banks are largely viewed as a *passive* player, little attention has been paid to how banks are *actively* responding to these challengers; we take the latter angle by studying whether and how traditional banks are catching up with penetrating fintech lenders. In a recent work, using Call Report data, Modi et al. (2022) document that banks with more fintech exposure tend to spend more on IT, and that their lending behaviors are also likely to resemble fintech companies.

Micro-level evidence on technology adoption. Our paper also broadly contributes to the literature studying firms' technology adoption behavior using micro-level 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 (2019) explores how software adoption explains the decline in business dynamism and the rise of market power.[14]

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, who then use it for marketing purposes or to better serve their clients. Firms have incentives to report their IT spending data

[14]While we use detailed IT budget data, several papers use the IT installment data that reports firm-level IT product installment. For instance, Charoenwong et al. (2022) study installment of IT products catering to compliance requirement, and Pierri and Timmer (2022) investigate whether banks installed with more PC's per employee can better survive financial crisis. Although both are maintained by Harte Hanks, the IT installment dataset is different from the IT budget data we use; the latter report detailed dollar amount for various IT categories which are crucial for our study.

truthfully to Harte Hanks as they also want to receive tailored advice for better IT services in the future.[15]

Our paper focuses on commercial banks.[16] The sample consists of 1,806 commercial banks in the U.S., which covers more than 80% of the U.S. banking sector in terms of asset size (Figure A1). 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 are both over 80%. However, for small banks with size below $100 million, our sample covers only 14.45% (14.23%) 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 1.8% (25th percentile) to 13.5% (75th percentile), suggesting a large cross-sectional variation across banks. Median IT spending as a share of net income is 7.1%, consistent with a 2012 McKinsey survey (Appendix Figure A4) reporting that banks' IT spending as a share of net operating income ranges from 4.7% to 9.4%.

2.2 IT Investment Categorization

Our dataset 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 6(a) to 6(d) of Figure A5.

Software is defined as software programs purchased from third parties, including those offered on an SaaS from a multi-tenant shared-license server accessible by a browser. More specifically, the category of software covers desktop applications, information management software, process-

[15] We make two further points regarding this dataset. First, based on a recent inquiry with the data vendor, the IT *budget* data used in this study is collected based on outbound survey; while the IT *installment* data is collected through both survey and algorithm-based extraction of publicly available information (say, a company's website, recruiting postings, annual report, etc.). Second, an important measurement issue is the method of allocating the total IT cost incurred at the headquarter level to branches. According to the data vendor, such spending is reflected in the branch's spending rather than in that of the headquarters. This claim is indeed supported by our data: for the largest 100 banks in our sample, we find no statistically significant difference between the IT spending (scaled by revenue) at the headquarters and branches.

[16] The Harte Hanks dataset has been used in the literature; for instance, Forman et al. (2012) investigate firms' IT adoption and regional wage inequality, and Bloom et al. (2014) study the impact of information communication technology on firms' internal control.

ing software, risk and payment management software. For desktop applications, one representative example is Microsoft Office.[17] Processing software specializes in automatically processing information from loan applicants' paper document packets through specialized programming and AI technologies, which would otherwise be done manually by loan officers, improving processing accuracy and speed.[18] Risk management software provides on-going risk assessment after loans have been issued, through augmenting borrowers' repayment status as well as real-time industrial and economic conditions.[19]

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. When there is a need to contact or interact directly with borrowers, these machinces allow bankers to conveniently talk to and see borrowers, which helps banks to effectively evaluate projects for which borrowers seek credit. In addition, communication equipment such as private branch exchanges facilitates exchange of information, opinions, and decisions within the bank branching networks.

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, and meanwhile they serve as the carriers of software and toolboxes.

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

[17] These software products are easy to grasp by bank employees who are then able to conduct basic calculations and visualization 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 with Microsoft Office.

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

[19] These software products, e.g. Actico, ZenGRC, Equifax, 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.

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.

As a summary of this section, 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 33% of total IT budget. Hardware constitutes about 17% of total IT budget, and communication is on average 9%. We conduct analysis on banks' IT spending at bank-year level in Section 3, while 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 Datasets

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

Bank Balance Sheet We obtain bank-level balance sheet information from Call Reports; for detailed matching procedures, see Appendix B.2. Bank-year-level control variables include Net income, Equity, and Deposits, all as a ratio of Assets. For bank-county or bank-county-year analysis, we utilize information on banks' revenues at the county level from Harte Hanks.[20] Our data cleaning procedure further requires that, at the county-year level, a bank must have non-missing total revenue and total number of employees. To construct the key left-hand side variables "IT spending/Revenue," we aggregate all branches' spending in a specific category of bank i in county c in year t, and scale it by the sum of revenues of all branches of that bank in that county. The control variable "Revenue per employee" is at the bank-county-year level, with total revenue and total number of employees both from Harte Hanks. When using this control

[20]Since branch-level revenue information is not available in Call Reports, we use branch-level revenue information supplied by Harte Hanks for our bank-county or bank-county-year analyses. For figures plotting aggregate spending trends, we use Call Report information, which is at bank level.

variable for bank-level analysis, we aggregate revenue and employees at the bank level across the nation and calculate this ratio.

Loans and Local Characteristics We obtain syndicated loan information on the frequency of a bank acting as 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.

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.[21] 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 (in our studies, bank holding 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 three- (two-) layers of hierarchical structure if the bank has three (two) types of locations in the family tree, and accordingly call the bank a single-layer bank if it has only one type of location. To give some concrete examples, Wells Fargo & Company has more than six thousand offices in the U.S., and the location types include all three categories, so we classify it as having three hierarchical layers; North Valley Bank with headquarters located in Corning (OH) is classified as having two layers, as it has one headquarters and seven branches; and First Place Bank located in Warren (OH) is classified as having only one layer in our sample because it only has a single location. 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 Appendix B.2 for more details).

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

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 shaped by their lending activities, by demonstrating several robust correlation patterns between IT spending and loan specializations (e.g., commercial loans versus personal loans). Finally, we explore other dimensions that can relate banks' IT spending to their operations, including the complexity of a bank's internal hierarchical structure and the role a bank normally plays in syndicated lending.

3.1 Time Trends of Banks' IT Investment

Figure 1 Panel A displays the average IT spending as a share of total expenses as well as of total revenue from 2010 to 2019. Overall, banks have drastically increased their investment in information technologies over the last decade: their IT budgets climbed up from nearly zero in 2010 to about 5% of their total expenses after 2015. To put these numbers in context, total IT spending across all banks in our sample is about 40% of their total interest expenses in 2016.

After a slight slowdown in 2015, there was a dramatic pick-up of IT spending in 2016 as shown in Figure 1 Panel A. This could be potentially driven by the release of a "white paper" by the Office of the Comptroller of the Currency on March 16, 2016, which set forth the regulators' perspective on supporting responsible innovation across all-sized banks.[22] As mentioned in this article, this white paper might have pushed banks to be more aggressive in embracing technology investment as part of their strategic planning.

What is more, the white paper also encouraged banks to collaborate with non-banks in developing responsible financial products that satisfy regulator requirements, and it is widely believed that they have been more actively investing in IT in order to better catch up with their fintech peers.[23] Figure 1 Panel B, which plots IT spending over years as a share of revenue

[22] 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."

[23] This article by McKinsey documents a fintech IPO boom as well as a fintech investment boom by venture capitalists since 2016.

by local banks for regions with high and low fintech presence,[24] offers evidence suggesting a potential "catching-up" behavior of the traditional banking sector (see more analysis in Section 5). While both groups share a common upward trend in IT spending, the high-fintech-presence group increases their IT spending at a faster rate than the group with low fintech presence.

3.2 Bank IT Spending across Bank Size

Banks of different size often behave differently in systematic ways. Following FDIC bank size classifications, we break banks into five size groups. Overall, large banks invest more in IT than their small peers do. As can be seen in Table A2, banks with total assets of less than \$0.1 billion have an average IT investment over revenue ratio of 1.5%, and this ratio monotonically increases to 4.5% for banks with \$10–\$250 billion asset size. This pattern could be due to the fixed-cost nature of IT spending, as small banks often cannot afford IT purchases that require significant lump-sum payments.[25]

Figure 2 Panel A presents the growing trend for banks' IT investments, as a fraction of non-interest expense, by each bank size group.[26] Despite this common upward trend, there are also some noticeable differences across bank size groups. IT spending in large banks (with asset size \$10–250 billion) has been steadily growing, while there is almost no growth in the smallest group (with asset size below \$0.1 billion).[27] In contrast, megabanks (with asset size above \$250 billion) only picked up their IT spending after 2015. While we do not aim to provide 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.

[24] County-level fintech presence is measured based on "fintech lending share in local mortgage market," as proposed in Fuster et al. (2019), and we define high-(low-)fintech-presence regions as counties whose fintech lending share is above-median (below-median).

[25] The ratio of IT investment as a share of revenue drops to 1.9% for banks with asset size above \$250 billion, presumably due to the economy of scale of IT investment for these "megabanks."

[26] The magnitude of IT budget as a share of non-interest 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 non-interest expenses in their survey. The trend of IT spending as a share of total revenue, as is shown in Figure A2, shares a consistent pattern with IT spending as a share of non-interest expense.

[27] Medium-sized banks (asset size bins \$0.1–1 billion and \$1–10 billion) saw the fastest growth in their IT spending during 2010–2014 but dramatically slowed down during 2015–2019. One possible explanation for the temporary slowdown in IT spending in 2015 might be that banks chose to pause or "wait and see" in 2015 before the release of the white paper in 2016 (see second paragraph in Section 3.1).

Another noticeable feature revealed by Panel B in Figure 2 is that smaller banks tend to allocate a higher fraction of their IT budget towards communication technology than larger banks do: the average communication over total spending ratio is 15.9% for small banks compared with 5% for large banks. For software spending, however, there are no significant differences across bank size groups. We will come back to this sharp contrast in Section 4, where we connect banks' IT spending categories to their lending activities that involve different ways of handling information. A full comparison of the spending on communication and software across different bank size groups is shown in Table A2.

3.3 Empirical Patterns of Bank IT Investment

We now present the first set of empirical results that relate banks' IT investment to their operations, from three specific angles: 1) relative specialization in loan making; 2) the role that a bank plays in syndicated loans; and 3) the complexity of bank's internal hierarchical structure.

3.3.1 Loan Specialization

Banks provide three major types of loans: commercial and industrial (C&I) loans, personal loans, and agricultural loans. Lending to different types of borrowers often involves distinct ways of dealing with borrower-specific information. As a consequence, if banks specialize in different types of loans, one should expect them to differ in their IT investment profiles.

In our benchmark empirical specification, we run the following bank-level regression (we leave the more granular bank-county level analysis for later):

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

Here, i refers to an individual bank, and the outcome variable of interest is $\frac{\text{Type S IT spending}}{\text{Revenue}}_{i,\text{10-19}}$, which is the average investment in a specific type of IT spending as a share of bank i's revenue over 2010-2019. The main explanatory variable $\frac{\text{Type L loan}}{\text{Total loan}}_{i,\text{10-19}}$ captures bank i's loan specialization; it is measured by the average share of a specific type of loan relative to bank i's total loan size.

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.

Table 3 reports the estimation results of (1) for C&I loans, together with detailed regression outcomes for control variables and fixed effects. Table 4 uses the same methodology for C&I loans, personal loans, and agricultural loans; but for exposition purposes, we only report key regression coefficients (i.e., those of specific IT spending shares).

A. Commercial and Industrial (C&I) Loans

Specialization in C&I loans is most positively associated with banks' spending in communication technology (Table 3 column 2). A one standard deviation (8%) increase in loan portfolio share allocated to C&I loans predicts a \$0.13 million higher expenditure on communication per year.[28] A higher degree of specialization in C&I loans also predicts more spending on hardware (column 3), although the magnitude is slightly smaller than that of the impact on communication spending. The coefficient of software spending, however, is insignificant (column 1).

Within C&I Loans Rows 2-3 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." While 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. Table 5 shows that this empirical pattern is robust to bank sizes.

B. Personal Loans

The second major category of loan type we examine is personal loans, as classified by the Call Reports. Row 5 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

[28] As is shown in Table 2, the standard deviation of communication/revenue is 0.0075, and the average revenue is \$344 million. Given a coefficient of 0.05, the implied increase of communication spending is $0.0075 \times 0.05 \times \$344$ million=\$0.13 million. Our economic magnitude calculation follows this way throughout our paper.

one standard deviation increase in personal loans share (an increase of about 7 percentage points) predicts an increase of $0.65 million in software spending per year. On the other hand, a higher personal loans share does not have qualitatively significant predictive power on communication, hardware, or services budgets.

Within Personal Loans Paralleling our analysis of Small Business loans within C&I loans, we also decompose personal loans into two subcategories: mortgage refinancing and everything else. We find that 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.

Additionally, the richness of mortgage data allows us to gain further insights by distinguishing "refinancing an existing loan" from "originating a new loan." The main results are reported in Row 8 of Table 4 and the bank-size dependent results reported in Table 5, and we postpone more detailed discussion to Section 4.3.

C. Agricultural Loans

In the last category of loan types, we examine the association between agricultural loan specialization and banks' IT spending profiles. As shown in Row 9 of Table 4, a higher agricultural loan share positively correlates with the bank's communication spending. A one standard deviation increase in the share of agricultural loans (4.8 percentage points higher) is associated with about $0.11 million more communication spending per year.

3.3.2 Complexity of 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 hierarchical layer defined in Section 2.3 as our main proxy of banks' hierarchical complexity. We find that when the number of banks' hierarchical layers increases, banks spend more across all IT categories, especially on communication. A one standard deviation increase in the hierarchical layers predicts about $0.22 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.[29] As a robustness check, we proxy banks' hierarchical complexity using the logarithmic of the total number of offices, and qualitatively similar results are obtained in the second row of Panel B.

Our results suggest that when the hierarchical complexity within a bank organization increases, the bank spends more on communication. As explained in Section 4.2.1, one can relate these findings to the analysis in Stein (2002), from the perspective of within-organization transmission of information that is difficult to be verified and relayed. 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. We will return to this issue shortly in Section 4.2.1.

3.3.3 Role in Syndicated Lending

Aside from specialization in different types of loans or having different levels of hierarchical complexity, banks may also differ 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. A natural empirical test then is to examine whether there exists a systematic difference in IT investment between lead and participant lenders.

Table 4 Panel C presents the same regression as in Eq. (1), except we replace the key right-hand side variable with "%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 $3.34 million more in the bank's annual communication budget, while $8.06 million lower in software. These findings,

[29] Recall that in Section 3.2 we show that smaller banks tend to allocate a larger portion of their IT budget on communication spending. Our findings here therefore suggest that despite its high correlation with bank size, the complexity of banks internal hierarchical structure has an additional impact on banks' IT spending on top of the bank size effect. Put differently, one cannot simply use the size of a bank as the empirical proxy for its hierarchical complexity.

as we will elaborate in Section 4.2, can be attributed to the 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 these banks' IT spending, and in particular, how can they be related—and contribute—to the development of banks' lending technology? We start with a conceptual discussion on 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 we established in Section 3. Finally, we study two credit demand shocks that involve different kinds of information handling, and establish their causal impact on banks' (endogenous) 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, in conducting their lending businesses, banks engage in two types/stages of activities: information *production/transmission* and information *processing*. More specifically, information *production/transmission*, which is broadly related to *soft* information in Stein (2002), refers to the stage in which information on borrowers needs to be created or gathered and then relayed to the hands of those who later make decisions accordingly. On the other hand, information *processing*, which is broadly related to *hard* information in Stein (2002), is more about the stage in which lenders assemble and examine existing (or readily available) information on borrowers for better decision making.

Communication IT and Soft Information Production/Transmission When facing borrowers with whom lenders have never dealt, or whose information structure 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 about borrowers 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 crucially 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, originated loans, and resolved problems only through in-person visits to the brick-and-mortar branches; now, they also use video conferencing, as it makes the direct—yet virtual—contact between loan officers and borrowers more efficient.[30] Moreover, video conferencing within a financial institution has also been welcomed by the banking sector for its advantage in facilitating effective internal communication and collaboration among employees.[31]

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 creditworthiness of their borrowers to determine loan amounts and rates. When banks are facing borrowers either whose information structure is relatively transparent or who they already know from previous interactions, lending decisions simply boil down to efficient utilization and processing of the existing information.

Accurate evaluations of borrowers' credit risk often require complicated modeling and simulations, which are impossible without the support of sophisticated software tools. Nowadays banks have actively adopted new software-based technologies to store, organize, and analyze large chunks of loan applicants' data, or data augmented by other software.[32] One popular form of software technology product is the credit scoring software utilized by banks when mak-

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

[31] See this article from Bankingdive for a detailed description of how video conferencing helps within-bank communication.

[32] For example, "nCino" is 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.

ing *refinancing* decisions,[33] which primarily involves the processing and assessment of *existing* information that lenders already possesses through past interactions.

In what follows, we explore in detail the lending technology adoption in the banking sector along these two dimensions—those targeting the production and transmission of soft information (in Section 4.2), and those targeting hard information processing (in Section 4.3). In short, communication devices facilitate gathering and dissemination of soft information, whereas software is for efficiently utilizing "hard" information that is readily available at hand. From this point on, we focus on two particular categories—*communication* and *software*—in our examination of banks' IT investment behavior.[34]

4.2 Bank IT Spending and Soft Information

4.2.1 Soft Information Production/Transmission in Bank Lending

In this section, by reviewing certain empirical results on banks' IT investment profile established in earlier sections, we discuss situations where banks' capacity for dealing with soft information is crucial to profitable lending.

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 from loan officers to borrowers' 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

[33]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.

[34]We will shortly show in Section 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 3.3.

consistent with our empirical finding in Section 3.3.1 that banks which specialize in small business lending (as measured by the ratio of small business loans to total loans) incur more spending on communication IT. As in general smaller banks extend more loans to small businesses (Berger and Udell, 2006; Chen et al., 2017), this helps explain the observation that smaller banks have a higher fraction of communication IT spending shown in Panel B of Figure 2; but the positive relationship between small business lending and communication spending is robust for bank-size subgroups with above- and below-median asset cutoff, as shown in Table 5 Panel A.[35]

Hierarchical Complexity We now revisit our earlier findings in Section 3.3.2 along the dimension of banks' hierarchical complexity. There, we find banks with a more complex hierarchical structure tend to have a higher intensity in their communication IT spending. This is in line with Stein (2002), who argues that a lower level of hierarchical complexity facilitates the within-organization transmission of soft information and thus encourages the institution to engage more in projects requiring soft information generation (e.g., small business loans).

We can dig one step further. In Table 5 Panel B, we show that given the same percentage increase in small business loan origination, banks with a more complex hierarchical structure (i.e., with more hierarchical layers) respond with a greater increase in their communication spending. This result is consistent with "hierarchical frictions" in soft information transmission: When banks face a need (or choose) to increase their engagement in the small business loan market, which implies a demand for improving their soft information handling capability, those with a more complex internal hierarchical structure often have to spend more on communication IT so as to overcome such frictions.[36]

Finally, as a placebo test, one should expect no systematic impact of banks' hierarchical

[35] The relatively lower communication spending by large banks is also consistent with recent empirical findings that large banks, who are more deep-pocket than small banks, are more frequently investing in or acquiring fintech startups (Hornuf et al., 2021; 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.

[36] Our finding echoes previous work on credit decision making. For instance, Paravisini and Schoar (2016) document that business loan decisions are often made in committee decisions; and when decisions cannot be made after committee discussions, the committees will refer to managers in an upper layer, say regional managers. The more hierarchical complexity there is, the more "transaction costs" it might take for loan decisions to be finally made.

complexity on the correlation between their software spending and mortgage refinancing activities, which is indeed confirmed in Table 5 Panel B. Overall, our empirical findings on banks' hierarchical complexity corroborate previous works studying banking organization structure and information production (Degryse et al., 2008; Levine et al., 2020; Skrastins and Vig, 2018), and more research needs to be done on this topic.

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 differs drastically if the lender is a lead bank as opposed to being a participant bank; see, e.g., Sufi (2007). Compared to 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.[37] 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 conceptual differences between lead and participant banks are empirically verified in Section 3.3.1: The frequency of a bank serving as a lead arranger in syndicated loans exhibits a strong positive association with the communication IT spending by this bank (Table 4 row 4).

4.2.2 Banks IT Spending and Demand Shock on Small Business Loans

This section provides the first piece of causal evidence on banks' adaptation of their lending technology by studying banks' response in their IT investment when hit by a positive credit demand shock in small business loans. As small business lending is associated with intensive soft information production/transmission, we predict 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 affects small businesses' credit de-

[37] Due to the vast reporting and coordination efforts, lead banks often charge an initiation fee, which can be as high as 10% (Ivashina, 2005).

mand, which hits the U.S. banking sector heterogeneously across different regions. The "Small Business Health Care Tax Credit" in the Affordable Care Act enacted between 2014 and 2015 aims to support small businesses by providing health care coverage to their employees. The program offers a tax credit to small business employers who pay health insurance premia on behalf of employees. To qualify, the employer needs 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 iv) have provided a health plan to employees that is qualified under the Small Business Health Options Program (SHOP) coverage requirements.[38]

There are many channels through which this program could boost local small businesses' credit demand.[39] For instance, small business owners who were unable to provide employee health coverage before this program can now borrow to cover the health coverage thanks to the subsidy provided by the program; they can also potentially initiate desired project expansions once the program relaxes their financial constraints. Moreover, as all business owners would like to receive the qualified credit by borrowing in advance to cover employee health packages and then repaying the loan once they have claimed the credit the following year, banks will be handling additional soft information—such as the employee hiring, health plans, etc—to screen for genuinely credit-worthy borrowers.

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

[38]See the guidance here for an introduction to the policy. According to the IRS, small business employers should apply for the tax credit by filling in Form 8941. The tax credit can be carried backward or forward to other tax years. Also, since the amount of the health insurance premium payments is more than the total credit, eligible small businesses can still claim a business expense deduction for the premia in excess of the credit, which means both a credit and a deduction for employee premium payments. Small businesses receive credit on a sliding scale based on firm size: the tax credit is highest for small companies with fewer than 10 employees who receive an average annual salary of $25,000 or less.

[39]For the economic reactions from these 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).

of credit demand in the local area would be indirect or limited.

Empirical Design: 2SLS Regression We run the following 2SLS regression:

$$\begin{aligned} \Delta \ln(\text{CRA})_{i,c,post} &= \tilde{\alpha}_i + \mu_1 \left(\frac{\text{\# Qualified small business est}}{\text{Total \# of establishments}} \right)_{c,pre} + \mu_2 \mathbf{X}_{i,c} + \epsilon_{i,c} \\ \Delta \ln \text{IT}_{i,c,post} &= \alpha_i + \beta \Delta \widehat{\ln(\text{CRA})}_{i,c,post} + \gamma \mathbf{X}_{i,c} + \epsilon_{i,c}. \end{aligned} \tag{2}$$

In the first-stage regression, the outcome variable $\Delta\ln(\text{CRA}_{i,c,\text{post}})$ 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 program. The instrumental variable $\frac{\text{\# Qualified small business est}}{\text{Total \# of establishments}}_{c,pre}$ is the proportion of total business establishments that have fewer than or equal to 20 employees, averaged between 2011 and 2013 before the policy shock;[40] and the idea is that the proportion of total number of business establishments that are "qualified small businesses establishments" (hereafter "QSB") in the pre-shock episode captures the local county's exposure to the credit program. In the second stage, we regress $\Delta\ln \text{IT}_{i,c,post}$, which is the change in logarithm of a specific type of IT spending of bank i in county c after the program implementation compared to before, on the fitted value from the first stage. [41]

The instrument in (2), i.e., the qualified small business 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 qualified small business share affects the cross-county growth rate in banks' IT spending around the policy shock only through affecting the volume of small business loans extended in the local economy. Furthermore, the parallel trend assumption requires that heterogeneity in qualified small business share explains divergent paths in local banks' IT spending only after the policy, which we empirically verify shortly.

It is worth noting that both the qualified small business share and the growth rate in bank IT

[40] Recall that only employers with 25 or fewer employees are qualified for this program. However, the "County Business Pattern" database provides categorization of small businesses sizes (number of employees) based on the following cut-offs: ≤ 5, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-1000, and ≥ 1000. Due to this data limitation, we chose the closest cut-off, which is "fewer than or equal to 20."

[41] We use ln(Spending) in all of our regression analysis. Since we aggregate branch-level observations to bank-county level, the occurrence of zero budget is below 1% in our sample. In the DID analysis of Section 4.2.2, nine observations have zero budget during the post episode and non-zero budget in the pre episode, and these occasions are also dropped from our analysis.

spending (or local small business loans) are scale invariant, which helps alleviate the concern that the heterogeneity in the shock exposure might be correlated with the size of the local economy (which may affect local banks' decisions about their IT investment).

To tease out the shock impact from other confounding variables, we include a rich set of pre-shock control variables in our regression analysis. To begin with, we control for revenue per employee and deposit market share at the bank-county level; they proxy for investment opportunity and market power of a bank in the local economy respectively. The second set of controls consists of a set of county-level economic characteristics, which include county size (proxied by the logarithmic of total number of establishments and logarithmic of total amount of small business loans) and local economic situation (proxied by population growth rate, changes in unemployment, and labor force participation ratio, and GDP per capita). Lastly, we include bank fixed effects, which 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.

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 18.079 is well above the conventional threshold for weak instruments (Stock and Yogo, 2005).

We find a positive and statistically significant response in banks' communication investment across counties in the second stage. In particular, banks who were facing a one standard deviation higher growth in their small business loan making—due to a higher shock exposure captured by qualified small businesses—experienced a 0.741 standard deviation higher growth in their communication spending; and this translates to an average of \$0.68 million more per year. On the other hand, one standard deviation higher growth in small business loans due to higher exposure to qualified small businesses lead to 0.213 standard deviation slower growth in software spending. Note, our estimation includes bank fixed effects, so the above result applies to "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 rather than on processing hard information.

Dynamic Treatment Effects To strengthen the analysis, we study the dynamics of IT spending for banks with different levels of policy exposure. This also helps us evaluate the validity of the instrumental variable by examining the pre-trend patterns of banks' IT spending. We run the following regression with observations of bank i at county c in year t:

$$\ln IT_{i,c,t} = \alpha_{i,t} + \alpha_{i,c} + \sum_{s\in[-3,3],s\neq-1} \beta_s \times \mathbb{1}_{\{t-2014=s\}} \times \text{High QSB exposure}_{pre} + \pi_1 \mathbf{X} + \epsilon_{i,c,t},$$

where $\alpha_{i,t}$ and $\alpha_{i,c}$ are bank-year and bank-county fixed effects; and "High QSB exposure" is an indicator variable which equals 1 (0) 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.

Figure 3 plots the set of estimated coefficients $\left\{\hat{\beta}_s\right\}$, which measures the intent-to-treat (ITT) effects of the small business tax policy change on $\ln IT_{i,c,t}$ through heterogeneous exposure as captured by the qualified small businesses share. The base year is chosen as 2013, which is one year before the policy year. 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. Since the policy year 2014, the communication spending of banks located in high-exposure counties see a continual growth for two consecutive years (left panel), while the software spending of banks (right panel) in high-exposure counties and low-exposure counties demonstrates no difference before 2014 and remain similar after. Finally, that $\left\{\hat{\beta}_s\right\}$ for communication IT spending (left panel) starts to decrease around 2016 might be due to the "capital" nature of IT investment. That is, having built up their "IT capital" stock after two years of high flow spending right after the policy shock, bank branches operating in high-exposure regions are likely to cut their spending, even if the demand for small business credit remains high in these high-exposure regions.

As a robustness check, we also construct the instrumental variable using the proportion of total employees of the county that work in qualified small business establishments, which captures the county's policy exposure from the angle of labor force in the qualified small businesses. The regression results in Table A4 and the dynamic treatment effect analysis in Figure A6 deliver

similar messages as in Table 6 and Figure 3.

Comparison: OLS Estimates We report the OLS estimates in Columns (4)–(5) of Table 6. Qualitatively, OLS estimates are similar to those obtained from the 2SLS method: within a bank, its branches in counties seeing a higher growth rate in small business loans invest more in communication than other branches, but not in software spending.

In terms of magnitude, the OLS coefficients are significantly smaller compared with those of the 2SLS estimators. 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 demand—that drive local banks to spend less on communication. Specifically, if the demand for mortgage refinancing positively correlates with that of small business loans, and if banks have a fixed amount of IT budget each year, then they will allocate more IT spending (say, on software) to cater mortgage refinancing demand, as we will show shortly. The omitted-variable problem then leads 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 the 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 3.3.1. We can move one step further and conduct a similar analysis within the mortgage lending business, by splitting it into mortgage origination and mortgage refinancing. As shown in Table 4 row 7, banks with a larger share of refinancing loans (as a fraction of their total mortgage lending in HMDA) spend more on software. As expected, communication spending

shows no correlation with activities in mortgage refinancing under both empirical settings.

We investigate further whether bank size plays any role in the positive association between mortgage refinancing and software spending. As reported in Table 5 Panel A, while above-median-size banks strongly increase their software spending in response to an increase in their mortgage refinancing activities, such response is relatively muted (though still statistically significant) among the group with below-median asset size. This is likely driven by the fixed-cost nature of banks' IT spending; as discussed in Section 3.2, tiny banks should be reluctant to adjust their IT spending—which is often lumpy—to changes in their lending activities.

These findings on the close linkages between commercial banks' spending on software IT and their engagement in refinancing is 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 loan, 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 in their technology adoption behavior 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 variation in mortgage refinance demand across different regions, following Eichenbaum et al. (2022) and Di Maggio et al. (2017) we construct an instrumental variable for county-level mortgage refinance propensity by utilizing the post-crisis low interest rate period. The nationwide mortgage rate decrease has prompted existing homeowners to refinance their mortgages, and an important determinant of homeowners' refinancing propensity is the pre-crisis mortgage characteristics in place before the low-interest episode kicked in. This

logic is also demonstrated in Berger et al. (2021), where authors show effectiveness of monetary policy is crucially dependent upon the previous levels of mortgage rates. For the period during 2011-2016, we construct the following county-level measure that captures the heterogeneity of each county's refinancing propensity:

$$\Delta\text{Payment}_c = Ave.(\text{Payments}_{\text{old interest rate}} - \text{Payments}_{\text{new interest rate}})_c.$$

In words, we calculate the average total remaining mortgage payment savings under old versus new interest rates at the county level. In constructing this measure, we use information about all local household outstanding mortgage loans and their mortgage rates at issuance by county since 2000.[42] We construct the hypothetical new interest rate using the interest rate of newly issued mortgages in county c matched with the loan maturity and FICO.[43]

Importantly for our identification purpose, the county-level payment savings measure constructed above features significant variation across regions. This variation in local homeowners' refinancing savings serves as an exogenous shifter on the mortgage refinance demand faced by local banks, and homeowners seeking to refinance could send applications to multiple banks in the area, escalating the amount of information banks need to process.

Empirical Design: 2SLS Regression We aim to identify whether IT investment specialized in processing existing information increases given a greater mortgage refinance demand compared with mortgage origination. The regression specification using Payments_c as the instrumental variable is:

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

[42] We construct the payment savings based on the 2011-2016 sample, because the Federal Funds rate and mortgage rate remained at the low level till 2016 (Figure A3). As a robustness check, we construct the variables using a shorter period of 2011-2013 and report the result in Table A5.

[43] We remove loans that were defaulted on or prepaid to ensure that the measure captures only refinance propensity from local households with outstanding loans. While this measure shares many similarities with the "interest rate gap" constructed in Eichenbaum et al. (2022), one difference is that we multiply the difference in interest rates of each loan by its remaining loan balance. This better reflects the "refinancing gap" as in Di Maggio et al. (2017) and therefore serves as a better proxy for the propensity of mortgage refinancing.

In the first stage we regress the bank i's logarithmic refinance loan relative to its mortgage loan origination volume in county c, averaged during the period of 2011-2016, on the instrument $\Delta\text{Payments}_c$; the second stage then regresses the logarithmic of IT spending of bank i in county c averaged during 2011-2016 on the fitted value. Similar as 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, logarithmic of number of establishments, and logarithmic of small business loans. We include bank fixed effects and cluster standard error at county level.

Estimation Results Table 7 reports our estimation results. In the first stage, the instrumental variable "$\Delta\text{Payments}_c$" predicts mortgage refinancing activities across different counties quite well, with a high F-statistics (20.345). 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 savings—leads to a 0.419 standard deviation increase in software spending, which amounts to \$1.3 million more budget on software per year.

By including bank fixed effects, our result is identified from within-bank-cross-county variations. It is also worth emphasizing that communication spending does not demonstrate significant changes in response to the refinancing demand captured by the predetermined refinance propensity, with a much smaller magnitude. This 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.

Dynamic Treatment Effects Paralleling our analysis in Section 4.2.2, we study the time trend of software spending and communication spending for banks located in counties with high exposure to mortgage refinance propensity compared with those located in low-exposure counties:

$$\ln IT_{i,c,t} = \alpha_{i,t} + \alpha_{i,c} + \sum_{s\in[0,6],s\neq 0} \beta_s \times \mathbb{1}_{\{t-2010=s\}} \times \text{High ref propensity}_{11-16} + \pi_1 \mathbf{X} + \epsilon_{i,c,t}$$

Here, $\alpha_{i,t}$ and $\alpha_{i,c}$ are bank-year and bank-county fixed effects. We define a bank as being operating in a county with high (low) refinance propensity, or "High ref propensity" equals 1 (0),

if $\Delta\text{Payments}_c$ lies in the top (bottom) tercile. The coefficients $\{\beta_s\}$ thus capture the over-time differences in IT spending trend between banks in high-refinance-propensity environment and those in low- refinance-propensity environment. As shown in Figure 4, banks in high-refinance-propensity counties increased their software spending significantly (relative to the low-propensity benchmark) during the first two years when the low-interest rate episode kicked in, and this difference started to taper in 2013. On the contrary, there is no significant difference between their communication spending during the entire low-interest rate episode. The figure is plotted from 2010 as our IT budget dataset starts from 2010.

Comparison: OLS Estimates We conduct the OLS version of the 2SLS regression in Eq. (3) and report the results in the last two columns of Table 7, with quantitatively smaller OLS estimators.[44] 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 post-crisis period (say, small business loans), which might then tilt local banks' IT budget towards 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.[45] 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?

[44] Table A3 shows the results of the same OLS specification with bank, year and county fixed effects and bank×year and county fixed effects.

[45] See here for one example of an article talking about this issue.

5.1 How do 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). While fintech lenders have been quickly gaining market share in various markets over the past decade, the exact ways through which incumbent commercial banks react to the aggressive fintech entry remain unclear. For instance, when banks and non-bank lenders offer complementary services, it is possible for banks to strategically shift investment towards areas with fewer activities from fintech lenders. Furthermore, from an information channel, the emergence of fintech lenders who have comparative advantages in information handling in certain markets would render traditional bank lenders more adversely selected in these markets. Concerning a more severe "winner's curse," banks might thus respond by decreasing their engagement in these credit markets. Both would imply a "falling back" of traditional banks from the markets with fintech entry and a lowered investment in the IT category that fintech lenders have comparative advantages in.

On the other hand, incumbent banks might instead choose to protect their market share and compete against these new fintech entrants; this implies that incumbent banks who worry about adverse selection would increase their software spending given fintech lenders' advantage in information processing capacity. Indeed, Figure 2(b) has shown that banks in areas with a higher fintech presence increase their IT spending at a faster rate than those in areas with a low fintech presence, suggesting a potential "catching-up" behavior of the traditional banking sector.

5.2 Entry of Lending Club and Local Bank IT Investment

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

Staggered Entry of Lending Club As one of the leading players in the fintech industry, Lending Club launched its platform in 2007. Since 2008, Lending Club has been pursuing

regulatory approval to conduct peer-to-peer lending in all 50 states. By October of 2008, forty States and the District of Columbia (DC) moved relatively fast to approve its entry; and between 2010 and 2016, another nine states approved Lending Club's entrance at different times.[46] Table 8 summarizes the timing of Lending Club's staggered entrance into different states.

Following Wang and Overby (2017) and Kim and Stähler (2020), we drop the 40 states who approved Lending Club's entry in our analysis.[47] For Kansas and North Carolina, the actual approval time was 2010Q4. Because 2010 is the starting year of our Harte Hanks dataset, 2010 as a pre-treatment period becomes 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.

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

Empirical Design and Results Our empirical method mainly follows the staggered difference-in-difference design as in Wang and Overby (2017). The regression specification is

$$\ln(\text{IT Spending})_{i,c,t} = \alpha_{i,c} + \alpha_t + \beta \times \text{LC}_{i,c,t} + \mu \mathbf{X} + \epsilon_{i,c,t}, \tag{4}$$

where IT Spending $\in$ {Total, Software, Communication}. We include the bank-times-year and county fixed effects, denoted by $\alpha_{i,t}$ and α_c respectively. $\text{LC}_{i,c,t}$ is a dummy variable that is equal

[46] As explained by Wang and Overby (2017), Lending Club launched its platform in 2007. In April 2008, Lending Club 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, Lending Club 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.

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

to one if Lending Club entered the state where county c is located in year t for bank i. X is a set of control variables, and the standard error is clustered at county level. Our main parameter of interest is β, which measures the average treatment effect of Lending Club approval on bank technology spending. Estimations are weighted by Lending Club loan volume after the entry.

Columns (1) to (2) in Table 9 Panel A report the results for software and communication spending, respectively. Consistent with the "catching-up" story, column (1) shows that, after Lending Club enters in country c, banks on average increase their software IT spending in county c by around 7.0%, and this estimate is statistically significant. The growth in communication spending right after Lending Club's entry is slightly negative (-1.5%), statistically insignificant.

Figure 5 graphically explores the dynamics of banks' IT spending within the 3-year time window around the fintech entrance year, from the following estimation:

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

The estimated $\{\hat{\beta}_s\}$ and the 95% confidence intervals are plotted. Importantly for our identification, there is no statistically significant trend in either type of IT spending before the fintech entrance. The lack of a pre-trend in banks' IT spending allows us to plausibly attribute changes in banks' IT spending to the penetration of fintech into the local economy. Consistent with Table 9, 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).[48] As shown in columns (4) to (5) of Table 9, the estimates are similar to, albeit a little larger than, those in columns (1) and (2).

[48] In this method, we run separate regressions in (4) for each group of states that are treated at the same year, with the not-yet-treated as the comparison group, and then aggregating 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 lending club within the three years after the Lending Club entry. Standard errors are based on Bootstrapping with 50 draws.

Heterogeneity in Response across Bank Sizes In Panel B of Table 9, 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 10.9% right after the Lending Club entry, and the increase is statistically significant, whereas small banks' software spending growth was only about one fifth of the magnitude compared with larger banks, and statistically insignificant. On the other hand, while small banks also barely display any response in their communication spending, large banks actually cut their spending on communication IT by 6.1% (which is statistically significantly) following the fintech entry.

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 finding is consistent with Balyuk et al. (2020), who find that fintech lending more often substitutes lending made by large banks rather than smaller banks whose lending technology is more relationship based. Given that smaller banks engage more in relationship-based small business lending, the entry of Lending Club—who is equipped with superior hard information processing capacity—will not strongly affect these banks' profit making.

Furthermore, that large banks significantly reduce 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 by 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 activities, which often rely on the support of communication IT, one should naturally expect them to reduce their communication IT spending.

Finally, our findings are also consistent with the notion that entry of fintech lenders helps convert soft information to hard information.[49] Linking this "hardening soft-information" effect to our analysis where the focus is placed on bank lenders' decision making, one should expect

[49] For instance, Beaumont et al. (2019) 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.

large banks—rather than small ones who specialize more in relationship-based soft information handling—to reallocate their investment away from communication to software due to a decreased (increased) need of dealing with soft (hard) information.

Summary and Discussion To sum up, the entrance of fintech lenders such as Lending Club into the credit markets overall 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 operating in the same local area to invest more in their lending technology to catch up. Furthermore, consistent with existing literature (say, Berg et al., 2021) that highlights the comparative advantage of fintech lenders in processing hard information and making prompt decisions, our finding shows 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 lenders' 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.

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 dataset 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 on 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 the 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 credit cycle, and monetary policy transmission? We leave these questions to future research.

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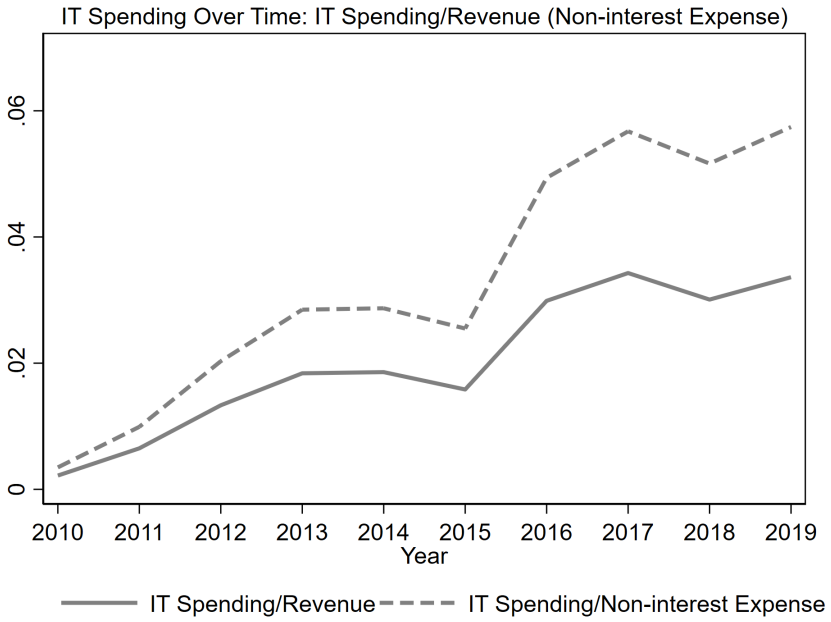
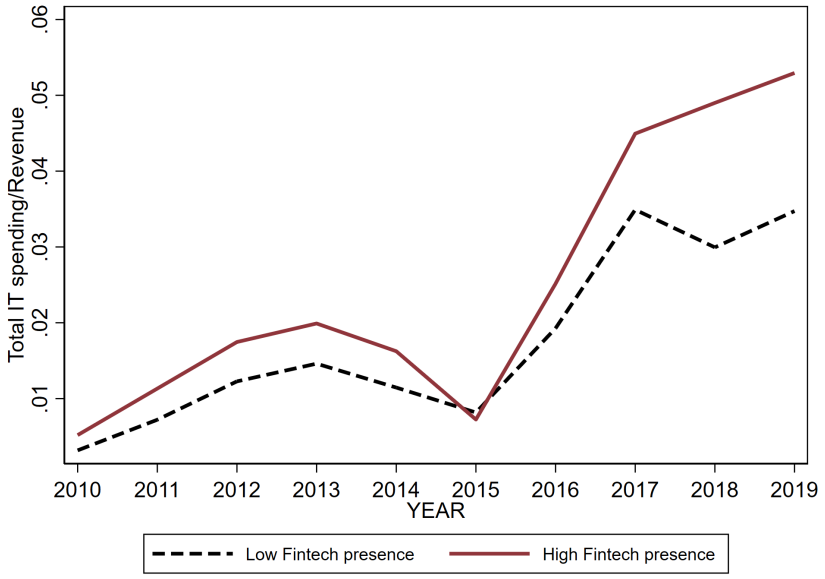
Figure 1. IT Spending: Time Trend

Panel A shows the time trend of banks' IT spending from 2010 to 2019. The solid line shows the average of banks' IT Spending as a share of banks' total revenue weighted by total assets; the dashed line shows the weighted average of banks' IT spending as a share of banks' non-interest expenses weighted by total assets. "Revenue" is constructed using the item RIAD4000 in the Call Report, and "Non-interest Expense" is the non-interest expenses reported by item RIAD4093 in the Call Report. Panel B shows the relationship between banks' IT spending and the presence of fintech companies in the local economy. The y-axis is the county-level "Total IT spending/Revenue" of local banks. Based on the average fintech lending share in mortgage market of a county during 2010-2019 used in (Fuster et al. (2019)), we define high and low fintech presence as counties with above-median and below-median fintech lending share in the local mortgage market, respectively.



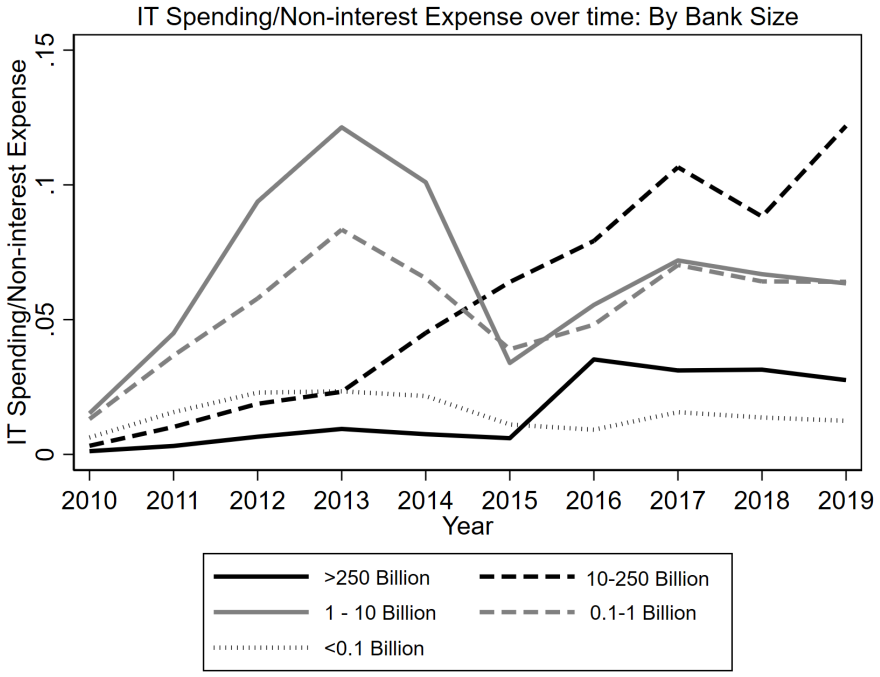
(a) Panel A



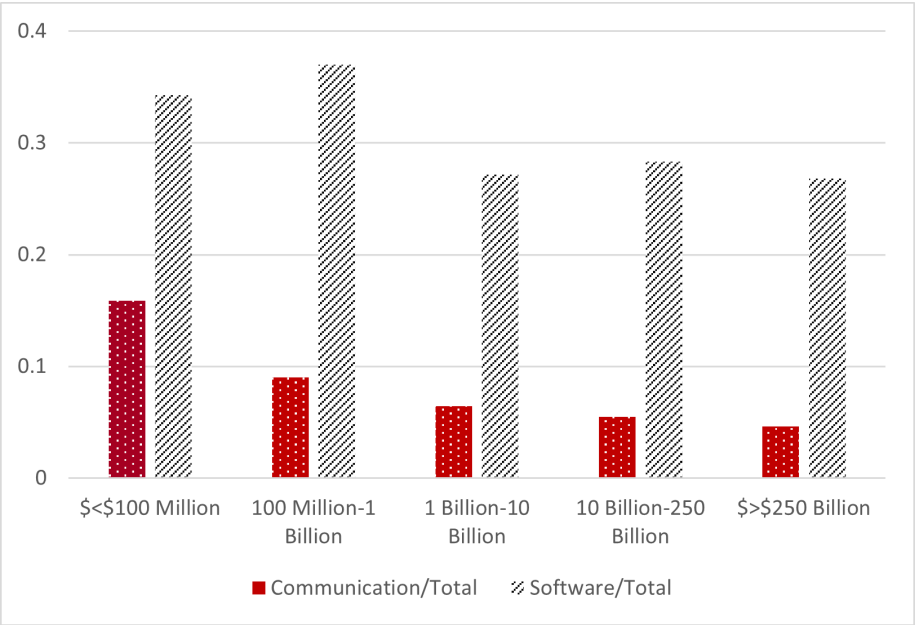
(b) Panel B

Figure 2. IT Spending Time Trend and Composition, by Bank Size

The figures show the time trend of banks' IT spending from 2010 to 2019 by the five categories of bank asset size groups (Panel A) and the differences in composition of IT spending by bank size groups (Panel B). In Panel A, The vertical axis is banks' total IT spending scaled by non-interest expenses. The asset size groups are categorized based on a bank's average asset size during 2010 and 2019. Non-interest expenses are calculated using banks' balance sheet item "RIAD4093" in the Call Report. In Panel B, the shaded bars show the average proportion of total IT budget spent on communication and software across bank size groups.



(a) Panel A



(b) Panel B

Figure 3. IT Spending Around Small Business Tax Credit Policy

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

$$\ln IT_{i,c,t} = \alpha_{i,t} + \alpha_{i,c} + \sum_{s\in[-3,3],s\neq-1} \beta_s \times \mathbb{1}_{\{\text{t-2014}=s\}} \times \text{High QSB exposure}_{pre} + \pi_1 \mathbf{X} + \epsilon_{i,c,t}$$

where for bank i at county c in year t, $\alpha_{i,t}$ are the bank-year fixed effects, $\alpha_{i,c}$ 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 2011-2013; "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 2011-2013. Bank 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, logarithmic of total number of establishments, logarithmic of total small business loans, and GDP per capita. Shaded regions are the 95% confidence interval of the estimated β_s. Standard errors are clustered at the county level.

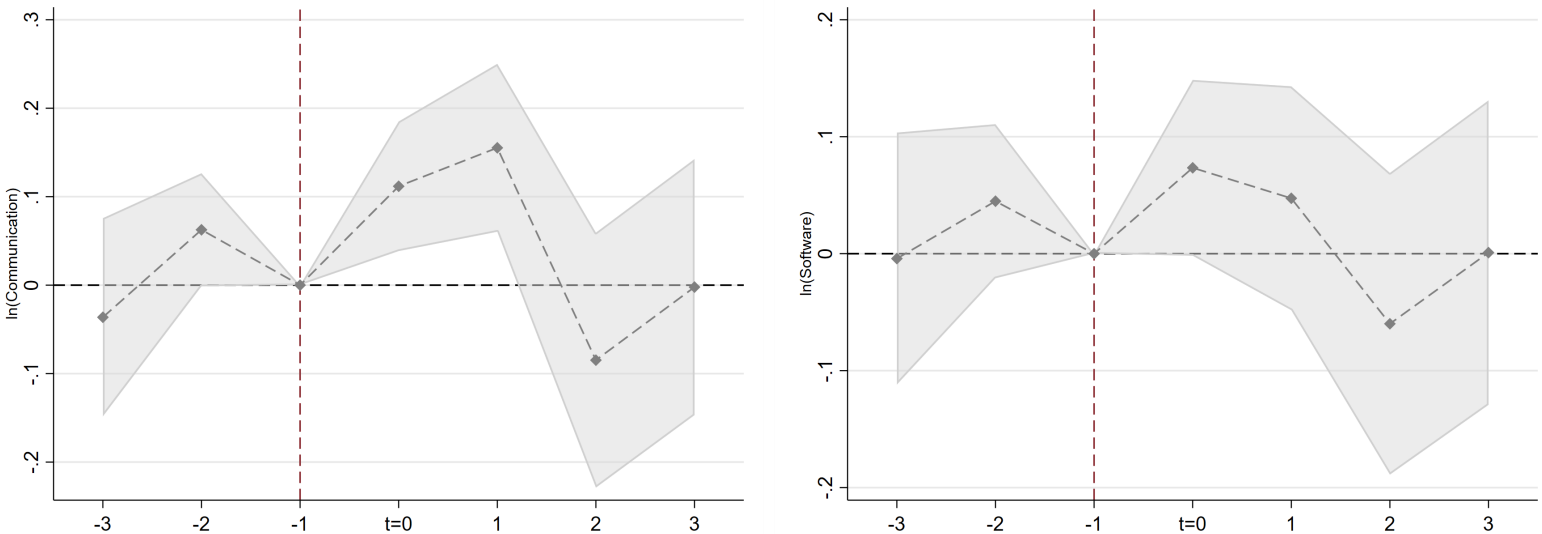


Figure 4. IT Spending and Mortgage Refinance during Low Interest Rate Episode

This figure reports the event studies of IT spending around the low interest rate episode between 2010 and 2016. The specification is

$$\ln IT_{i,c,t} = \alpha_{i,t} + \alpha_{i,c} + \sum_{s\in[0,6],s\neq 0} \beta_s \times \mathbb{1}_{\{\text{t-2010}=s\}} \times \text{High ref propensity}_{11-16} + \pi_1 \mathbf{X} + \epsilon_{i,c,t}$$

where for bank i at county c in year t, $\alpha_{i,c}$ are the bank-county fixed effects, $\alpha_{i,c}$ are bank-county fixed effects. "High ref propensity$_{11-16}$" is equal to one if $\Delta\text{Payments}_c$ is within the top tercile between 2011-2016; 'High ref propensity$_{11-16}$" is equal to zero if $\Delta\text{Payments}_c$ is within the bottom tercile between 2011-2016. The detailed definition of ΔPayments is provided in Section 4.3.2. Bank 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, logarithmic of total number of establishments, logarithmic of total small business loans, and GDP per capita. Shaded regions are the 95% confidence interval of the estimated β_s. Standard errors are clustered at the county level.

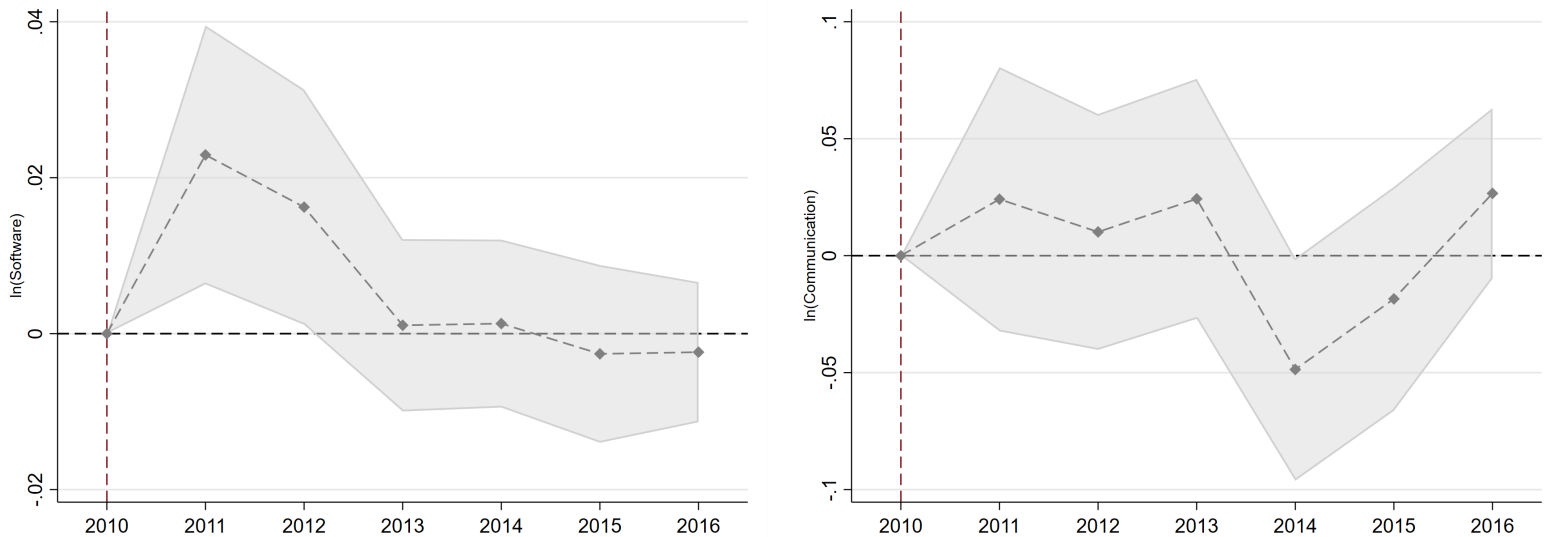


Figure 5. IT Spending Around Fintech Entrance

This figure reports the event studies of IT spending around the entrance of Lending Club. The specification is

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

where for bank i at county c in year t, $\alpha_{i,c}$ are the bank-county fixed effects, 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 distance between the observation year t and the Fintech entrance year into the state where county c is located is s. For Panel A, the left-hand-side variable is logarithmic spending on software IT. For Panel B, the left-hand-side variable is logarithmic spending on communication IT. Shaded regions are the 95% confidence interval of the estimated β_s. Standard errors are clustered at the county level.

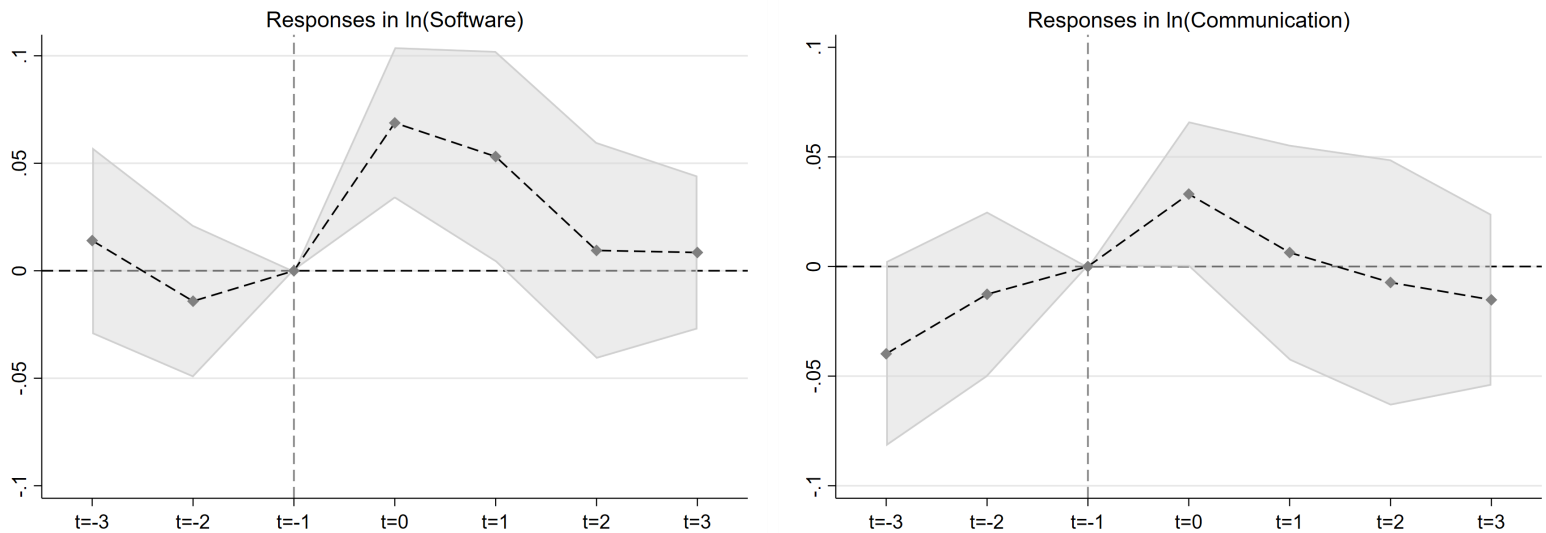


Table 1. Sample Coverage

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 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 Call Report, and column 6 shows the percentage of sample coverage in terms of total asset size compared with the population in Call Report.

Coverage of data	Sample		Call Report		Freq %	Asset %
Average Assets 2010-2019 (Billion)	Num banks	Ave Assets	Num banks	Ave Assets		
>$250 Billion	6	1184.24	7	787.34	85.71%	96.66%
$10 Billion–$250 Billion	88	42.30	106	43.69	83.02%	73.22%
$1 Billion–$10 Billion	474	2.90	590	2.78	80.34%	89.43%
$100 Million–$1 Billion	942	0.40	4161	0.32	22.64%	29.44%
<$100 Million	296	0.06	2048	0.05	14.45%	14.23%

Table 2. IT Spending Summary Statistics

This table shows the summary statistics of banks' IT Spending. Total IT Spending is the sum of all types of IT spending in millions of dollars. No. of IT employees is the total amount of IT-related employees. IT Spending/Revenue is total IT Spending scaled by banks' total gross income; IT Spending/Non-interest expense is total IT spending scaled by non-interest expenses; IT spending/Net income is total IT spending scaled by total income minus the gross total expenses. The different categories of IT spending are the four categories of IT spending scaled by total IT spending.

	Mean	S.d.	p(25)	Median	p(75)
Total IT Spending (Million)	7.311	111.354	0.030	0.215	1.056
No. of IT Employees	133.434	872.102	7.000	21.578	56.400
Storage Amount(PB)	3.517	25.522	0.107	0.476	1.779
IT Spending/Revenue	0.031	0.155	0.003	0.010	0.023
IT Spending/Net income	0.597	18.475	0.018	0.051	0.135
IT Spending/Expenses	0.037	0.191	0.004	0.012	0.028
IT Spending/Non-interest Expenses	0.044	0.213	0.005	0.014	0.034
Communication/Total	0.092	0.117	0.028	0.052	0.105
Communication/Revenue	0.0016	0.0075	0.0001	0.0005	0.0014
Software/Total	0.334	0.161	0.220	0.321	0.474
Software/Revenue	0.011	0.066	0.001	0.003	0.007
Hardware/Total	0.171	0.119	0.063	0.158	0.235
Services/Total	0.327	0.137	0.243	0.323	0.417
Other/Total	0.056	0.099	0.008	0.014	0.062

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

This table presents the results of the regression of banks' C&I loan 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.

$$\frac{\text{Type S IT spending}}{\text{Revenue}}_{i,\text{10-19}} = \alpha + \beta \frac{\text{C\&I Loan}}{\text{Total loan}}_{i,\text{10-19}} + \gamma \mathbf{X} + \epsilon_i$$

C&I Loan/Total Loan is commercial and industrial loan of bank i scaled by total loan between 2010-2019, Software/Rev is software spending scaled by total revenue, Communication/Rev is communication spending scaled by total revenue, Hardware/Rev is Hardware spending scaled by total Revenue, Services/Rev. 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 within bank i. Fixed effects include bank size and banks' headquarters state fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Software/Revenue	Communication/Revenue	Hardware/Revenue	Services/Revenue
	(1)	(2)	(3)	(4)
C& I loans/Total loan	0.031	0.050**	0.049**	0.043*
	(0.025)	(0.024)	(0.024)	(0.025)
Net income/Total Assets	-0.142***	-0.217***	-0.242***	-0.107***
	(0.028)	(0.028)	(0.028)	(0.029)
Deposits/Assets	-0.013	0.028	0.032	-0.008
	(0.031)	(0.030)	(0.030)	(0.031)
Revenue per Employee	-0.267***	-0.347***	-0.301***	-0.298***
	(0.035)	(0.034)	(0.034)	(0.035)
Salaries/Assets	-0.018	-0.132***	-0.099***	-0.034
	(0.026)	(0.025)	(0.025)	(0.026)
Equity/Assets	0.070**	0.051*	0.046*	0.071***
	(0.028)	(0.027)	(0.027)	(0.028)
Size FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
AdR-squared	0.098	0.162	0.150	0.110
N	1798	1798	1798	1798

Table 4. Bank Characteristics and Banks' IT Spending

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

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

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 1-4 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; "Other personal loans" is the deduction of "Mortgage refinance" from "Personal and mortgage loans." %Refinance is the frequency of refinance as a percent of total number of mortgage issuances that are reported in HMDA. Software/Rev is software spending scaled by total revenue, Communication/Rev is communication spending scaled by total revenue, Hardware/Rev is Hardware spending scaled by total revenue, Services/Rev is services spending 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 logarithmic of 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.

	Software/Revenue	Communication/Revenue	Hardware/Revenue	Services/Revenue
	(1)	(2)	(3)	(4)
Panel A: Loan Specialization				
C& I loans/Total loan	0.031	0.050**	0.049**	0.043*
	(0.025)	(0.024)	(0.024)	(0.025)
CRA/Total loan	-0.150***	0.113***	0.063**	0.039
	(0.029)	(0.028)	(0.029)	(0.029)
Other C&I/Total loan	0.050**	0.036	0.041*	0.039
	(0.025)	(0.024)	(0.024)	(0.025)
Personal loan/Total loan	0.045*	0.033	-0.014	0.025
	(0.027)	(0.026)	(0.023)	(0.023)
Mortgage refinance/Total loan	0.093***	-0.032	0.033	0.027
	(0.033)	(0.034)	(0.035)	(0.029)
Other personal loans/Total loan	-0.028	0.039	0.019	0.011
	(0.026)	(0.028)	(0.035)	(0.026)
% Refinance/Total Mortgage	0.081***	-0.002	0.041*	0.055**
	(0.024)	(0.024)	(0.024)	(0.023)
Agricultural loans/Total loan	0.026	0.073**	0.048	0.043
	(0.031)	(0.030)	(0.030)	(0.031)
Panel B: Hierarchical Complexity and IT Spending				
Hierarchical layer	0.00859	0.0484**	0.0147	0.0144
	(0.0233)	(0.0232)	(0.0232)	(0.0231)
ln(num of offices)	-0.00506	0.0528**	0.0166	0.0121
	(0.0239)	(0.0238)	(0.0238)	(0.0237)
Panel C: Banks' Role in Syndicated Lending				
% Lead bank/Total syndicate	-0.612*	1.759***	1.393***	1.083***
	(0.333)	(0.295)	(0.278)	(0.262)

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

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.

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

In Panel A, small (large) banks are defined as the banks with asset size below (above) median asset size in our sample. "Size Group FE" refers to the fixed effects of small (large) banks. In Panel B, "Hierarchical layer" is the number of types of its locations as defined in Section 2.3. "Size FE" refers to the fixed effects of the five bank asset groups defined in Section 3.2. 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.

Panel A: Bank Size and IT Spending

	Software/Rev	Communication/Rev
	(1)	(2)
Small × Refinance/Total loan	0.0794*	
	(0.0438)	
Large × Refinance/Total loan	0.194***	
	(0.0506)	
Small × CRA/Total loan		0.423***
		(0.142)
Large × CRA/Total loan		0.156***
		(0.0335)
State × Size Group FE	Y	Y
AdR-squared	0.113	0.171
N	1792	1789

Panel B: Bank Hierarchical Structure and IT Spending

	Software/Rev	Communication/Rev
	(1)	(2)
Hierarchical layer=1 × Refinance/Total loan	0.0761	
	(0.0807)	
Hierarchical layer=2 × Refinance/Total loan	0.0870*	
	(0.0523)	
Hierarchical layer=3 × Refinance/Total loan	-0.0160	
	(0.0496)	
Hierarchical layer=1 × CRA/Total loan		0.0558
		(0.0724)
Hierarchical layer=2 × CRA/Total loan		0.0872**
		(0.0406)
Hierarchical layer=3 × CRA/Total loan		0.164***
		(0.0494)
Size× Layer Group FE	Y	Y
State× Layer Group FE	Y	Y
AdR-squared	0.0962	0.177
N	1779	1778

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Soft Information and Banks' IT Spending

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:

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

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

The last two columns show the following OLS specification:

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

$\Delta\ln\ (\text{CRA})_{i,c,post}$ 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 pre-shock revenue per employee and deposit market share of the bank in a county. County level control variables include the pre-shock unemployment rate, labor force participation rate, population growth rate, logarithmic of total number of establishments, logarithmic of total small business loan, and GDP per capita. Fixed effects include bank fixed effects. Standard errors are clustered at county level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	First stage	ln(Software)	ln(Communication)	ln(Software)(OLS)	ln(Communication)(OLS)
	(1)	(2)	(3)	(4)	(5)
$\frac{\text{Qualified small businesses establishments}}{\text{Total establishments}}_{c,pre}$	0.969***				
	(0.250)				
$\Delta \widehat{\ln(CRA)}$		-0.213	0.741**		
		(0.330)	(0.348)		
$\Delta \ln(CRA)$				0.020*	0.036***
				(0.011)	(0.011)
Bank FE	Y	Y	Y	Y	Y
Clustered	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
F-stat	18.079				
AdR-squared	0.430	-0.216	-0.568	0.105	0.096
N	19,819	19,815	19,814	19,815	19,814

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Hard Information and Banks' IT Spending

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

$$\ln(\text{Refinance/Origination})_{i,c} = \tilde{\alpha_i} + \mu_1 \times \Delta\text{Payments}_c + \mu_2\ \mathbf{X}_{i,c} + \epsilon_{i,c}$$

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

Column (4) and (5) 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 logarithmic of banks' IT spending during 2011 and 2016. $ln(\text{Refinance/Origination})_{i,c}$ is the average logaithmic of amount of mortgage refinance loan relative to mortgage origination issued by bank i in county c during 2011 and 2016. Payments gap is the hypothetical amount of interest payments that could be saved due to the interest rate decrease, if local households chose to refinance their mortgages during the year of 2011 and 2016. Bank control variables include banks' revenue per employee and deposit market share of the bank in a county. County level control variables include unemployment rate, labor force participation rate, population growth rate, logarithmic of total number of establishments, logarithmic of total small business loan, and GDP per capita. Fixed effects include bank fixed effects. Standard errors are clustered at county level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	First stage	ln(Software)	ln(Communication)	ln(Software)(OLS)	ln(Communication)(OLS)
	(1)	(2)	(3)	(4)	(5)
$\Delta\text{Payment}_c$	1.099***				
	(0.259)				
$\text{Ln}(\widehat{\text{Refinance/Originagion}})$		0.419**	0.294		
		(0.207)	(0.192)		
Ln(Refinance/Originagion)				0.024***	0.017**
				(0.007)	(0.007)
Bank FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Clustered	Y	Y	Y	Y	Y
F-stat	20.345				
AdR-squared	0.384	-0.116	0.061	0.374	0.387
N	15,541	15,541	15,541	15,545	15,541

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. Staggered Entry of Lending Club to 9 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

Table 9. Fintech Exposure and Banks' Lending Technology Adoption

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

$$\ln(\text{IT Spending})_{i,c,t} \quad = \quad \alpha_{i,c} + \alpha_t + \beta \times \text{LC}_{i,c,t} + \gamma \mathbf{X} + \epsilon_{i,c,t},$$

where $\alpha_{i,c}$ and α_t are the bank-county and year FE, respectively. Column (1) and (2) of Panel A show the baseline results. Column (3) and (4) of Panel A use the interacted TWFE method as in Callaway and Sant'Anna (2021). 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. The estimations in Panel B are based on the 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.

Panel A: IT Spending and Fin-tech Entrance

	Baseline		Callaway and Sant'Anna (2021)	
	ln(Software)	ln(Communication)	ln(Software)	ln(Communication)
	(1)	(2)	(3)	(4)
After	0.070***	-0.015	0.073***	-0.031
	(0.021)	(0.019)	(0.029	(0.033)
Fixed Effects	Bank×County, Year, Size group			
AdR-squared	0.799	0.784		
N	13,552	13,552		

Panel B: Responses by bank sizes

	Baseline		Callaway and Sant'Anna (2021)	
	ln(Software)	ln(Communication)	ln(Software)	ln(Communication)
	(1)	(2)	(3)	(4)
Small×After	0.036	0.037	0.034	0.067
	(0.028)	(0.026)	(0.042)	(0.047)
Large×After	0.109***	-0.061***	0.119***	-0.127***
	(0.023)	(0.021)	(0.029)	(0.039)
Fixed Effects	Bank×County, Year, Size group			
AdR-squared	0.786	0.771		
N	13,546	13,546		

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Internet Appendix
— "Investing in Lending Technology: IT Spending in Banking"

A Additional Figures and Tables

Figure A1. Total Asset of Banks in Sample

This figure shows the sum of total asset size of all banks in our sample from 2010 to 2019 U.S. The red dashed line is the sum of all commercial banks' asset size in U.S., data source is Board of Governors of the Federal Reserve System (US), Total Assets, All Commercial Banks [TLAACBW027SBOG]. The red solid line is the sum of total asset sizes of banks in our sample. The black solid line is the sample bank size out as a share of total nation-wide banks' total asset size.

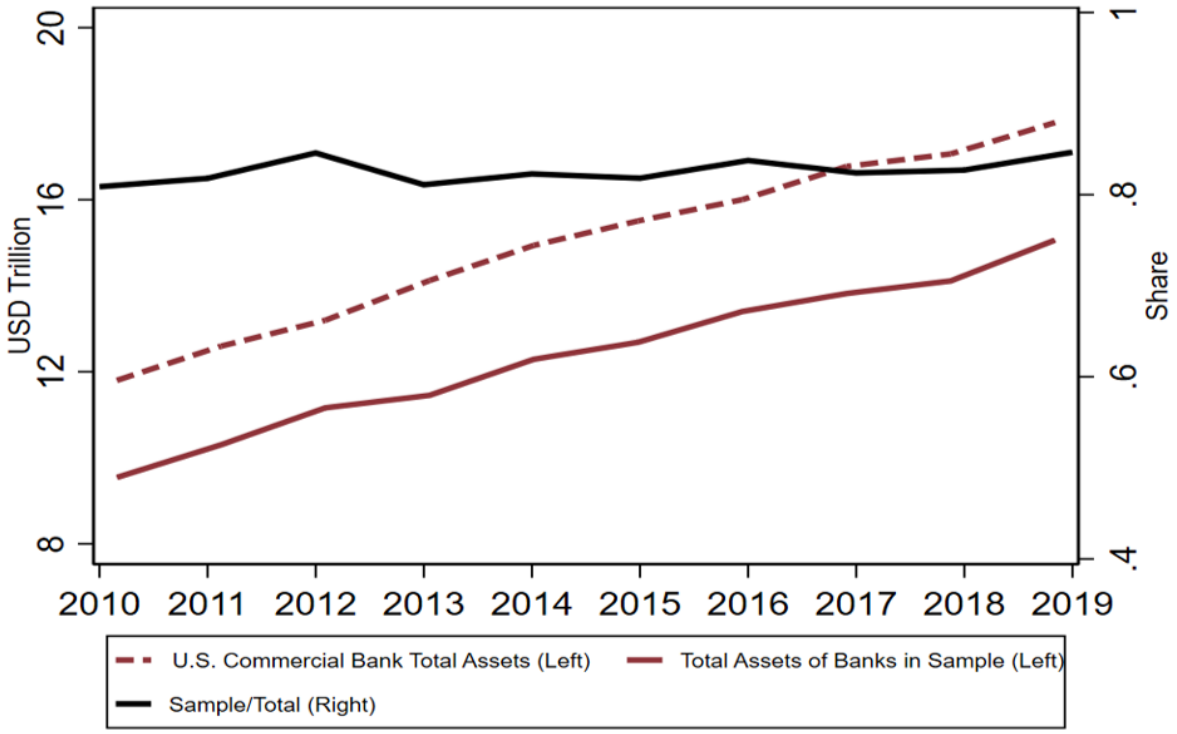


Figure A2. IT Spending Time Trend: IT Spending as a Share of Total Revenue

The figures show the time trend of banks' IT spending from 2010 to 2019 by the five categories of bank asset size groups. The vertical axis is banks' total IT spending scaled by banks' total revenue. The asset size groups are categorized based on a bank's average asset size during 2010 and 2019. Total revenue is calculated as the sum of banks' net interest income (RIAD4074) and non-interest income (RIAD4079).

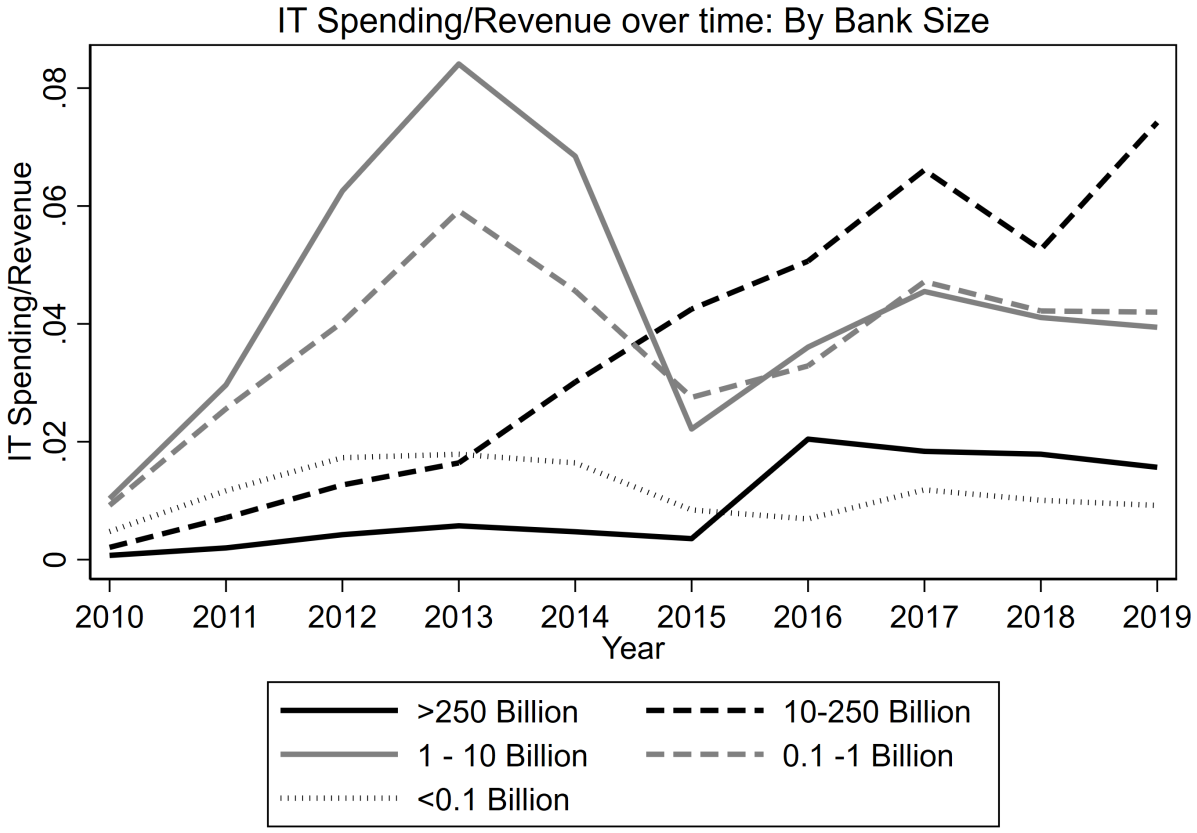


Figure A3. "Low Mortgage Rate Episode"

The figure show the time-series of aggregate mortgage interest rate and the Federal Funds Rates. "MORTGAGE30US" is the 30-Year Fixed Rate Mortgage Average in the United States from Freddie Mac. "FEDFUNDS" is the effective Federal Funds Rate by Board of Governors of the Federal Reserve System.

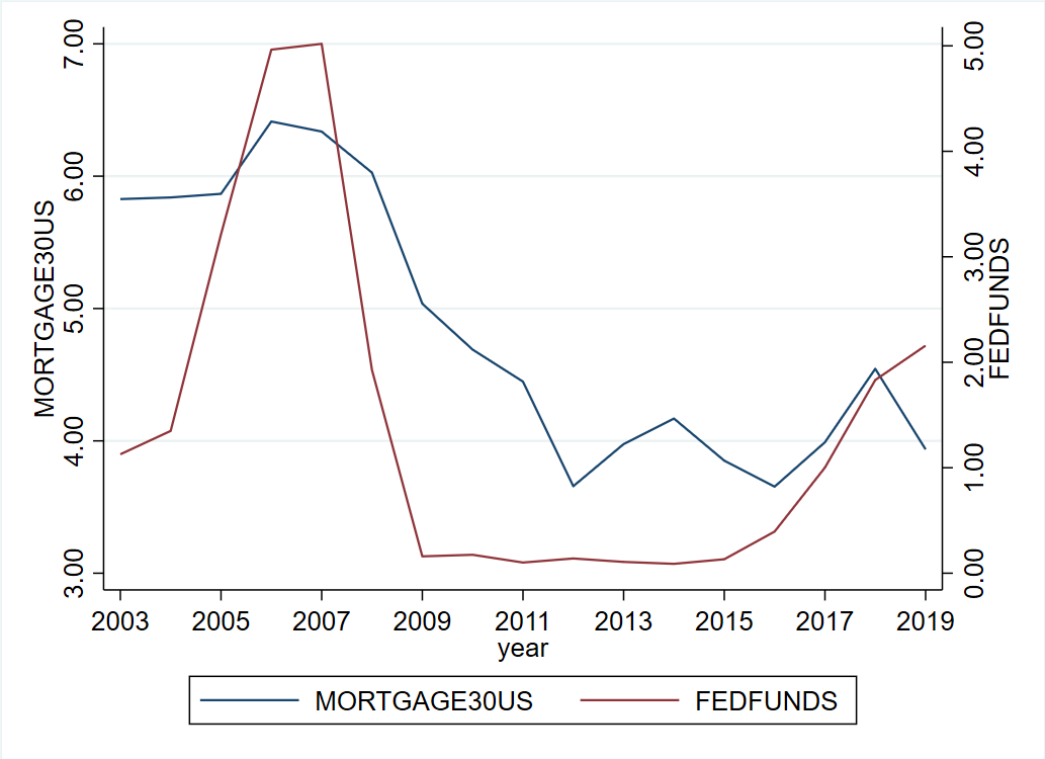


Figure A4. McKinsey (2012) "Breakthrough IT Banking"

BUSINESS TECHNOLOGY OFFICE

Breakthrough IT banking

Some Asian banks achieve superior returns despite relatively low IT expenditures. What's their secret?

Sai Gopalan, Gaurav Jain, Gaurav Kalani, and Jessica Tan

Banks have long relied on technology to introduce products such as online banking, ATMs, and mobile payments, and to improve back-office efficiency. But that reliance comes with a price. Globally, the banking sector spends an average of 4.7 percent to 9.4 percent of operating income on IT, while other sectors spend less: insurance companies and airlines, for example, spend 3.3 percent and 2.6 percent of income, respectively.

Our Asian Banking IT Benchmarking Study[1] finds, however, that a bank's high IT expenditures do not always correlate with superior performance. Some banks with large IT budgets often have trouble leveraging investments to generate commensurately high revenue growth and operational efficiency. Survey data show that 66 percent of banks with higher-than-average IT spending relative to income generated lackluster results, with revenue growth 0.4 percentage points lower than the industry standard and a cost-income (C/I) ratio 2.5 percentage points higher.

By contrast, 23 percent of the 44 banks surveyed outperformed the market on both revenue growth (up 10.9 percentage points) and C/I ratio (down 4.6 percentage points) while spending 29 percent less on IT than other banks in our study. These outperforming banks are more likely to view IT as a strategic enabler, and their investments mirror this outlook. Outperformers direct a higher share of spending toward technologies designed to create new business value and a lower share of spending on support operations, such as finance and human resources. These banks are also more likely than the lower performers to promote efficiency through a consolidated IT footprint as well as formal vendor- and demand-management practices.

The common denominator linking high-performing Asian banks is a commitment to strong governance and spending alignment with the needs of the business. This finding supports our experience with bank clients in Europe and the Americas, and prompted us

[1] The 2010 biennial McKinsey Asian Banking IT Benchmarking survey comprised 44 banks across 11 Asia-Pacific countries, with the results tracked against prior year benchmarks from 2006 onward.

Figure A5. Definition of Different Types of IT Spending

- ***COMM_BUDGET***

The modeled IT budget for communication services at this site.
It is defined as the network equipment that companies operate to support their communications needs.
It includes:

- routers
- carrier line equipment
- fiber optic equipment
- switches
- private branch exchanges (PBXes)
- radio and TV transmitters
- Wi-Fi transmitters
- desktop telephone sets; wide-area network (WAN) and local-area network (LAN) equipment
- videoconferencing and telepresence equipment
- cable boxes
- other network equipment.
- end-client mobile devices like cell phones/iPhones that are bought by individuals

(a) Figure A

- ***SOFTWARE_BUDGET***

The modeled IT budget for software at this site.
It is defined as software from third parties, whether that software is packaged or semipackaged software delivered on CD and installed within the company, hosted by a third party, offered on a SaaS basis from a multitenant shared-instance server accessible by a browser, or custom-created for a company by third-party contractors or consultants.
It includes:

- license, maintenance, subscriptions and software vendor-provided services revenues for all categories of middleware software (including storage management systems, database management systems, IT management systems, security software, application servers and application development software)
- application software such as :
  - desktop applications
  - information management software (like business intelligence and enterprise content management)
  - process applications (like ERP, CRM, SCM or PLM)
  - ePurchasing software
  - risk and payment management software

  . We also include vertical industry applications (like banking management systems, security trading systems, insurance underwriting or claims management software, retail management software, or hospital information systems). Finally, we include computer operating systems software, even though that cost is often bundled
- vertical industry applications (like banking management systems, security trading systems, insurance underwriting or claims management software, retail management software, hospital information systems)
- computer operating systems software (even though that cost is often bundled)

(b) Figure B

- ***SERVICES_BUDGET***

The modeled IT budget for IT-related services at this site.
It is defined as project-based consulting or systems integration services that vendors provide to businesses and Governments, whether on or off-site.
It includes:

- contractors, consulting services for IT strategy, security assessments and process change
- systems integration
- project services
- mainframe outsourcing, desktop support outsourcing, distributed systems outsourcing, network outsourcing, application hosting, application management outsourcing and application testing. These applications are single-instance software deployments, generally owned rather than subscribed to, and thus are different from SaaS.
- computer hardware support and maintenance services.

(c) Figure C

- ***HARDWARE_BUDGET***

The modeled IT budget for hardware at this site.
It includes the classic computer hardware that IT departments buy and support, regardless of whether the IT department itself operates that equipment (such as servers) or oversees the use of this equipment by employees (such as PCs):

- PCs: personal computers (laptops, desktops, and tablets)
- Servers/Mainframes
- Peripherals: monitors, terminals, printers, keyboards, mice, USB devices, etc...
- Storage: storage devices (NAS, DAS, tape)
- Other hardware: hardware specific to the industry (point-of-sales equipment based on PCs, smart cards, embedded computer chips, etc…)

(d) Figure D

Table A1. Bank Characteristics and IT Spending

This table presents the results of regression of banks' IT spending structure between 2010 and 2019 on banks' loan portfolio on balance sheet before the financial crisis. The regression specification is as follows:

$$\frac{\text{Type S IT spending}}{\text{Total}}_{i,2010-2019} = \alpha + \beta \frac{\text{Type l Loan}}{\text{Total loan}}_{i,2005-2009} + \gamma X + \epsilon_i$$

C&I loan/Total loan is commercial and industrial loan scaled by total loan; Personal loan/Total loan is personal loan and the real estate loan to 1-4 families scaled by total loan; agriculture loan/Total loan is agricultural loan scaled by total loan. All the three types of loans as a share of total loans are the bank-level average loan proportions from 2005 to 2009. IT spending profiles are defined as each type of IT spending scaled by total IT spending, and taking an average at the bank level between 2010 and 2019. 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; control variables are at bank-year level. Fixed effects include bank fixed effects, year fixed effects and county fixed effects. Standard errors are clustered at county and bank level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Software	Communication	Hardware	Services
	Total 10−19	Total 10−19	Total 10−19	Total 10−19
	(1)	(2)	(3)	(4)
Panel A				
C&I loan/Total loan(05-09)	-0.001	0.047***	0.041***	-0.011
	(0.022)	(0.015)	(0.015)	(0.016)
Net income/Total Assets	0.217	-0.166	-1.878***	2.017***
	(0.351)	(0.200)	(0.210)	(0.289)
Revenue per Employee	0.051**	0.041**	0.020	-0.026
	(0.025)	(0.017)	(0.014)	(0.028)
Equity/Assets	0.103	-0.008	-0.122*	0.087
	(0.100)	(0.071)	(0.071)	(0.085)
Salaries/Assets	1.304***	-0.334	0.215	0.580**
	(0.238)	(0.331)	(0.616)	(0.268)
Deposits/Assets	-0.044	0.018	0.026	-0.037
	(0.053)	(0.029)	(0.029)	(0.036)
AdR-squared	0.199	0.161	0.110	0.220
N	1649	1649	1649	1649
Panel B				
Personal loans/Total loan(05-09)	0.052***	-0.058***	-0.038***	-0.010
	(0.014)	(0.011)	(0.009)	(0.009)
Net income/Total Assets	0.382	-0.335*	-1.985***	1.981***
	(0.346)	(0.201)	(0.213)	(0.294)
Revenue per Employee	0.058**	0.041***	0.021	-0.030
	(0.027)	(0.015)	(0.013)	(0.027)
Equity/Assets	0.086	0.006	-0.114	0.092
	(0.101)	(0.071)	(0.071)	(0.085)
Salaries/Assets	1.244***	-0.269	0.257	0.592**
	(0.226)	(0.306)	(0.599)	(0.266)
Deposits/Assets	-0.043	0.023	0.031	-0.038
	(0.053)	(0.029)	(0.029)	(0.036)
AdR-squared	0.205	0.172	0.114	0.220
N	1649	1649	1649	1649
Panel C				
Agriculture loan/Total loan(05-09)	-0.082***	0.057***	0.028**	0.025**
	(0.015)	(0.015)	(0.013)	(0.011)
Net income/Total Assets	0.441	-0.307	-1.942***	1.945***
	(0.353)	(0.203)	(0.217)	(0.290)
Revenue per Employee	0.050**	0.049**	0.026*	-0.027
	(0.025)	(0.019)	(0.015)	(0.028)
Equity/Assets	0.079	0.003	-0.118*	0.096
	(0.100)	(0.071)	(0.071)	(0.085)
Salaries/Assets	1.211***	-0.271	0.245	0.609**
	(0.213)	(0.298)	(0.601)	(0.259)
Deposits/Assets	-0.055	0.031	0.036	-0.035
	(0.052)	(0.029)	(0.029)	(0.036)
AdR-squared	0.208	0.165	0.109	0.221
N	1649	1649	1649	1649

Figure A6. IT Spending Around Small Business Tax Credit Policy

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

$$\ln IT_{i,c,t} = \alpha_{i,t} + \alpha_{i,c} + \sum_{s=\in[-3,3],s\neq-1} \beta_s \times \mathbb{1}_{\{\text{t-2014}=s\}} \times \text{High exposure}_{pre} + \pi_1 \mathbf{X} + \epsilon_{i,c,t}$$

where for bank i at county c in year t, $\alpha_{i,t}$ are the bank-year fixed effects, $\alpha_{i,c}$ 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 QSB exposure$_{pre}$" is equal to one if the average $\frac{\text{Employees of qualified small businesses}}{\text{Total employees}}$ among the top tercile between 2011-2013, and is equal to zero if the average $\frac{\text{Employees of qualified small businesses}}{\text{Total employees}}$ in the bottom tercile between 2011-2013. Bank control variables include banks' revenue per employee and deposit market share of the bank in a county. County level control variables include unemployment rate, labor force participation rate, population growth rate, logarithmic of total number of establishments, logarithmic of total small business loan, and GDP per capita. Standard errors are clustered at county level.

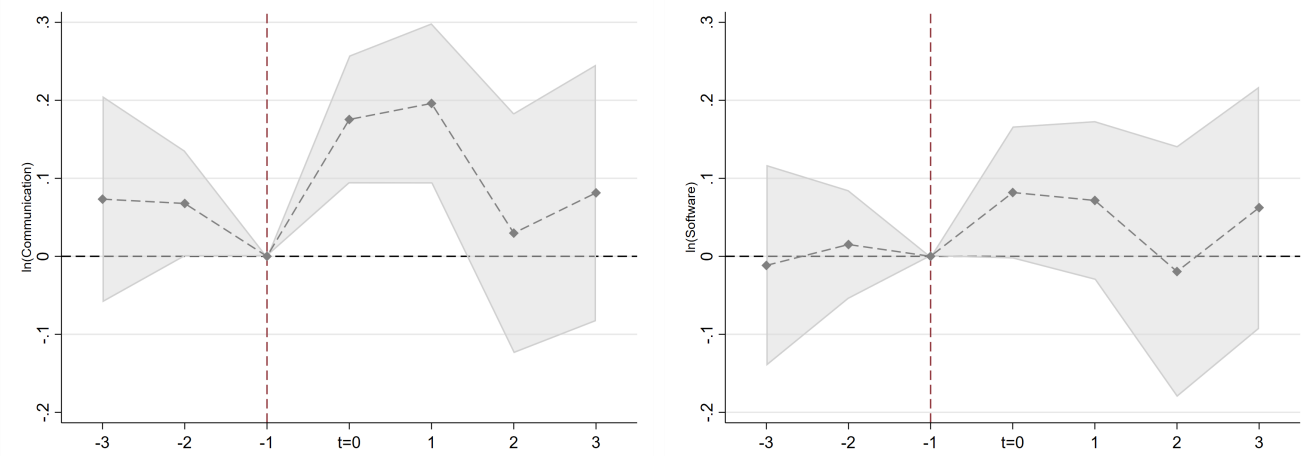


Table A2. Summary Statistics of Banks' IT Spending by Bank Size Group

This table presents the summary statistics of banks' IT spending by banks' size groups. Banks in the sample are split into five groups. Total IT Spending is the sum of all types of IT spending in millions of dollars. No. of IT employees is the total amount of IT-related employees. IT Spending/Revenue is total IT Spending scaled by banks' total income, IT Spending/Non-interest expense is total IT spending scaled by non-interest expenses. The different categories of IT spending are the four categories of IT spending scaled by total IT spending.

	Mean	S.d.	Median
< $100 Million			
IT Spending/Revenue	0.015	0.048	0.005
IT Spending/Expenses	0.019	0.075	0.007
Communication/Total	0.159	0.176	0.086
Software/Total	0.343	0.132	0.341
Services/Total	0.330	0.138	0.340
Hardware/Total	0.206	0.133	0.203
PC/Total	0.102	0.132	0.075
Server/Total	0.100	0.127	0.066
Terminal/Total	0.023	0.081	0.004
Printer/Total	0.022	0.081	0.003
Storage/Total	0.092	0.135	0.040
Other/Total	0.098	0.137	0.037

	Mean	S.d.	Median
$100 Million-$1 Billion			
IT Spending/Revenue	0.028	0.140	0.009
IT Spending/Expenses	0.040	0.200	0.014
Communication/Total	0.090	0.109	0.052
Software/Total	0.370	0.155	0.348
Services/Total	0.308	0.124	0.316
Hardware/Total	0.167	0.115	0.158
PC/Total	0.066	0.090	0.053
Server/Total	0.070	0.087	0.052
Terminal/Total	0.012	0.047	0.004
Printer/Total	0.011	0.047	0.003
Storage/Total	0.051	0.091	0.022
Other/Total	0.056	0.097	0.014

	Mean	S.d.	Median
$1 Billion-$10 Billion			
IT Spending/Revenue	0.043	0.193	0.014
IT Spending/Expenses	0.062	0.262	0.021
Communication/Total	0.064	0.078	0.042
Software/Total	0.272	0.166	0.231
Services/Total	0.361	0.152	0.336
Hardware/Total	0.165	0.117	0.140
PC/Total	0.056	0.064	0.043
Server/Total	0.065	0.063	0.050
Terminal/Total	0.007	0.021	0.004
Printer/Total	0.007	0.022	0.003
Storage/Total	0.033	0.061	0.017
Other/Total	0.036	0.072	0.012

	Mean	S.d.	Median
$10 Billion-$250 Billion			
IT Spending/Revenue	0.045	0.249	0.012
IT Spending/Expenses	0.067	0.310	0.019
Communication/Total	0.055	0.052	0.042
Software/Total	0.283	0.161	0.233
Hardware/Total	0.147	0.105	0.108
Services/Total	0.335	0.137	0.293
PC/Total	0.047	0.041	0.029
Server/Total	0.057	0.041	0.038
Terminal/Total	0.006	0.009	0.004
Printer/Total	0.005	0.010	0.003
Storage/Total	0.027	0.036	0.011
Other/Total	0.032	0.057	0.010

	Mean	S.d.	Median
> $250 Billion			
IT Spending/Revenue	0.019	0.049	0.005
IT Spending/Expenses	0.031	0.075	0.008
Communication/Total	0.046	0.041	0.031
Software/Total	0.268	0.137	0.228
Services/Total	0.357	0.149	0.328
Hardware/Total	0.158	0.103	0.138
PC/Total	0.051	0.043	0.039
Server/Total	0.062	0.044	0.050
Terminal/Total	0.007	0.011	0.004
Printer/Total	0.006	0.012	0.003
Storage/Total	0.031	0.039	0.018
Other/Total	0.036	0.061	0.012

Table A3. Small Business Loan, Mortgage Refinance and Bank IT Spending: II

This table presents regression results of banks' new mortgage issuance on the four major categories of banks' IT spending and relevant control variables at bank-county-year level. The sample period is 2010 to 2019.

$$\frac{\text{Type S IT spending}}{\text{Revenue}}_{i,c,t} = \alpha_i + \mu_{c,t} + \beta \ln(\text{refinance})_{i,c,t} \text{ or } \ln(\text{CRA})_{i,c,t} + \gamma X + \epsilon_{i,c,t}$$

ln refinance$_{i,c,t}$ is the natural logarithm of newly issued mortgage refinance of bank i at county c in year t in reported in HMDA, ln CRA$_{i,c,t}$ is the natural logarithm of small business loans issued by bank i in county c and in year t. Software(Communication)/Revenue is software (communication) spending scaled by total revenue, measured at bank-county-year level. 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; control variables are at bank-year level. Fixed effects include bank fixed effects, county × year. Standard errors are clustered at county and bank level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A

	Software/Revenue			Communication/Revenue		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(refinance)	0.027***	0.035***	0.034***	-0.002	0.003	0.002
	(0.006)	(0.007)	(0.010)	(0.008)	(0.007)	(0.007)
Revenue per Employee		-0.213***	-0.225***		-0.228***	-0.236***
		(0.014)	(0.015)		(0.011)	(0.012)
Net income/Assets		0.004	0.004		0.028***	0.033**
		(0.011)	(0.012)		(0.010)	(0.014)
Equity/Assets		0.013	0.003		-0.007	-0.012
		(0.028)	(0.027)		(0.011)	(0.012)
Deposits/Assets		0.104	0.106*		0.022	0.024
		(0.070)	(0.060)		(0.029)	(0.023)
Salaries/Assets		-1.560	-1.382		-0.899	-0.800
		(1.064)	(1.089)		(1.281)	(1.349)
Fixed effects			Bank, **County×Year**			
Bank Controls	Y	Y	Y	Y	Y	Y
AdR-squared	0.449	0.477	0.487	0.468	0.496	0.501
N	179713	176486	159732	179759	176532	159778

Panel B

	Software/Revenue			Communication/Revenue		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(CRA)	0.005	0.006*	0.006	0.014***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Revenue per Employee		-0.212***	-0.224***		-0.228***	-0.235***
		(0.014)	(0.015)		(0.011)	(0.012)
Net income/Assets		0.003	0.002		0.026**	0.028**
		(0.010)	(0.011)		(0.010)	(0.013)
Equity/Assets		0.011	0.002		-0.006	-0.010
		(0.028)	(0.027)		(0.011)	(0.012)
Deposits/Assets		0.097	0.101*		0.022	0.025
		(0.068)	(0.059)		(0.029)	(0.023)
Salaries/Assets		-0.702	-0.548		-0.394	-0.304
		(0.825)	(0.880)		(0.988)	(1.049)
Fixed effects			Bank, **County×Year**			
Bank Controls	Y	Y	Y	Y	Y	Y
AdR-squared	0.459	0.485	0.497	0.479	0.506	0.511
N	184314	181056	163775	184363	181105	163824

Table A4. Soft Information and Banks' IT Spending

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:

$$\Delta \ln(\text{CRA})_{i,c,post} = \tilde{\alpha_i} + \mu_1 \times \frac{\text{Emp of qualified small businesses establishments}}{\text{Total employee}}_{c,pre} + \mu_2 \mathbf{X}_{i,c} + \epsilon_{i,c}$$

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

The last two columns show the following OLS specification:

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

Δln $(\text{CRA})_{i,c,post}$ 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 pre-shock revenue per employee and deposit market share in the county. County level control variables include the pre-shock unemployment rate, labor force participation rate, population growth rate, logarithmic of total number of establishments, logarithmic of total small business loan, and GDP per capita. Fixed effects include bank fixed effects. Standard errors are clustered at county level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	First stage	ln(Software)	ln(Communication)	ln(Software)(OLS)	ln(Communication)(OLS)
	(1)	(2)	(3)	(4)	(5)
$(\frac{\text{Emp of qualified small businesses establishments}}{\text{Total employee}})_{c,pre}$	0.731***				
	(0.217)				
$\Delta \widehat{\ln(CRA)}$		0.290	1.157**		
		(0.424)	(0.544)		
$\Delta \ln(CRA)$				0.020*	0.036***
				(0.011)	(0.011)
Bank FE	Y	Y	Y	Y	Y
Clustered	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
F-stat	14.168				
AdR-squared	0.360	-0.765	-0.088	0.105	0.096
N	18,319	18,314	18,315	19,815	19,814

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5. Hard Information and Banks' IT Spending

This table presents the results of the regressions discussed in Section 4.3.2 as a robustness check.
The first three columns show the results for the 2SLS specification below:

$$\ln(\text{Refinance/Origination})_{i,c} = \tilde{\alpha_i} + \mu_1 \times \Delta\text{Payments}_c + \mu_2\ \mathbf{X}_{i,c} + \epsilon_{i,c}$$

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

Column (4) and (5) 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 logarithmic of banks' IT spending during 2011 and 2013. $ln(\text{Refinance/Origination})_{i,c}$ is the average logaithmic of amount of mortgage refinance loan relative to mortgage origination issued by bank i in county c during 2011 and 2013. Payments gap is the hypothetical amount of interest payments that could be saved due to the interest rate decrease, if local households chose to refinance their mortgages during the year of 2011 and 2013. Bank control variables include banks' revenue per employee and deposit market share of the bank in a county. County level control variables include unemployment rate, labor force participation rate, population growth rate, logarithmic of total number of establishments, logarithmic of total small business loan, and GDP per capita. Fixed effects include bank fixed effects. Standard errors are clustered at county level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	First stage	ln(Software)	ln(Communication)	ln(Software)(OLS)	ln(Communication)(OLS)
	(1)	(2)	(3)	(4)	(5)
$\Delta\text{Payment}_c$	1.375***				
	(0.320)				
Ln($\widehat{\text{Refinance/Origination}}$)		0.276**	0.172		
		(0.129)	(0.141)		
Ln(Refinance/Origination)				-0.006	-0.009
				(0.006)	(0.006)
Bank FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Clustered	Y	Y	Y	Y	Y
F-stat	18.454				
AdR-squared	0.388	-0.041	0.087	0.161	0.169
N	10,618	10,618	10,618	10,618	10,618

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6. IT Spending and IT Employment

This table presents the results of association between banks' IT investment and banks' employment, with a distinction between IT employees and non-IT employees. The regression equations are as follows:

$$\Delta \ln \text{ IT Emp or } \Delta \ln \text{Non-IT employees} = \beta \Delta \ln(\text{Software spending})_{i,c,t} \text{ or } \Delta \ln(\text{Communication spending})_{i,c,t} + \alpha_{i,t} + \mu_{c,t} + \gamma X + \epsilon_{i,c,t}$$

Δlog IT Emp and Δlog Non-IT Emp are the logarithm of IT related employees and Non-IT related employees respectively. Software/Revenue is software spending scaled by total revenue, Communication/Revenue is communication spending scaled by total revenue. The IT spending scaled by revenue is at bank-county-year level. 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; control variables are at bank-year level. Fixed effects include bank-year fixed effects and county-year fixed effects. Standard errors are clustered at county and bank level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Δ ln IT Emp	Δ ln Non-IT Emp	Δ ln IT Emp	Δ ln Non-IT Emp
	(1)	(2)	(3)	(4)
Δ ln Software	-0.148***	-0.117***		
	(0.051)	(0.043)		
Δ ln Communication			0.043**	0.086***
			(0.022)	(0.022)
County×Year FE	Y	Y	Y	Y
Bank×Year FE	Y	Y	Y	Y
Control	Y	Y	Y	Y
AdR-squared	0.237	0.231	0.236	0.232
N	148617	148617	148617	148617

B Data Construction

This Online Appendix consists of three sections. In Section 1, we describe how we extract and clean IT spending data in Harte Hanks. In Section 2, we provide data-construction details on how to map banks in the IT spending data set with "Summary of Deposits" and "Call Report." In Section 3, we provide the construction details of the other supporting data sets utilized in the paper.

B.1 Construction of IT Data

In this part, we provide details on how to extract the relevant information in the original Harte Hanks IT data sets and create the panel data of banks' characteristics and IT spending at bank-county-year level. Harte Hanks collects the establishment-level (hereafter "site-level") information on IT spending and the characteristic annually. For each given year, the site-level IT spending and site characteristics are saved in two different files, "IT Spend" and "Site Description," respectively. We extract site level variables from the two files and combine them together to get the panel data of site-level IT spending and characteristics. First, for each year, from the site characteristics file, we restrict the data to one-digit SIC code equal to 6. Then we keep "site ID," company name, location (zip code), homepage url, revenue, and number of employees as our site level characteristics variables. "Site ID" is the unique identifier of the site across years in the Harte Hanks data. Second, from the IT Spend file, we get the site-level IT budget data including total budget, communication budget, software budget, services budget, hardware budget, etc, as well as the site ID. Then we merge the site characteristics and site-level IT Spending using "Site ID." Repeating the process for each year gives us a panel data set of site-level IT spending information and site level characteristics.

Next, we aggregate the number of sites, IT spending variables, revenues and employees at the zip code-year-bank level. Most sites include a url variable that labels the homepage website address of the bank. When aggregating site-level variables into county level, we first aggregate the variables by url. For those sites without a url, we aggregate by the cleaned company names. Cleaned company names are defined as the lowercase of company names after removing "national association", "n.a.", "fsb", "s.b." etc. This gives us IT spending profile and revenue and employee profile of a bank at zip code and year level.

Finally, we crosswalk zip codes to fips code (the commonly used county identifier) and aggregate all the variables at the county level, this gives us banks' IT budget and characteristics at bank-county-year level. When mapping zip codes into fips code, we noticed that some zip codes are mapped into multiple different counties. This is because some zip code areas are at the border of multiple different counties and some of the businesses or residents reside in one county while the rest of the zip code's businesses or residents are located in the other counties. For instance,

zip code 49963 is mapped into both "Houghton, MI" and "Ontonagon, MI." To correctly account for the IT spending of banks located in zip codes like this into the two counties, we multiply the IT spending of a bank in this zip code with the ratios of addresses in this zip code that belongs to the two counties, before aggregating to county level IT spending. In the above example, 23% of the addresses in zip code 49663 belongs to "Houghton, MI," while 77% of the addresses in zip code 49663 belongs to "Ontonagon, MI." We multiply a bank's IT spending in zip code 49663 by 0.23 and aggregate this adjusted number to "Houghton, MI"; we multiple a bank's IT spending in zip code 49663 by 0.77 before and aggregate the adjusted number to "Ontonagon, MI." We obtain the the information on the ratio of a zip code's addresses that belong to each county for each zip code from the Office of Policy Development and Research. We use "TOTAL RATIO" provided by the Office of Policy Development and Research, which is the ratio of all types of addresses in the zip code that belongs to a county, to adjust for the spending before aggregation.[1]

B.2 Matching Bank Names in Two Datasets

We now explain the procedure to match bank names in the IT Dataset and those in Summary of Deposits.

Matching at Bank-Year Level This subsection describes how do we match bank names in Summary of Deposits (hereafter SOD) and bank names in the IT data at the bank level and construct the panel data containing bank IT and bank characteristics at bank-year level.

To start with, we take the bank names from SOD data set and obtain the banks' homepage from Google. The first step is to extract a smaller set of site names in the site-level bank IT data that are similar to the names of the banks in SOD. We drop the suffixes ", national association", "national association", ", fsb", "fsb", ", n.a.", "n.a.", " f.s.b.", " f. s. b.", ", f. s. b.", ", s.b.", ", s/b", ", s.b.", ", ssb", ", s.s.b.", " (west), fsb", ", fsb", ", fsb", ", a fsb", and ", a federal savings and loan association", "bank", and "national bank", etc in the SOD data. We split the names into at most two key words by spaces. For example, Wells Fargo Bank is labeled as "Wells" and "Fargo." This is because many site names in the IT data set, which is going to be merged later, are written without spaces. In the Wells Fargo Bank case, the site names could be written as "wellsfargo bank" or "thewellsfargobank." Given that most sites in the IT data set also include a url variable that label the website address of the bank's homepage, we conduct the matching using url first, and if matching with url doesn't work, we match using keywords in names constructed above. For those sites with url, we first outer merge the names from the "Site Description" files with the url of the banks' website address (after dropping "www." and ".com"), and retain the sites whose url contains the url of the banks' website address. Then we can match sites names with SOD bank names with the url's. For those sites without a url, we

[1] See the link to Office of Policy Development and Research's webpage for the relevant files.

outer merge the names from the "Site Description" files with the key words constructed in SOD, and only keep the sites of which the names contain all the keywords from SOD. These above procedures give us the extracted site names whose names as close to names of banks in SOD. In the last step, we assign these extracted sites names with a bank name from the names of banks in SOD that has the largest Levenshtein score. We aggregate the site level IT Spending using the matched bank names in the Bank IT data and merge with SOD through the matched bank names. This gives us the panel data of banks IT spending, total assets and deposits in SOD, matched bank names, and the bank identifier RSSDID in SOD, at bank-year level. The bank identifier RSSDID is also utilized to merge with other data sets such as "Call Reports" and HMDA, etc.

Matching at Bank-County-Year Level In this subsection, we describe how we match the banks in the IT data constructed in Section 1 with banks in Summary of Deposits (SOD) and merge the IT data with bank characteristics in SOD at county level. The output of this matching procedure generates the panel data on banks' IT spending (from the IT data) and bank assets, deposits, and bank identifier (from the SOD) at bank-county-year level.

We get total assets, year, total deposits and bank names from the SOD data set. We convert the bank names in SOD data set to its lower case. We drop the suffixes ", national association", "national association", ", fsb", "fsb", ", n.a.", "n.a.", " f.s.b.", " f. s. b.", ", f. s. b.", ", s.b.", ", s/b", ", s.b.", ", ssb", ", s.s.b.", " (west), fsb", ", fsb", ", fsb", ", a fsb", and ", a federal savings and loan association". We then collapse the above SOD information by zip code, bank name and year. This gives us a panel of banks in SOD with bank names, location information (zip codes), total assets, total deposits, RSSDID, and year.

To match the SOD panel data with the IT spending panel data, we first merge these two data sets using zip code and year, this gives us all the possible pairs of bank names in SOD and IT spending for each combination of zip code and year. Then for each bank name showing up in IT spending data at the zip code-year level, we calculate the Levenshtein distance of the string names between this bank name string and all the string names showing up in SOD within the same zip code and year. For the merged observations, we keep the RSSDID (the unique bank identifier) from the SOD data set with the highest Levenshtein score and we keep the observations with the calculated highest Levenshtein score larger than 2/3. This gives us a panel data of banks at zip code level that match with banks in SOD at zip code level, other variables include IT spending, bank identifier (RSSDID), total assets and total deposits.

Finally, we employ the same method described in Part I to aggregate the matched bank IT spending panel data at zip code-year level to county-year level by adjusting the ratio of addresses of a zip code that could potentially show up in multiple counties. This gives us a panel data of banks' IT spending and banks' deposits and assets, and RSSDID (bank identifier) at county-year

level.

B.3 Construction of Other Data Sets

Call Report In this subsection, we describe how do we construct loan portfolio information and bank-level control variables using "Call Reports." We get the banks' balance sheet information from "Call Reports" quarterly data for the year of 2010-2019. We collapse the key variables by the last quarter of a bank within a year. The linkage between Call Reports and our IT data set is through RSSDID. We define C&I loan share as the "ciloans" scaled by "qavgloans," we define personal loan share as (personal loans) "persloans" scaled by "qaveloans," and we define agriculture loan share as "agloans" scaled by "qavgloans." Banks' Profitability ("prof") is defined as net income (netinc) scaled by "qavgassets," Equity/assets is defined as "equity" scaled by "assets," Deposits/assets is defined as "dep" scaled by "assets," Salary/assets is defined as "sal" scaled by "assets," and number of employees per thousand dollar assets is defined as number of employees (nume multiplied by 1000) scaled by assets (this is because number of employees is in the unit of 1000), we define revenue per employee as income scaled by number of employees.

Home Mortgage Disclosure Act Data This subsection describes the construction of refinancing and origination amount for each bank in each year in a county.

We use the panel of "HMDA nationwide records" files to construct origination and refinance volumes. We define loan as origination if "loan purpose" is equal to 1 and define loan as refinance if loan "loan purpose" is equal to 3. We aggregate the total loan amount of each bank (identified by respondent id) at state code-county code and year level, for origination and refinance, respectively. We then construct the fips code (county identifier) by combining the state code with county code. Finally, we crosswalk respondent id to RSSDID provided in the "HMDA institution" files.

Freddie Mac Single-Family Loan-Level Data Set This subsection describe how do we construct the potential mortgage repayment savings using the Freddie Mac Single Family Loan Data Set at the county-year level.

We first use the Historical data to get the average interest rate between 2010 and 2015 at the zip code-maturity-FICO group level. Specifically for each year, we assign loans into 12 FICO bins: <620, ..., 780-800, 800-820, and >820. We then calculate the average interest rate by year, zip code, FICO group and maturity. We then use loans originated between 1999 and 2009 from the Historical Time Data to get the payment savings. Specifically, for each loan originated between 1999 and 2009, we first keep those that are not pre-paid or defaulted between 2010 and 2015, and the calculate the remain balance separately based on the loans' original interest rate and the hypothetical interest rate as the zip code-maturity-fico group average from 2010 to 2015.

We then take the average payment saving by each zip code, and aggregate the data to the county level.

Mergent Intellect This subsection describes how we construct the bank hierarchical structure data using Mergent Intellect.

We download all the information of banks' family trees in Mergent Intellect with two-digit SIC code "60" and "61." We replace "Domestic Parent Name" with "Company Name" if an entity's "Domestic Parent Name" is missing. We then sum up the number of "Headquarters," number of "Single Location" and number of "Branch" offices within the "Domestic Parent Name." Banks with only one type of locations is defined as having 1 layer in their hierarchy; banks with two different types of locations is defined as having 2 layers in their hierarchy and banks with three different types of locations is defined as having 3 layers in their hierarchy.

To match the bank names in the cleaned version of Mergent Intellect as described above, we link bank names in Mergent Intellect with the institution names provided by FDIC and then link the matched results with banks in our sample. Specifically, we first remove the words "Bank", "INC", "National Association", "LLC", "CORPORATION", "COMPANY", "THE", "CORP", "SERVICES" from the names in Mergent Intellect, and unify names of entities within the Mergent Intellect, then we append cities' names where the banks are located to bank names. Next, we repeat the same process with our sample data. Finally, we merge bank names and cities in the Mergent Intellect with bank names and cities in our sample data using Jarodistance algorithm and keep the matched pairs with the highest Jarodistance score.