Bank Technology: Productivity and Employment

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Abstract

The impact of technology investment on bank productivity and employment is examined. Using a new technology spending dataset of US listed commercial banks from 2000-2017, we estimate the parameters of a firm-level production function correcting for endogenous input choices. On average, technology contributes more than 12% to the net output of the banks. Interestingly, the contribution of technology to bank productivity became stronger after the financial crisis. Moreover, bank employment and total tasks are positively correlated with their lagged technology spending in the cross-section, supporting the task-based framework in Acemoglu and Restrepo (2018). Overall, these findings suggest that technology investment is highly productive to US commercial banks, and use of technology leads to more employment for the listed banks during the sample period, which is likely to due to the creation of new tasks associated with adoption of new technologies.

Key Words: Bank technology, Productivity, Task, Employment

1. Introduction

Advances in technology has transformed many aspects of the production process in different industries over the past decades (e.g., Brynjolfsson and McAfee, 2014; Autor, 2015; Ford, 2015). The banking industry, one of the most technology-intensive industries in the U.S. (Triplett and Bosworth, 2006), has also been significantly influenced by technology advances (e.g., Berger 2003; Greenwood and Scharfstein, 2013; Philippon, 2016).[1] Technology has become a critical component in the production of U.S. banks and has revolutionized how financial institutions operate - from their customer services, the banking process, "Know Your Customer" (KYC) activities, to business Application Programming Interface (API), and many others (DeYoung, 2010).[2] While many believe that use of new technologies improves bank productivty, little empricial evidence is provided to quantify the impact of technology capital on bank productivity. Given the significance of technology adoption to the banking industry, it is interesting to examine to which extent technology investment contributes to bank productivity over the past decades.

Meanwhile, with the rapid development in new technologies, many are worried about that technology adoption and automation displaces or destroys jobs.[3] There is a growing literature investigating how use of new technologies affects employment in agriculture, manufacturing and service sectors of US (e.g., Acemoglu and Autor, 2011; Harrison et al., 2014; Fort, Pierce, and Schott, 2018). The evidence from these studies, however, is mixed, which is not surprising, especially for the service sector. From a theoretical perspective, technology investment can impede employment via its labor-saving or displacement effect (e.g., Goos, Manning, and Salomons, 2014; DeCanio, 2016). Yet, others argue that the productivity effect related to technological innovation can overcompensate the

[1] Figure 1 shows that technology spending by U.S. commercial banks almost tripled from 2000 to 2017 (in 2017 dollar).
[2] See an industrial report from www.EY.com, "Global banking outlook 2015: Transforming banking for the next generation technology reshaping banking."
[3] See an article from *MIT Technology Review* on June 12, 2013, "How technology is destroying jobs", and also an article from *BBC News* on 6 August 2015, "Will machines eventually take on every job?"

displacement effect (Harrison et al., 2014). For example, Acemoglu and Restrepo (2018) develop a theoretic framework on automation and job, suggesting that technological innovation can improve firm productivity and generate new tasks, which in turn increases employment via its productivity or employment-stimulating effect. Thus, to understand the overall effect of technology on employment, the countervailing force must be considered and additional empirical evidence is needed.

For the banking sector, many research suggests that a large number of jobs will be lost in this service industry due to the technology adoption in the future. For instance, a report from Citibank estimates that about 30% of banking jobs are likely to be lost from 2015 to 2025.[4] Also, Martin-Oliver and Salas-Fumas (2008) find that one million Euros IT investment by Spanish banks can replace 25 existing employees. On the other hand, others contend that new technologies create more opportunities for business expansion and generates new tasks in the banking sector.[5] Bogliacino and Pianta (2010) suggest that a major driver for employment growth of firms are technology and innovation. David (2015) shows that one of the greatest technology inventions in banking - automatic teller machines (ATMs) - does not eliminate but increase teller jobs.[6] With the mixed findings, more research on the effect of technology on employment of banks is warranted.

In this paper, we examine the contribution of technology capital in bank productivity and investigate how use of technology affects employment in the U.S. banking industry. Technology is considered as an essential core competency and a key driving force for the future growth of banks.[7] Yet, use of technology is expensive, especially for small banks. Hence, it is interesting to examining whether the expanded technology adoption increases the net output of banks. Moreover, while AI and machines replace some types of banking jobs, use of new technologies could create new tasks or jobs and

[4] See an article from *CNN News* on April 4, 2016, "30% of bank jobs are under threat".
[5] See an article from *The Guardian* on August 18, 2015, "Technology has created more jobs than it has destroyed, says 140 years of data", and from *U.S. News* on December 7, 2015, "Machines reshape more jobs than they destroy".
[6] See an article from *The Economist* on June 15, 2011, titled "Are ATMs stealing jobs?"
[7] See page 52 in the 2015 Annual Report of JPMorgan Chase & Co.

counteract the displacement effect. Thus, it is intriguing to know which effect plays a dominating role in the bank employment: the displacement effect or the productivity effect. These questions are of great importance to practitioners, academics, and policymakers, as evidenced by academic research, extensive media coverage and industrial reports in recent years.

Using a unique sample of U.S. listed commercial banks from S&P Global Market Intelligence database from 2000 to 2017,[8] we first estimate the parameters of a value-added bank production function correcting for endogenous input choices to quantify the contribution of technology capital to the net output of banks. The results show that the estimated parameters for technology capital are statistically significant in different specifications. On average, technology capital contributes about 12.85% to the net output of banks. The median net marginal product of bank technology ranges from $0.41-$0.81 per dollar of investment on technology. These results indicate that technology investment is highly productive to U.S. commercial banks. Interestingly, the parameters of the technology input become stronger after the recent financial crisis, suggesting that technology has played a more important role in bank production in recent years. We also document a dramatic growth in technology spending by banks over the sample period. The median technology expenses rose by 185% (from $1.16 million to $3.31 million) over the sample period, while the median number of employees and staff expenses increased by 70% and 100%, respectively. Note that the trend in bank technology spending almost monotonically increases, including the financial crisis period.

Next, we examine the impact of technology investment on bank employment and total tasks in the cross-section. Using number of employees and staff expense to measure bank employment, we find a strong correlation between residual bank employment (i.e., number of a bank's employees or staff expense controlling for firm size) and their lagged residual technology spending (i.e., technology

[8] Unless otherwise specified, in the rest of the paper, "commercial banks", "U.S. banks" or "banks" refer to U.S. listed commercial banks, whose two-digit SIC code is 60.

spending controlling for firm size), suggesting that when banks invest more on technology, on average, their employment growth tends to be higher. Moreover, as the primary function of banks is to accept deposits from the public and to provide loans and advances of various forms, we use total loans and deposits, value-added, and number of branches as proxies to measure tasks of banks. The results show that the residual of bank tasks (i.e., the measures of bank tasks controlling for firm size) are positively and significantly associated with their previous-year residual technology spending, indicating that banks investing more in technology are likely to create more tasks. The latter result is consistent with the task-based framework of Acemoglu and Restrepo (2018), which argue that exogenous technology adoption can create new tasks in the process of production for the next period.

Finally, we conduct a range of robustness checks on the production function estimation and the correlation between bank employment/tasks and technology spending. The main results still hold. Specifically, we estimate the production function and run the residual employment and task regression by controlling bank M&A activities, excluding the Too-Big-To-Fail banks, and focusing on the data from the post financial crisis period. Moreover, since the commercial banks in urban areas and rural areas may face different demand for adopting technology, we also conduct the empirical analysis for urban banks and rural banks separately. Again, these robustness tests confirm the main results, suggesting that our findings on the contribution of technology on bank productivity and the positive correlation between bank employment and technology investment are robust to a variety of tests.

This paper contributes to the literature in the following ways. First, we use direct information on technology spending to investigate the impacts of technology on bank productivity at the firm level. Previous research uses either non-US bank data or survey data to examine the impact of technology on bank productivity. Our study overcomes the data limitation in the literature. The firm-level technology spending data include more than seven thousand annual observations of U.S. banks from S&P Global Market Intelligence, which takes a “deep dive” into the banking sector and collects memo items, regulatory filings, supplemental financial schedules and financial reports from banks. This unique data set allows us to provide direct empirical evidence on the contribution of technology capital to bank productivity. Also, we estimate a value-added production function of banks correcting for endogenous input choices and the measurement errors in technology capital. Thus, the evidence is arguably more reliable than previous research.

Second, this paper is one of the first studies examining how employment and tasks of U.S. banks are correlated with their technology investment in the cross-section. We document that banks investing more in technology tend to have higher employment growth and create more new tasks. As banks play a preeminent role in the financial system and economic development,[9] the findings highlight the importance of technology in the U.S. economy and have important policy implications. Moreover, the empirical evidence focusing on banking, a service industry, may shed light on other industries, especially other service industries, in terms of the impact of technology investment on employment and tasks.

2. Related Literature

Some studies argue that technology and innovation are major drivers of employment growth of firms (e.g., Mokyr, 1992; Van Reenen, 1997; Bogliacino and Pianta, 2010; Harrison et al., 2014). Theoretically, technology investment has labor-saving effect (i.e., displacement effect), which impedes employment, as well as employment-stimulating effect (i.e., compensation effect), which enhances employment. For example, research focusing on manufacturing and agriculture industries show that machines replace the labor-intensive tasks (e.g., Bresnahan, 1999; Manyika et.at., 2013; Frey and Osborne, 2017; Bessen, 2017). On the other hand, the development of computers and software generates a huge demand for technician and services positions. In a task-based framework, Acemoglu and

[9] See Federal Reserve Bank of San Francisco (2001). What is the economic function of a bank? https://www.frbsf.org/education/publications/doctor-econ/2001/july/bank-economic-function/

Restrepo (2018) argue that technological automation tends to reduce employment, while the creation of new tasks by technology adoption increase employment since technology adoption will increase productivity, generate new tasks, deepen automation, and encourage capital automation.

There is some empirical evidence on the effect of technology adoptions on employment in the banking industry. Examining the effects of the introduction of automated teller machines (ATMs) on the employment of bank tellers, Bessen (2015) and David (2015) document that ATMs does not eliminate the teller job but increase it. They argue that there is more demand on tellers since ATMs reduce the operating costs of banks and encourage bank branching activities. However, early banking literature shows that the decline in the number of branches is delayed due to technology adoption (Saloner and Shepard, 1995). With a static production function framework assuming constant elasticity of substitution, Martin-Oliver and Salas-Fumas (2008) find that an additional 1 million Euros investment in IT may be substituted for 25 employees in Spanish commercial banks.

Regarding the effects of technology investment on productivity, most empirical studies found in economics, finance, and management literature employed survey data from large manufacturing firms or hospitals (e.g., Hitt and Brynjolfsson, 1996; Lee, McCullough, and Town, 2013).[10] The results are mixed and inconclusive. For example, Baily (1986), Brynjolfsson (1993), Morrison (1997), Loveman (1994), and Berndt and Morrison (1995) find a negative or inconclusive relationship between use of technology and firm productivity, while Lichtenberg (1995), Brynjolfsson and Hitt (1995, 1996, 2003), Bresnahan, Brynjolfsson, and Hitt (2002), and Bloom, Sadun, and Van Reenen (2012) show a positive correlation.[11] Moreover, Hall and Khan (2003) show that the choice of technology adoption is between adopting it now or deferring the decision until later, but not a choice between adopting and not adopting,

[10] For instance, besides proprietary data, International Data Group *(IDG)* annual survey and *Information Week* annual survey are commonly used.
[11] See Brynjolfsson and Yang (1996) and Sichel and Oliner (2002) for reviews.

since that firms should invest or adopt new technologies at some points of time to stay competitive and provide better customer services.

Despite the importance of technology investment in the banking industry, research on its impact on U.S. banks is limited. One main reason is the lack of data on technology investment or spending, as this information is not typically disclosed to the public through bank financial reports and regulatory filings. Following a seminal work by Sealey and Lindley (1977), a few studies examine the impacts of technology investment using either survey data from U.S. banks or data from European banks. Based on data from 1984 to 2001, Berger (2003) find that technology significantly improves the quality of banking services and technological progress facilitates banking consolidation. With data from U.S. community banks from 1999-2001, DeYoung, Lang, and Nolle (2007) find that internet adoption improves performance for community banks, mainly through increased revenues from deposit service charges.[12] Using a sample of 737 European banks from 1995 to 2000, Beccalli (2007) finds no relationship between total IT investment and bank performance or efficiency. Examining the theory and measurement of financial intermediation, Philippon (2015) shows that the adoption of financial technology does not reduce intermediation costs.

Based on a survey data set on U.S. retail banking institutions from 1993-1995, Prasad and Harket (1997) show that increase in IT investment does not benefit banks in both productivity and performance. They argue that the use of IT is more of a strategic necessity for banks to stay in the competition. Martin-Oliver and Salas-Fumas (2008) examine the impact of information technology (IT) in the output of Spanish banks in the 1983-2003 period and find that one-third of output growth of banks can be explained by the growth in the stock of IT capital. Later, Martin-Oliver, Ruano, and Salas-Fumas (2013)

[12] Based on various proxies for technology, other studies also examine the role of technology in banking, including small business lending (e.g., Petersen and Ranjian, 2002), Internet usage (e.g., Hernando and Nieto, 2007; Hernández-Murillo, Llobet, and Fuentes, 2010; Dandapani, Lawrence, and Rodriguez, 2016). And, some earlier studies also include Hunter and Timme (1986) and Hamid and Verma (1994), which are based on banking data more than two decades ago.

provide similar results via different methodologies, using data from Spanish commercial banks during the 1992-2007 period.

To sum up, most of the studies related to technology in the banking literature are based on some proxies for technology usage (e.g., the number of ATMs, the transaction website adoption), limited survey data from U.S. bank, or data from European banks. Most of the papers use short-term data before the "network" era of computing, and thus unable to capture the full effects of the dramatic increase in technology adoption by banks. The results based on European bank data may not apply to the U.S. banks since there are significant differences between U.S. banking system and European banking system (e.g., capital market dependence, market structure, bank regulations, economic and banking industry size[13]). Lastly, most of the prior research focuses on the effects on bank productivity and the relationship between technology investment and bank performance. Little research has been done on how technology investment influences employments in the US commercial banks.

3. Research Methodologies

3.1. Technology and Production

Early literature does not properly differentiate among technology capital, non-technology capital, and labor in their bank production models. For example, Martín-Oliver and Salas-Fumás (2008) and Martín-Oliver, Ruano, and Salas-Fumás (2013) first discuss and estimate the contribution of investment in information technology (IT) to the output of banks. In their specification, the bank-level output of the production function is total loan and deposit, and the bank-level inputs are IT capital and labor, which is defined as the number of employees (MRS Model, hereafter). The results from the MRS Model shows that one-third of output growth of banks can be explained by the growth in the stock of IT capital on

[13] GDP of Spain in 2015 is roughly 6.6% of the GDP of U.S. The total asset of Spanish banks in 2016 is about 2.7 trillion Euros based on a BBVA research report and the total asset of U.S. commercial banks at the same year is 12 trillion Dollars based on FRED economic data.

their pre-crisis Spanish bank data. The issue with the MRS Model is that it does not take account of Non-IT physical capital, which includes but not limited to all machinery, equipment, and buildings, etc.

Another issue when examining the impact of technology investment on banks is how to model the contribution of the increase of technology capital on revenue growth. Since there are well-known endogeneity issues on the estimation of production function (e.g., Marschak and Andrews, 1944; Ackerberg, Caves, and Frazer, 2006, 2015), as inputs are unobserved by the econometrician but may be observed by firm managers, standard approaches of parameter estimation will be biased due to simultaneity and correlation between inputs and productivity shocks.

Built upon the MRS Model, we propose an augmented model, in which the production function in each bank is assumed to be a Cobb-Douglas, whose inputs are technology capital ($TK_{i,t}$), conventional capital or non-technology capital ($CK_{i,t}$), and labor ($L_{i,t}$)[14]. The analysis starts with the following log-transformation production function:

$$y_{i,t} = \beta_{tk} tk_{i,t} + \beta_{ck} ck_{i,t} + \beta_l l_{i,t} + v_{i,t} \tag{1}$$

where $y_{i,t}, tk_{i,t}, ck_{i,t}$ and $l_{i,t}$ are the natural logarithm of net output ($Y_{i,t}$), technology capital, conventional capital and labor of bank i at year t, respectively. The primary interest is the β_{tk}s, which measure the technology capital contribution. The term $v_{i,t}$ represents the information that bank managers possess, which may be used for input selection. The major concern on the estimation of the above firm-level production function econometric to correct for the endogenous bias in the estimation of the elasticity of the output with respect to technology capital, conventional capital and labor caused by the

[14] Several studies on IT-based production model have used a similar model but dividing the labor into IT labor and conventional labor (e.g., Loveman, 1994; Lichtenberg, 1995; Brynjolfsson and Hitt, 1996; Prasad and Harker, 1997; Lee, McCullough, and Town, 2013). Due to data availability, we are not able to divide the labor information into IT labor and non-IT labor as theirs.

fact that the quantity of those inputs used in production might themselves be determined the value of the productivity shock (Griliches and Mareisse, 1998).

We first estimate the production parameters using dynamic panel data (DPD) model of Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998, 2000), firm fixed-effects (FE) approach and traditional ordinary least squares (OLS) approach. In these models, the last term $\upsilon_{i,t}$ in Equation (1) can also be further decomposed into four components:

$$\upsilon_{i,t} = a_i + \gamma_t + \eta_{i,t} + \epsilon_{i,t} \tag{2}$$

where a_i is a time-invariant firm fixed-effect and γ_t is a time-varying productivity shock. These factors are likely to be related to the observed inputs. $\eta_{i,t}$ is an unobserved productivity term, which might be correlated with the observed inputs, and evolves as an autoregressive process, $\eta_{i,t} = \rho\eta_{i,t-1} + \omega_{i,t}$, where $\omega_{i,t}$ is a pure stochastic component. The innovation on unobserved productivity, $\omega_{i,t}$, is assumed to be uncorrelated with the observed inputs. The last term, $\epsilon_{i,t}$, reflects a productivity shock, which might be correlated with the observed inputs and might evolve as a moving average process. The impact in time for $\epsilon_{i,t}$ might also last for a long period.

Even if the term $\upsilon_{i,t}$ consists of a firm fixed-effect and a component of the evolving productivity, it is likely to be correlated with the observed inputs. By solving for $\eta_{i,t-1}$ and substituting it into the empirical model in Equation (1), a dynamic form is generated as follows:

$$\begin{aligned} y_{i,t} = \rho y_{i,t-1} + \beta_{tk} tk_{i,t} - \rho\beta_{tk} tk_{i,t-1} + \beta_{ck} ck_{i,t} - \rho\beta_{ck} ck_{i,t-1} + \beta_l l_{i,t} \\ - \rho\beta_l l_{i,t-1} + a_i - \rho a_i + \gamma_t - \rho\gamma_{t-1} + \omega_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

we obtain an equation that can be estimated by renaming the respective coefficients and grouping the error components, as Equation (4):

$$\begin{aligned} y_{i,t} = \delta_1 y_{i,t-1} + \delta_2 tk_{i,t} + \delta_3 tk_{i,t-1} + \delta_4 ck_{i,t} + \delta_5 ck_{i,t-1} + \delta_6 l_{i,t} + \delta_7 l_{i,t-1} \\ + a_i^* + \gamma_t^* + \omega_{i,t}^* \end{aligned} \tag{4}$$

where the common factor restrictions are $\delta_3 = -\delta_1 * \delta_2$, $\delta_5 = -\delta_1 * \delta_4$ and $\delta_7 = -\delta_1 * \delta_6$, with $a_i^* = a_i(1-\rho)$, $\gamma_t^* = \gamma_t(1-\rho)$ and $\omega_{i,t}^* = \omega_{i,t} + \epsilon_{i,t}$. Assuming all the common factor restrictions hold, the traditional ordinary least squares (OLS) approach will yield consistent parameters only when $E(a_i^* x_{i,t}) = 0$, $E(\omega_{i,t} x_{i,t}) = 0$ and $E(\epsilon_{i,t} x_{i,t}) = 0$, where x are state variables in the production estimation. Consistent parameters can be obtained in firm fixed-effect model only if $E(\omega_{i,t} x_{i,t}) = 0$ and $E(\epsilon_{i,t} x_{i,t}) = 0$.

We then estimate the production parameters using Olley and Pakes (1996) methodology (OP for short). The OP model employs a two-step estimation on the parameters using a proxy variable to control the productivity shocks. It the OP methodology, the term $v_{i,t}$ can be decomposed as:

$$v_{i,t} = \eta_{i,t} + \epsilon_{i,t} \tag{5}$$

where $\epsilon_{i,t}$ is a normally distributed idiosyncratic error term. $\eta_{i,t}$ is assumed to be the unobserved productivity or technical efficiency term and evolves according to a first-order Markov process, $\eta_{i,t} = E_t(\eta_{i,t} | \eta_{i,t-1}) + \zeta_{i,t} = g(\eta_{i,t-1}) + \zeta_{i,t}$, where $\zeta_{i,t}$ is a random shock component, which is assumed to be uncorrected with the productivity term, $ck_{i,t}, l_{i,t}$ and $tk_{i,t-1}, ck_{i,t-1}, l_{i,t-1}$.

There are several key assumptions in the OP methodology. First, it assumes that $\eta_{i,t}$ is observed by the firm manager and that $\eta_{i,t}$ is used by the firm manager to decide the amount of inputs. Second, it assumes that firm-level investments ($inv_{i,t}$) is a function of $ck_{i,t}, l_{i,t}$ and $\eta_{i,t}$, that $inv_{i,t}$ is strictly monotone in $\eta_{i,t}$. $\eta_{i,t}$ is scalar unobservable in $i_{i,t} = i(.)$. Third, the levels of $inv_{i,t}$, $ck_{i,t}$ and $l_{i,t}$ have been chosen prior to period t. The level of $tk_{i,t}$ is then decided after the realization of the shock $\zeta_{i,t}$. In other words, the productivity shock proxy must be monotonically increasing with respect to the true productivity shock. These assumptions ensure the invertibility of $inv_{i,t}$ in $\eta_{i,t}$, and lead to the following partially-identified model:

$$\begin{aligned} y_{i,t} &= \beta_{tk} tk_{i,t} + \beta_{ck} ck_{i,t} + \beta_l l_{i,t} + h\left(inv_{i,t} + ck_{i,t}, +tk_{i,t}\right) + \epsilon_{i,t} \\ &= \beta_l l_{i,t} + \psi\left(inv_{i,t}, ck_{i,t}, tk_{i,t}\right) + \epsilon_{i,t} \end{aligned} \tag{6}$$

where ψ is approximated with a second-order polynomial series in technology capital and conventional capital. Equation (6) can be estimated by non-parametric approach. In the first stage, the production function parameters are estimated by taking advantage of the Markovian nature of the productivity process and the assumptions above as moment conditions. In the second stage, the residual term is derived as follows:

$$y_{i,t} - \widehat{\beta}_l l_{i,t} = \beta_{tk} tk_{i,t} + \beta_{ck} ck_{i,t} + g\left(\eta_{i,t-1} + \vartheta_{i,t},\right) + \epsilon_{i,t} \tag{7}$$

where g(.) is typically unspecified and approximated by an *n-th* order polynomial and $\vartheta_{i,t}$ is an indicator function for the attrition in the market.

The DPD approach provides consistent parameters under less restrictive assumptions than the OLS approach and the fixed-effects (FE) approach. We adopt a system GMM approach that simultaneously estimates the production function using both levels and difference specifications. The system GMM estimators are designed for dynamic "small-T, large-N" panels that may contain fixed-effects and idiosyncratic errors that are heteroskedastic and correlated within, but not across firms.

Managers are likely to choose their input levels because productivity is known to them (Marschak and Andrews, 1944). Since measurement errors and endogeneity may exist in the production input measures, the OLS estimators will be biased towards zero. The DPD approach allows for a time-invariant firm fixed-effect, which it is important since there are different business strategies and production inputs among banks in different locations and various customer focus. Nonetheless, there is no agreement in academics about which parameter estimation approach is more appropriate. In this paper, we adopt all four models – OLS, DPD, FE, and OP, based on the full sample, rural bank sample, and urban bank sample, respectively, to evaluate the sensitivity of the estimated parameters under different kinds of identification assumptions. [15]

3.2. Technology and Employment

Many assume that technology investment by U.S. banks is largely exogenous (see Acemoglu and Restrepo, 2018), even if there exists some endogeneity concern that bank employment may also drive its technology investment. Arguably, the technology adoption of banks, to a large extent, is driven by the general economic conditions, the competitive environment and the rapid development of technology.[16] Banks have to face the challenges of rapid development and creation of new technologies: online banking, data security, DLT system, clouds, etc. Vítor Constâncio, Vice-President of the

[15] Levinsohn and Petrin (2003) aimed to overcome the empirical issue that there are usually quite a lot of zeros in the investment data and proposed to use intermediate inputs (materials) to estimate the production shock. However, it is too difficult to define what are the intermediate inputs (materials) of banks. See Martín-Oliver, Ruano and Salas-Fumás (2013) for some attempts using this methodology.

[16] See an article from *The Telegraph* on April 2, 2017, “Mark Carney warns of fintech threat to traditional banks”.

European Central Bank, states that "beyond increased competition from non-banks, the banking sector faces competition from Financial Technology (FinTech) firms…"[17] The indeterminacy nature of the banking system and the astonishing adoption of technology, not the supply of ordinary employees, have made radical transformations in the way how banks do business and continue to change even further.

Bank employment is highly persistent (continuous workflow and difficult to hire or fire) over time and that there exist automation of old tasks and creation of new tasks (see Figure 2 in Acemoglu and Restrepo, 2018). There exist labor-saving effects as well as employment-stimulating effects in technology investment. Hence, we would also like to see whether banks with a higher level of technology adoption would have more employees in the next period.

It is important to control heterogeneity in firm size in our analysis, given our goal is to examine the effect of technology investment on firm-level employment. Following the methodology of Cheng, Hong, and Scheinkman (2015), we regress the technology expense of banks on their size in the cross-section. Specifically, we estimate the following specification based on ordinary least squares (OLS), as in Equation (8), using the data in each year. We obtain residual technology spending, the independent variable of interest, from this regression.

$$LnTechSpending_i = \beta_0 + \beta_1 Firm\,Size_i + \varepsilon_i \tag{8}$$

Since we also need to compare the differentials of employment and tasks of firms at the equal size, residual employment and tasks are also obtained by replacing the dependent variable of equation (8) to the measures of employment and tasks of banks.

[17] See a lecture on July 7, 2016, titled "Challenges for the European banking industry," by Vítor Constâncio at the conference of "European banking industry: What's next," organized by the University of Navarra.

With residual firm-level technology spending and employment estimated, we can examine the relationship between employment and technology spending in the cross-section, on the full sample, rural bank sample and urban bank sample, respectively, by the following equation using OLS model with standard errors are clustered at the firm-level and are heteroscedasticity-robust:

$$ResEmployment_{i,t} = \beta_0 + \beta_1 ResTechSpending_{i,t-1} + \beta_2 MTB_{i,t-1} + \beta_3 Leverage_{i,t-1}$$
$$+\beta_4 ROA_{i,t-1} + \beta_5 NonIntIncome_{i,t-1} + \beta_6 Tier1Capital\ Ratio_{i,t-1} + \eta_i + \alpha_t + \varepsilon_{i,t} \quad (9)$$

where η_i and α_t represent firm and year fixed effects, respectively. The coefficient of interest, β_1, measures the cross-sectional relationship between previous-year technology spending and employment at the firm-level. The effect is pooled across cross-sections in the panel, net of interacted firm characteristics within each year.

To examine how a firm’s technology investment influences its tasks, we run a similar model as what we do in examining the relationship between employment and technology spending as in Equation (9) on the full sample, rural bank sample, and urban bank sample, respectively, by replacing residual employment into residual tasks in the right-hand side of the equation, as follows:

$$Residual\ Tasks_{i,t} = \beta_0 + \beta_1 ResTechSpending_{i,t-1} + \beta_2 MTB_{i,t-1} + \beta_3 Leverage_{i,t-1} +$$
$$\beta_4 ROA_{i,t-1} + \beta_5 NonIntIncome_{i,t-1} + \beta_6 Tier\ 1\ Capital\ Ratio_{i,t-1} + \eta_i + \alpha_t + \varepsilon_{i,t} \quad (10)$$

4. Data Description

4.1. Data Source

The empirical analysis uses annual data on firm characteristics of U.S. listed commercial banks (two-digit SIC code: 60) from the Compustat banking database and the S&P Global Market

Intelligence's (formally SNL Financial) banking database from 2000- 2017. The technology and communication expense, the number of automatic teller machines (ATMs), the total number of branches and offices, the Metropolitan Statistical Area (MSA) of each branch and office, the deposits in each branch and office, and mergers and acquisitions activities are collected from the S&P Global Market Intelligence, while all other annual financial characteristics are collected from Compustat.[18]

The technology and communication expense (technology expense) reported in the S&P Global Market Intelligence database is primarily constructed based on U.S. GAAP standard FAS No. 86. The item includes expenses paid for communications such as telephone and fax usage charges, internet data plans, and mobile phone and internet plans, data processing and technology such as computers, wire services, modems, routers and switches, as well as software purchases and subscriptions to cloud-based services. The value of technology and communication expense is constructed via original data from the bank's financial reports and bank regulatory filings. For instance, the 2015 technology expense of Citigroup (Ticker: C) in our sample is $6,581 million, which comes from the technology/communication item ($6,581 million) in its annual report (10-K). The 2015 technology expense of Bank of America (Ticker: BAC) is $3,938 million, which comes from the telecommunications item ($823 million) and data processing item ($3,115 million) in its annual report. The 2015 technology expense of Community First Bancorp, Inc (Ticker: CMFP) is $399,000, which comes from data processing item ($162,616), telephone item ($59,150), internet banking item ($87,643) and ATM expenses item ($89,771) on its annual report. The 2015 technology expense of Pandora Bancshares, Inc. (Ticker: PDRB) is $736,000, which comes directly from tech & communications expense item ($736,000) on its bank regulatory filings, even if a data processing item ($505,000), which is smaller than the reported number in its bank regulatory filings, is reported on its annual report.

[18] Missing financial characteristics in year *t* are replaced by estimates from this formula: $Var_{i,t}^{x} = \left(Var_{i,t+1}^{x} + Var_{i,t-1}^{x}\right)/2$, where $Var_{i,t}^{x}$ is the information of x of bank i in year t.

4.2. Variable Construction

There is no agreement in academics and practitioners about how to define and measure the net output of the service industries, especially for banks (see Griliches, 1992; Griliches, 1994; Triplett and Bosworth, 2004; Prasad and Harker, 2007; Berger and Humphrey, 2008; Basu, Inklaar, and Wang, 2011). According to the Bureau of Economic Analysis (BEA), "banks are compensated for some services by a portion of the interest that they charge on loans or by a reduction in the interest rates that they pay to depositors—rather than by charging explicit fees." (Hood, 2013). We operationalize our net output measure for banks as its net interest income, which measures the difference between the revenue generated from a bank's assets and the costs of its materials and services (liabilities). We measure the labor input by the compensation and benefits of employees (staff expense) as it can capture the difference in the skill level of employees (as in, for example, Prasad and Harker, 1997; Brynjolfsson and Hitt, 2003; Levine and Warusawitharana, 2014). Conventional capital is defined as total assets excluding intangible assets and technology capital. The technology investment in the Olley and Pakes (1996) methodology is measured as investment expenditure.

The complication for the construction of technology capital is that S&P Global Market Intelligence and Compustat do not report the actual value of the banks' technology capital stock. Hence, we construct the value of technology capital using the technology and communication expense recorded in S&P Global Market Intelligence each year. First, we follow Martín-Oliver, Ruano, and Salas-Fumás (2013) and estimate the physical technology capital stock from the annual technology expense of banks assuming a perpetual inventory model with a depreciation ratio of 35%. Alternatively, we also use a four-year linear depreciation schedule to construct the annual physical technology capital stock for each bank, as in Lee, McCullough, and Town (2013). In the Financial Accounting Manual for Federal Reserve Banks, the maximum estimated useful life for standard technology personal computers (PCs) is three years, and state-of-the-art technology PCs is four years, while it is six years for operating equipment with 10% salvage value.[19]

We recognize that technology expense likely includes both physical technology equipment and services. There is no practical way for us to disentangle the components of the expense. To address the concern whether it is a proper technology capital measure, we examine its relation to the adoption of ATMs. We regress the natural log of technology capital estimated from perpetual inventory model and linear depreciation schedule, respectively, to the natural log of the number of ATMs with standard errors that are clustered at the bank-level and are heteroscedasticity-robust. The estimated parameter of the number of ATMs is positive (0.892 and 0.887) and highly statistically significant (t-statistic: 35.33 and 35.18). In this univariate regression, the number of ATMs accounts for a very large portion of the overall variation in technology capital (R-squared: 0.725 and 0.728). The correlation between the two measures of technology capital and the number of ATMs are 0.852 and 0.854, and statistically significant at the 1% level. This evidence gives us confidence in the validity of our technology capital measure.

Our technology capital measure is, to some extent, different from the technology capital or IT capital in previous bank production literature. In the extent of U.S. banks, Prasad and Harker (1997) use survey data from large retail banks on their IT spending during 1993-1995 to construct the IT-related expense. In the extent of Spanish banks, Martín-Oliver and Salas-Fumás (2008) and Martín-Oliver, Ruano, and Salas-Fumás (2013) construct their total IT capital of banks as the sum of the book value of IT capital on the asset side of the balance sheet and the estimated IT capital stock. The huge differential of inputs in the production functions in this paper and the previous papers might lead to the difference in our results comparing to theirs. The ratio of IT capital and non-IT capital in Prasad and Harker is about 0.106, while the ratio of IT capital and physical capital in the year 1983 is 0.105 and that in the

[19] For more details, please see Section 30.78 Maximum Useful Lives and Salvage Values Table of the document. https://www.federalreserve.gov/federal-reserve-banks/fam/chapter-3-property-and-equipment.htm

year 2003 reaches 0.621 in Martín-Oliver, Ruano, and Salas-Fumás (2013), according to the summary statistic tables of their papers. The ratio of technology capital and conventional capital in this paper is, on average, only 0.39% when technology capital is estimated using perpetual inventory model and 0.38% when technology capital is estimated using linear depreciation schedule. The ratio of the mean (median) of the technology expense related to total current operating expense is 4.12% (3.63%), which is close to the number in Mai, Speyer, and Hoffmann (2012) and the McKinsey report. Comparing with previous studies, we are likely to have a much more rigorous definition of technology capital and a broader sense of conventional capital as it includes tangible capital that is not technology capital.

As we construct our technology capital measure using expense information and assumption of depreciation, there are possibilities that it systematically over- or under-represent the true value of technology capital of each bank. The over- or under- estimations is a common issue on production analysis, which generally relies on survey or accounting information that naturally embodies assumptions and depreciation and expenditure classification. The more concern issue is that how we can estimate consistent parameters, given there exist measurement errors in the input and endogenous issue between input and productivity shocks as we discussed in the previous sections.

The employment of a bank is measured as the number of employees it employs and the staff expense it pays. Although the number of employees and staff expense gives us an idea of how employees a bank has, it suffers from one major drawback: it does not adjust for the bank's size, thus making it hard to compare how many staff one bank employs related to another. Similarly, although technology expense gives us an idea of how much technology investment a bank is doing, it is very difficult to compare how much one bank is investing relative to another. Hence, we use residual employment and technology expense, which can be used to compare employment and technology expense among firms with equal firm size, as key variables in our regressions.

The bank task measures are extremely difficult to quantify, not to say to distinguish these tasks into old tasks and new tasks recently generated. The traditional banking business is to accept deposits and make loans.[20] Since the primary functions of banks is (a) to receive various types of deposits from individuals, businesses, financial institutions, and governments, and (b) to lend money in various forms to businesses, other financial institutions, individuals, and governments,[21] the total loans and deposits of a bank should be a proper proxy of its tasks. As the main business of banks is to collect deposits and make loans, the total loans and deposits of a bank should represent the amounts of tasks it has. Alternatively, we also employ net output and the number of branches as two proxies of bank tasks. The net output reflects the wealth created by a bank through the production process. The number of branches of a bank reflects its complexity. Hence, both can be used as a measure of the amounts of tasks.

Other variables used in this study include are as follows. Bank's size (Firm Size) is defined as the natural log of market capitalization at the end of the fiscal year. Market to book ratio (Market to Book) is defined as the ratio of total book assets to total book equity. Leverage ratio (Leverage) is defined as the ratio of total book assets to total book equity. Return on Assets is defined as the ratio of earnings before extraordinary plus depreciation and amortization to total book assets. Non-interest income ratio (Non-Interest Income) is defined as the ratio of banks' non-interest income to the sum of net interest income and non-interest income. Risk-adjusted tier1 capital ratio (Tier 1 Capital Ratio) is obtained from Compustat.

4.3. Summary Statistics

The definitions for all variables used are listed in appendix A1. Reducing noises in our analysis, we exclude firms with fewer than five consecutive years of technology expense and total asset

[20] See Bhattacharya and Thakor (1993) for a review.
[21] Diamond and Dybvig (1986) argue that main functions of bank as asset services to the borrowers, liability services to the depositors, and transformation services.

information during our sample period. We also exclude firms with missing values of the relevant variables. Finally, all the variables are winsorized at the 1% and 99% tails of the distributions to avoid the influence of extreme observations. The final sample consists of 8,030 firm-year observations for 781 banks during the 2000-2017 period.

Figure 1 displays bank technology expense trends over the sample period. In 2017 dollars, the median of bank technology spending jumps to $3.31 million in 2017 from $1.16 million in 2000. This figure shows that there exists a steady increase in the technology spending of banks for most of the years over this time. [22]

[Insert Figure 1 here]

Table 1 reports the summary statistics of regression variables used in this paper. The mean (median) market capitalization in our panel is $1,191 million ($110.16 million), while the mean (median) total assets is $7,613 million ($966 million)]. The technology expense of $15.69 million and a median of $1.58 million. In term of production variables, the mean (median) of net output, technology capital estimated with a perpetual inventory model, its corresponding conventional capital, labor, and investment is $204.96 ($31.19) million, $35.06 ($3.39) million, $7,329.40 ($954.60) million, $113.31 ($14.55) million, and $8.62 ($1.56) million, respectively. The typical bank has an average (median) total loans and deposits of $9,225.38 ($1,398.39) million and average (median) number of branches of 57.766 (15.00). On average (median), it employs 1,648 (264) employees and pays $113.31 ($14.55) million as staff expense.

[Insert Table 1 here]

[22] When we keep firms that record technology and communication expense in each year during 2000-2017 and illustrate their trends (medians) of technology and communication expense, we also find a monotonic increase in the technology spending in the sample period. There is a total of 97 firms in this sample. See the appendix B1for details.

Figure 2 illustrates the evolution of the median of technology spending, the number of employees and staff expense of banks during the sample period. All monetary values are adjusted for inflation using GDP deflator and are normalized to equal one in the year 2000. The figure shows that technology expense grew about 250%, much faster than the number of tasks and employment, from 2000 to 2017. In the meanwhile, the median number of total loans and deposits increased by about 100%, and the median number of employees increased by about 70%. The dramatical increase of expense on technology draws our attention to evaluate its contribution to the production of banks, and its relationship with employment.[23]

[Insert Figure 2 here]

5. Empirical Results

5.1. Technology in Production

As stated in the methodologies section, we start our analysis by estimating the contribution of technology capital on banks using a firm-level production function and examine whether banks benefit from their technology investments. We start with the model that technology capital is calculated from a perpetual inventory model. The production function estimates are presented in Panel A of Table 2.

The first column represents the parameter estimated from the DPD model. The estimated parameter for technology capital in the DPD model is 0.112 and statistically significant at the 1% level. Common factor restrictions are rejected. The *p*-value associated with the null hypotheses of constant return to scale ($\beta_{tk} + \beta_{ck} + \beta_l = 1$) is 0.812. Columns (2), (3) and (4) report the FE, OLS and OP estimates. The parameter estimates for technology capital are 0.065 from FE model and 0.067 from OLS model. All are statistically significant at the 1% level. Common factor restrictions and constant return to

[23] When we keep firms that record technology and communication expense in each year during 2000-2017 and illustrate the evolution of the median of technology spending, the number of employees and staff expense of those banks, we also find similar evolution patterns in the sample period. There is a total of 97 firms in this sample. See the appendix B2 for details.

scale are rejected for both models. The parameter estimate for technology capital in the OP model is 0.085 and statistically significant at the 1% level. The null hypotheses of constant return to scale are rejected in the OP model. Standard errors for the OP model are generated via bootstrap based on 300 replications. The results indicate that technology capital is very productive.

[Insert Table 2 here]

These results are also consistent with the literature on the production function parameter estimation and the notion that the production input choices could be endogenous. The results also confirm our worry on the measurement errors on the technology capital input. Our measure is likely to underestimate the true value of technology capital. Besides, the investment proxy in the OP (1996) methodology is much easier to observe and more precious, as these numbers are usually disclosure in their financial reports.

We further examine the implications of our production function parameter estimates on the historical contributions of the technology capital input of banks to their net output. To measure the historical contribution of technology capital, we calculate the difference in each bank's net output under 2017 and 2003 technology capital input levels. Net output grew an average of 225% over this period - an approximately 5.78% compound growth rate. Technology capital grew an average of 554% over this period - an approximately 9.70% compound growth rate. On average, technology inputs accounted for an approximately 12.85% increase in net output of banks. The result suggests that there exists a huge economically significant return from technology investments of banks during this period.

Next, we assess whether the contribution of technology investment is greater than its cost. The median net marginal product for technology on banks based on the estimated parameter range from $0.41

for the FE model (p-value < 0.001) and $0.81 for the DPD model ($p$-value < 0.001).[24] Even if technology capital is assumed to have an average service life as little as three years,[25] the median net marginal product still ranges from $0.22 for the FE model and $0.61 for the DPD model and be greater than zero at statistical significance at the 1% level. Their results suggest that the substantial increases in technology investment would be beneficial.

These net marginal products are similar to estimations in other industries. For instance, the net marginal product is $0.67 for technology in Brynjolfsson and Hitt (1996), whose sample is of U.S. large firms (Fortune 500). They range from $0.73 to $1.29 in Lee, McCullough, and Town (2013), whose focus is California hospitals.

Concerning there may be systematically over- or under- represent the true value of technology capital of each firm, alternatively, we estimate the production function parameters using technology capital stock estimated from a four-year linear depreciation schedule as a production input. Panel B of Table 2 reports the result. The estimated parameters for technology capital (0.083 from DPD, 0.050 from FE, 0.053 from OLS, and 0.071 from OP) are quantitively similar with that in Table 2, where technology capital is estimated using a perpetual inventory model. Common factor restrictions are quite similar to those in Panel A. The null hypotheses of constant return to scale cannot be rejected in the OP model and the DPD model but rejected in the other models. The levels of statistical significance are consistent as well. The consistent results provide further evaluation of the sensitivity of the estimated parameters under different kind of construction methods on technology capital stock.

Based on the estimations in Panel B, technology input, on average, accounted for an approximately 9.27% increase in net output of banks. The median net marginal product for technology

[24] Following Brynjolfsson and Hitt (1996), the gross marginal product for technology capital is the output elasticity, which is the estimated parameter to technology capital, multiplied by the ratio of output to technology capital input. Hence, the net marginal product is calculated as gross marginal products subtract 14%.

[25] Thus, the net marginal product is calculated as gross marginal products subtract 33.33%.

range from $0.32 for the FE model and $0.58 for the DPD model and are greater than zero at statistical significance at the 1% level. Assuming technology capital have an average of three years' service life, the median net marginal products still range from $0.10 to $0.38 and are greater than zero at statistical significance at the 1% level.

Concerning the effect of technology adoption in rural banks and urban banks may be different, we also estimate the contribution of technology capital on banks in the production function in rural bank sample and urban bank sample, respectively. For rural banks, as in Panel A of Table 3, the estimated parameters for technology capital estimated using a perpetual inventory model are 0.078 in the DPD model, 0.062 in the FE model, and 0.042 in the OLS model and are statistically significant at the 1% level, while the estimated parameter is 0.024 in the OP model and statistically insignificant, as in Columns (1)-(4) of Panel A, Table 3. When the technology capital is estimated using a linear depreciation schedule, the estimated parameters are quantitively similar (0.066 from DPD, 0.051 from FE, 0.035 from OLS, and 0.024 from OP). They are also statistically significant at the 1% level in the first three models and insignificant in the last model.

[Insert Table 3 here]

Panel B of Table 3 presents the production function parameter estimates for urban banks. While the estimated parameter of technology capital estimated using a perpetual inventory model is positive but insignificant in DPD, as in Column (1), they are 0.087 in FE, 0.046 in OLS, and 0.097 in OP and statistically significant at the 1% level, as in Columns (2)-(4). On the other hand, the estimated parameters of technology capital estimated using a linear depreciation schedule (0.005 in DPD, 0.071 in FE, 0.035 in OLS, and 0.037 in OP as in Column (5)-(8)) are quantitatively and qualitatively similar to those in Column (1)-(4) that the technology capital estimated using a perpetual inventory model is evaluated. The results indicate that technology capital played a meaningful role and was beneficial, and that technology capital was highly productive, in both rural banks and urban banks.

5.2. Technology and Employment

In this subsection, we also explore whether their previous-year technology spending can explain bank employment. We first compute the residual technology spending of banks using equation (8). Columns (1) to (4) of Panel A, Table 4 report the cross-sectional regression results of the natural log of technology expense on firm size, which is the log of market capitalization at the end of the fiscal year, for four years: 2000, 2005, 2010 and 2015. The estimated coefficients of firm size are highly consistent in each of the cross-section regression: 0.828 in 2000, 0.855 in 2005, 0.658 in 2010, and 0.782 in 2015. All the estimated coefficients are highly statistical significance at the 1% level (*t*-statistics range from 22.35 to 32.26). The *R*-squared range from 0.655 to 0.818. Columns (5) reports the results based on a pooled regression for all the cross-sections from 2000 to 2017. Again, the estimated coefficient is 0.767, with *t*-statistics of 35.14 and *R*-squared of 0.760. Thus, through this regression, we compute residual technology spending and exclude the effects of firm size on technology spending. Using the same method, we also calculate residual employment and residual tasks adjusting the effects of firm size. These results are reported in Table A2 of the appendix.

Panel B of Table 4 shows the results on the persistence tests of residual technology spending and residual employment of banks. The residuals in year *t* are strongly correlated with their corresponding residuals in year *t-1*. Specifically, in Column (1), the estimated coefficient for residual technology spending is 0.905, with *t*-statistics being 133.59 and *R*-squared being 0.823. The coefficients of the residual number of employees and residual staff expense are 0.901 and 0.884, respectively, both being highly statistically significant, as in Column (2) and (3). These results indicate the residual technology spending and residual employment of banks are highly persistent over time. These findings suggest that there exists a permanent firm effect in technology spending and firm employment.[26]

[Insert Table 4 here]

After documenting the persistence of technology spending and employment at the firm-level, we examine to the extent to which bank employment is related to previous-year technology spending. Table 5 reports the results from Equation (9). Overall, the results provide evidence that the firms that invest more in technology have higher employment, controlling for firm size, growth strategy, financing, performance, fee income ratio, and financial strength.

Columns (1) and (2) of Table 5 report the univariate regression results. When the dependent variable is residual number of employees, the estimated coefficient of the previous-year residual technology spending is positive (0.348) and statistically significant at the 1% level. Concerning residual staff expense, the estimated coefficient is also positive (0.390) and statistically significant at the 1% level. The economic significance of the relationship between number of employees (staff expense) and technology spending is 0.455 (0.513) standard deviations.[27] The baseline result suggests that banks with more technology spending employ more staff.

Columns (3) and (4) present the multivariate regression results. Positive relations between firm-level employment and technology spending are evident. The estimated coefficients of the previous-year technology spending variable are 0.196 when the dependent variable is residual number of employees

[26]Appendix A2presents the results on the correlations of residual technology spending and residual employment. The residual technology spending in year *t* is strongly correlated with the residual technology spending in year *t-1*, with the correlation being 0.908. Similarly, the correlation of residual number of employees (staff expense) in year *t* with residual number of employees (staff expense) in year *t-1* is 0.900 (0.880). Moreover, residual employment is correlated with residual technology spending in the previous year. The correlation is 0.579 for residual number of employees and 0.599 for residual staff expense.
[27] We compute economic significance by taking the coefficient of residual technology spending and multiplying it by the unconditional standard deviation of residual technology spending and dividing by the unconditional standard deviation of residual employment measures.

and 0.202 when the dependent variable is residual staff expense. Both display statistically significant at 1% level. The economic significance is 0.256 (0.273) standard deviations for the relationship between number of employees (staff expense) and technology spending. Aside from the coefficients of our main interests, we also show that bank employment is negatively correlated with the previous-year market-to-book ratio and return on assets and positively correlated with the previous-year leverage and non-interest income. The result is also consistent with Van Reenen (1997), which finds a positive and significant effect of innovations on employment based on the British firm-level panel data. [28]

[Insert Table 5 here]

The positive relationship between employment and technology spending holds consistently throughout our panel, which plots the relationship between residual number of employees (Figure 3) and residual staff expense (Figure 3) and residual technology spending for nine cross-sections, 2001, 2003, 2005, 2007, 2009, 20011, 2013, 2015 and 2017.

Next, we examine the extent to which firm-level tasks are related to previous-year technology spending, using a similar approach as in the previous analysis. Table 6 reports the results from Equation (10). When the dependent variable is residual loans and deposits, the estimated coefficients of the previous-year technology spending variable are 0.308 in the univariate regression, as in Column (1), and 0.137 in the multivariate regression, as in Column (4), with statistical significance at the 1% level. When the dependent variable is residual net output, the estimated coefficients are 0.301 in the univariate regression and 0.161 in the multivariate regression, and statistically significant at the 1% level, as in

[28] We rerun our analysis by measuring size using book asset values rather than the market value of equity, based on the idea that book asset values reflect both debt plus equity and thus may constitute a better proxy for the scale of the firm. Results are very similar. See appendix A3 for details. Moreover, we rerun our analysis by measuring firm size as total loans and deposits, based on the idea that the basic business model of banks is to make loans and collect deposits and most of their assets should be in loans and deposits and thus may constitute a better proxy for the scale of the firm. Similar results are reported, as in Table A4 of the appendix.

Column (2) and (5). When the dependent variable is residual number of branches, the estimated coefficients are 0.324 in the univariate regression and 0.191 in the multivariate regression, and statistically significant at the 1% level, as in Column (3) and (6). The economic significance is ranging from 0.203 to 0.508 standard deviations for the relationship between bank tasks and technology spending. We also show that bank tasks are positively correlated with the previous-year leverage and negatively correlated with the previous-year market-to-book ratio and return on assets, non-interest income, and tier 1 capital ratio.

Next, we explore whether there exist differentials on technology spending and bank employment and tasks relationship between rural banks and urban banks. Panel A of Table 7 presents the results of the relationship between employment and technology spending. When the dependent variable is number of employees, the estimated coefficients for technology spending are 0.169 in rural bank sample (Column 1) and 0.209 in urban bank sample (Column 3), and are statistically significant at the 1% level. When the dependent variable is staff expense, the statistically significant estimated coefficients are 0.163 in rural bank sample (Column 2) and 0.231 in urban bank sample (Column 4). The results imply that banks with higher previous year's technology spending, on average, have more employees. Both coefficients from the urban bank sample are greater than that from the rural bank sample might imply that urban banks might better capture the benefits from technology investment and thus hire more staff.

[Insert Table 7 here]

Panel B presents the results on the relationship between bank tasks and technology spending in rural banks and urban banks. Again, the estimated coefficients for technology spending in rural banks (0.118 when the dependent variable is loans and deposits, 0.118 when the dependent variable is net output, and 0.118 when the dependent variable is number of branches) are slightly less than those in the urban banks (0.152 when the dependent variable is loans and deposits, 0.183 when the dependent variable is net output, and 0.223 when the dependent variable is number of branches). All the estimated coefficients are statistically significant at the 1% level. The result confirms that there exists a positive relationship between bank task and their previous technology spending in both rural banks and urban banks and that urban banks might benefit more from technology investment compared with rural banks.

Collectively, our cross-sectional results provide strong evidence that bank employment and tasks are positively related to their previous-year technology spending on the full sample, rural banks sample and urban banks sample, implying that on average, banks adopting more technology tend to increase their number of employees and create more tasks.

5.3. Robustness Checks

In this section, we present results for robustness checks in this subsection. We also re-estimate our main analysis by 1) keeping observations only in the post financial crisis period (2010-2017), 2) excluding too-big-to-fail (TBTF) banks, which are also called systematically important financial institutions (SIFIs), 3) excluding banks that are involved with mergers and acquisitions activities during the sample period, and 4) excluding banks with missing information on technology and communication expense in any year during the sample period. We also use the total income (net-interest income plus non-interest income) of banks as output to re-estimate the production function.

In recent years, the banking industry gradually recovered from the financial crisis. Banks have adapted well to the new business environment and regulations.[29] They have bolstered their balance sheets and adjusted product portfolios, business strategies, and even operation models. Thus, the bank production process or business model might be quite different during the pre- and post- financial crisis

[29] See a report by Bank for International Settlements, Committee on the Global Financial System on January 2018, "Structural changes in banking after the crisis," CGFS Papers, No. 60.

period. To ensure our results hold in the new era, we re-estimate our main analysis in the post-financial crisis period (2010-2017). In Panel A of Table 8, the estimated parameters for technology input during the post financial crisis period are quantitatively and qualitatively greater than that in Table 2. The estimated parameters of technology capital estimated using a perpetual inventory model are 0.239 in DPD, 0.133 in FE, 0.107 in OLS, and 0.131 in OP in the post financial crisis period, as in Columns (1)-(4), comparing with 0.112 in DPD, 0.065 in FE, and 0.067 in OLS, and 0.085 in OP in the full sample period as in Table 2. In the post-crisis, the estimated parameters of technology capital estimated using a linear depreciation schedule (0.189 in DPD, 0.103 in FE, 0.085 in OLS, and 0.127 in OP) are quantitatively similar to those in Table 2 that the full sample period is evaluated. The results indicate that technology investment played a greater role and was more beneficial, and that technology capital was highly productive in recent years.

[Insert Table 8 here]

It is believed that the extremely large banks operate in very different models and are under different degrees of regulation, supervisions, and supports. To ensure those banks do not overly influence our results, we re-estimate our main analysis excluding banks whose gross total assets exceed $50 billion in 2017 dollars. While too-big-to-fail banks excluded, as in Panel B of Table 8, the estimated parameters for technology capital estimated using a perpetual inventory model (0.114 in DPD, 0.064 in FE, 0.007 in OLS, and 0.065 in OP) and estimated using a linear depreciation schedule (0.087 in DPD, 0.049 in FE, 0.056 in OLS, and 0.058 in OP) are largely consistent with those estimated to the full sample as in Table 2. The main result on the production function parameter estimates remains unchanged when we drop TBTF banks from the sample.

Another concern on the contribution of technology on bank production is that consolidation or mergers and acquisitions may drive our results since banks experienced a tremendous consolidation during the past decades.[30] The consolidation activities or mergers and acquisitions of banks can impact firm-level technology and communication expenses as well as general and administrative expenses, and in turn influence the production function parameter estimates and the regression results in the paper. Panel C of Table 8 addresses this concern by excluding banks involved in mergers and acquisitions activities (Non-M&A banks) during the period of 2000-2017, and estimating the bank-level production function. The parameter estimates for technology capital input are significantly positive in the DPD, FE and OLS models, which are consistent with the baseline results in Table 2. The only exception is when we use the OP, the parameter estimates are not statistically significant. The result suggests that technology capital make a meaningful contribution to bank production for those banks without large variations on their sizes due to consolidations or M&A activities.

The technology and compensation expense of banks is not mandatorily required in their 10K reports. However, many banks choose to voluntarily disclose information on technology spending since technology becomes more and more important to the banking industry (Feng and Wu, 2019). Due to the voluntarily disclose nature, a large number of banks did not report their technology spending in some years. Hence, there exists a concern that the reliability of the results estimated from unbalanced penal data. To address the concern, in Panel D of Table 8, excluding banks that have missing technology and communication expense information in any given year during the period of 2000-2017, and estimating the bank-level production function. In the DPD, FE, and OLS models, the parameter estimates for technology capital input are positive and statistically significant. The parameter estimates in the OP

[30] See an article from *American Banker* on January 30, 2018, "Survival strategy: Cut the number of banks in half", among many others.

model are positive but statistically insignificant. Generally, the strongly balanced sample results are consistent with the baseline results in Table 2.

Concerning net interest expense might not fully represent the net output of banks nowadays since banks have a substantially large percentage non-interest income during the past decades,[31] the measurement errors in the output may influence our results on the production function parameter estimates. Panel E of Table 8 addresses the concern by using the total income (net-interest income plus non-interest income) as bank's output in the bank-level production function. The parameter estimates for technology capital are quantitatively and qualitatively similar to those in main results in Table 2. The parameter estimates are 0.056 in DPD, 0.058 in FE, 0.071 in OLS, and 0.056 when the technology capital is estimated using a perpetual inventory model, as in Columns (1)-(4). They are 0.052 in DPD, 0.060 in FE, 0.067 in OLS, and 0.040 when the technology capital is estimated using a linear depreciation schedule, as in Columns (5)-(8). All parameter estimates are statistically significant. In sum, the results confirm the contribution of technology capital in bank production.

Furthermore, robustness checks on the positively and significantly relationship between technology spending and bank employment and tasks are also conducted. Panel A of Table 9 presents the results on the relationship between employment and technology spending in the post financial crisis, in the too-big-to-fail excluded banks, in the Non-M&A banks, and in banks with all 18 years technology spending data. Consistent estimated coefficients for technology spending are found. When the dependent variable is number of employees, the coefficients are 0.174 in the post-crisis period, 0.183 in TBTF excluded banks, 0.210 in Non-M&A banks, and 0.195 in the strongly balanced subsample, respectively. At the meanwhile, the coefficients for technology spending in term of staff expense are 0.206 in post-crisis period, 0.190 in TBTF excluded banks, 0.222 in Non-M&A banks, and 0.199 in the strongly

[31] U.S. Bank's Non-Interest Income to Total Income ratio is about 40.12% during the period of 2000-2014, accouring to the FRED Economic data from the Federal Reserve Bank of St. Louis.

balanced subsample, respectively. All the estimated coefficients are statistically significant at the 1% level. The result confirms a positive relationship between bank employment and their previous technology spending.

[Insert Table 9 here]

Lastly, Panel B of Table 9 presents robustness checks on the relationship between technology spending and bank tasks. The consistent, significantly positive estimated coefficients for technology spending are found in Columns (1)-(12), regardless whether the dependent variable is loan & deposits, net output our number of branches, in all four subsamples. The results further support the notion that technology adoption creates new tasks (Acemoglu and Restrepo, 2018).

Overall, these robustness results provide supporting evidence that the substantial increases in bank technology investment would be beneficial. Technology plays an important role in bank production and positively related to bank employment in the cross section, in the post financial crisis period, controlling for too-big-to-fail banks, mergers and acquisitions activities, and data reporting issues.

6. Conclusions

Technology is considered as the lifeblood of banks given the rapid advances of technology in the banking industry. Meanwhile, many believe that automation and technology adoption can destroy millions of banking jobs in the future. While the impacts of technology advances in the U.S. banking sector are significant, research in this area is limited. We fill this gap in the literature by examining the benefit of technology capital in bank production and the effect of technology spending on bank employment. To the best of our knowledge, this is one of the few empirical studies on the impacts of technology investment on banks.

Based on a sample of U.S. listed commercial banks data from 2000 to 2017, we first document strong growth trends in the technology adoption by banks. The median bank technology spending increased by 185%, while the median loans and deposits and the number of employees of banks increased by 100% and 70%, respectively, during the sample period. We then estimate the parameters of a bank production function correcting for endogenous input choices and the measurement errors to assess the returns that banks earn from technology capital. Technology capital is shown as a major contributing factor to the output generated by banks. On average, technology capital accounts for more than 12% increase in the net output of U.S. banks. Interestingly, the contribution of technology input becomes stronger after the financial crisis, consistent with the notion that technology has played a more important role in bank production in recent years. These results suggest that technology capital is highly productive and that substantial increases in technology investment would be beneficial.

As the main functions of banks are to collect deposits and make loans, we use total loans & deposits and number of branches as proxies for bank tasks. We measure bank employment as the number of employees it employs as well as the staff expense it pays. We find strong evidence that bank employment and tasks are positively correlated with lagged technology investment. This is consistent with the task-based framework of Acemoglu and Restrepo (2018), which suggest technology can impede employment via its labor-saving effects and enhance employment via its employment-stimulating effects.

Collectively, our findings show the importance of technology investment to bank productivity and employment. This research also opens the door for additional research on the technology development and adoption of banks and the service industry in general. When technology investment is a necessity, instead of a strategic choice, for firms to succeed in future competition, further research that examines in detail the importance of the components of technology investment concurrent with financing decision, mergers and acquisitions, and corporate governance, management, operational structure and risk may yield considerable insights.

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Table 1. Summary Statistics

This table reports the summary statistics of regression variables in our sample. All variables are defined in appendix A1. To reduce noises in our analysis, we exclude firms with fewer than five consecutive years of technology expense and total assets information. Variables have been winsorized at the 1% and 99% tails of the distributions to avoid the influence of extreme observations.

	Mean	**Median**	**Std. Dev.**	**Min**	**Max**	**Obs.**
Market Capitalization ($M)	1,191.36	110.16	5,096.43	4.01	43,060.26	7,759
Total Asset ($M)	7,612.55	965.85	31,864.82	97.17	268,298.00	8,030
Technology Expense ($M)	15.69	1.58	77.16	0.12	653.00	8,030
Net Output ($M)	204.96	31.19	798.29	2.95	6,839.70	8,027
Technology Capital - Perpetual ($M)	35.06	3.39	176.17	0.18	1,516.53	8,030
Conventional Capital - Perpetual ($M)	7,329.40	954.60	30,366.10	96.58	255,449.13	8,030
Technology Capital - Linear ($M)	33.67	3.31	167.82	0.18	1,429.78	8,030
Conventional Capital - Linear ($M)	7,329.50	954.76	30,362.91	96.57	255,380.50	8,030
Labor ($M)	113.31	14.55	478.86	1.25	3,937.00	8,012
Investment ($M)	8.62	1.59	28.28	-1.73	213.00	6,380
Loans and Deposits($M)	9,225.38	1,398.39	34,817.88	133.47	280,620.00	8,030
Number of Branches	57.66	15.00	174.34	1.00	1,404.00	7,825
Number of Employees	1,648.09	264.00	6,439.30	26.00	52,277.00	7,201
Staff Expense ($M)	113.31	14.55	478.86	1.25	3,937.00	8,012
Market to Book	1.33	1.21	0.65	0.18	3.64	7,758
Leverage	11.15	10.56	3.99	4.31	32.19	8,029
Return on Asset (%)	0.82	0.95	0.84	-3.41	2.47	7,324
Non-Interest Income (%)	21.98	20.31	12.31	-2.24	68.88	8,026
Tier 1 Capital Ratio (%)	12.34	11.80	3.57	5.75	26.04	7,703

Table 2. Production Function Parameter Estimates

This table reports the results from regressions of the natural log of net output as the dependent variable on the natural log of technology capital, which is estimated using a perpetual inventory model or using a linear depreciation schedule, conventional capital, and labor. The production variables are converted to 2017 dollars using the GDP deflator. The standard errors are reported in parentheses. t-statistics based on standard errors are in brackets. Significance at the 1%, 5% or 10% levels is shown with 3, 2, or 1 asterisks, respectively. Production function variables are converted to 2017 dollars using the GDP deflator. The estimation models, which are dynamic panel data (DPD), fixed-effects (FE), ordinary least squares (OLS), and Olley and Pakes (OP), are indicated in the column header.

Panel A. Technology Capital Estimated using a Perpetual Inventory Model

	(1)	(2)	(3)	(4)
Variables	**DPD**	**FE**	**OLS**	**OP**
Technology Capital, t_t	0.112***	0.065***	0.067***	0.085***
	(0.032)	(0.009)	(0.007)	(0.031)
	[3.44]	[7.25]	[9.63]	[2.71]
Conventional Capital, k_t	0.452***	0.371***	0.449***	0.621***
	(0.025)	(0.011)	(0.010)	(0.039)
	[17.71]	[34.39]	[42.90]	[16.05]
Labor, l_t	0.428***	0.424***	0.435***	0.253***
	(0.033)	(0.011)	(0.011)	(0.025)
	[12.90]	[37.32]	[41.13]	[9.96]
ρ	0.873***	0.630***	0.926***	-
	(0.024)	(0.009)	(0.005)	-
	[37.04]	[69.06]	[200.59]	-
Common factor	0.000	0.000	0.000	-
p-value: $\beta_{tk} + \beta_{ck} + \beta_l = 1$	0.812	0.000	0.000	0.286
Observations	7,151	7,151	7,151	6,149
Firms	781	781	781	770

Panel B. Technology Capital Estimated using a Linear Depreciation Schedule

	(1)	(2)	(3)	(4)
Variables	**DPD**	**FE**	**OLS**	**OP**
Technology Capital, t_t	0.112***	0.065***	0.067***	0.085***
	(0.032)	(0.009)	(0.007)	(0.031)
	[3.44]	[7.25]	[9.63]	[2.71]
Conventional Capital, k_t	0.452***	0.371***	0.449***	0.621***
	(0.025)	(0.011)	(0.010)	(0.039)
	[17.71]	[34.39]	[42.90]	[16.05]
Labor, l_t	0.428***	0.424***	0.435***	0.253***
	(0.033)	(0.011)	(0.011)	(0.025)
	[12.90]	[37.32]	[41.13]	[9.96]
ρ	0.873***	0.630***	0.926***	-
	(0.024)	(0.009)	(0.005)	-
	[37.04]	[69.06]	[200.59]	-
Common factor	0.000	0.000	0.000	-
p-value: $\beta_{tk} + \beta_{ck} + \beta_l = 1$	0.812	0.000	0.000	0.286
Observations	7,151	7,151	7,151	6,149
Firms	781	781	781	770

Table 3. Production Function Parameter Estimates in Rural Banks and Urban Banks

This table reports the results from regressions of the natural log of net output as the dependent variable on the natural log of technology capital, which is estimated using a perpetual inventory model or using a linear depreciation schedule, conventional capital, and labor, in rural banks and urban banks, respectively. The production variables are converted to 2017 dollars using the GDP deflator. The standard errors are reported in parentheses. *t*-statistics based on standard errors are in brackets. Significance at the 1%, 5% or 10% levels is shown with 3, 2, or 1 asterisks, respectively. Production function variables are converted to 2017 dollars using the GDP deflator. The estimation models, which are dynamic panel data (DPD), fixed-effects (FE), ordinary least squares (OLS), and Olley and Pakes (OP), are indicated in the column header.

Panel A. Rural Banks

	Tech Capital - Perpetual Inventory Model				*Tech Capital - Linear Depreciation Schedule*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**DPD**	**FE**	**OLS**	**OP**	**DPD**	**FE**	**OLS**	**OP**
Technology Capital, t_t	0.078***	0.062***	0.042***	0.024	0.066***	0.051***	0.035***	0.024
	(0.026)	(0.016)	(0.013)	(0.046)	(0.023)	(0.015)	(0.011)	(0.039)
	[3.04]	[3.79]	[3.36]	[0.53]	[2.91]	[3.54]	[3.12]	[0.61]
Conventional Capital, k_t	0.431***	0.391***	0.431***	0.512***	0.431***	0.392***	0.431***	0.508***
	(0.041)	(0.023)	(0.022)	(0.094)	(0.041)	(0.023)	(0.022)	(0.113)
	[10.46]	[16.65]	[19.19]	[5.45]	[10.49]	[16.70]	[19.24]	[4.50]
Labor, l_t	0.455***	0.461***	0.459***	0.264***	0.458***	0.464***	0.461***	0.268***
	(0.058)	(0.025)	(0.023)	(0.048)	(0.058)	(0.025)	(0.023)	(0.049)
	[7.83]	[18.18]	[20.31]	[5.51]	[7.88]	[18.39]	[20.47]	[5.45]
ρ	0.840***	0.639***	0.904***	-	0.837***	0.638***	0.904***	-
	(0.020)	(0.020)	(0.010)	-	(0.021)	(0.020)	(0.010)	-
	[41.66]	[31.95]	[88.20]	-	[40.32]	[31.86]	[87.99]	-
Common factor	0.000	0.195	0.000	-	0.000	0.405	0.000	-
p-value: $\beta_{tk} + \beta_{ck} + \beta_l = 1$	0.552	0.002	0.003	0.065	0.437	0.001	0.001	0.073
Observations	1,886	1,886	1,886	1,665	1,886	1,886	1,886	1,665
Firms	212	212	212	207	212	212	212	207

Panel B. Urban Banks

	Tech Capital - Perpetual Inventory Model				*Tech Capital - Linear Depreciation Schedule*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**DPD**	**FE**	**OLS**	**OP**	**DPD**	**FE**	**OLS**	**OP**
Technology Capital, t_t	0.021	0.087***	0.046***	0.097**	0.005	0.071***	0.035***	0.087**
	(0.025)	(0.019)	(0.015)	(0.039)	(0.021)	(0.017)	(0.013)	(0.035)
	[0.86]	[4.52]	[3.08]	[2.50]	[0.23]	[4.11]	[2.66]	[2.51]
Conventional Capital, k_t	0.525***	0.372***	0.529***	0.588***	0.523***	0.374***	0.531***	0.589***
	(0.044)	(0.023)	(0.021)	(0.068)	(0.044)	(0.023)	(0.021)	(0.077)
	[11.96]	[16.41]	[24.83]	[8.62]	[11.80]	[16.45]	[24.94]	[7.65]
Labor, l_t	0.311***	0.290***	0.297***	0.297***	0.317***	0.293***	0.300***	0.293***
	(0.042)	(0.022)	(0.020)	(0.049)	(0.042)	(0.022)	(0.020)	(0.046)
	[7.45]	[13.48]	[14.80]	[6.12]	[7.56]	[13.61]	[14.97]	[6.34]
ρ	0.898***	0.635***	0.939***	-	0.897***	0.634***	0.939***	-
	(0.019)	(0.017)	(0.008)	-	(0.020)	(0.018)	(0.008)	-
	[46.33]	[36.33]	[110.72]	-	[45.17]	[36.11]	[110.55]	-
Common factor	0.002	0.007	0.000	-	0.002	0.000	0.000	-
p-value: $\beta_{tk} + \beta_{ck} + \beta_l = 1$	0.002	0.000	0.000	0.839	0.000	0.000	0.000	0.704
Observations	1,662	1,662	1,662	1,439	1,662	1,662	1,662	1,439
Firms	198	198	198	149	198	198	198	149

Table 4. Persistence in Technology Spending and Employment

Panel A report results from cross-sectional regressions of the natural log of technology and communication expense of banks as the dependent variable on the natural log of their market capitalization (Firm Size) for four sample years, as well as a pooled panel regression with year fixed effects. The standard errors are computing using HC3 robust standard errors for the first four columns and are clustered at the firm-level at the last column. The standard errors are reported in parentheses. *t*-statistics based on standard errors are in brackets. Panel B reports cross-sectional regression results for persistence in technology spending and employment of banks. The dependent variables are residual technology spending and employment measures in year *t*, and the independent variables are residual technology spending and employment measures in year *t-1*. The standard errors are clustered at the firm-level and reported in parentheses. *t*-statistics based on robust standard errors are in brackets. Significance at the 1%, 5% or 10% levels is shown with 3, 2, or 1 asterisks, respectively.

Panel A. Technology Spending and Firm Size					
	(1)	(2)	(3)	(4)	(5)
Variables	**2000**	**2005**	**2010**	**2015**	**Pooled**
Firm Size	0.828***	0.855***	0.658***	0.782***	0.767***
	(0.027)	(0.027)	(0.029)	(0.024)	(0.022)
	[31.10]	[31.52]	[22.35]	[32.26]	[35.14]
Constant	-3.576***	-4.035***	-2.213***	-3.053***	-3.294***
	(0.126)	(0.140)	(0.138)	(0.130)	(0.097)
	[-28.28]	[-28.91]	[-16.03]	[-23.41]	[-34.13]
Observations	301	426	474	500	7,758
Firms	301	426	474	500	780
R-squared	0.818	0.800	0.655	0.777	0.760
Year FE	NO	NO	NO	NO	YES

Panel B. Persistence in Technology Spending and Employment			
	(1)	(2)	(3)
Variables	**Residual Technology Spending**	**Residual Number of Employees**	**Residual Staff Expense**
Residual Technology Spending, *t-1*	0.905***		
	(0.007)		
	[135.59]		
Residual Number of Employees, *t-1*		0.901***	
		(0.007)	
		[126.17]	
Residual Staff Expense, *t-1*			0.884***
			(0.008)
			[114.41]
Constant	0.026***	0.020***	0.023***
	(0.004)	(0.003)	(0.003)
	[6.87]	[6.28]	[7.19]
Observations	6,903	6,213	6,885
Firms	780	740	780
R-squared	0.823	0.809	0.789

Table 5. Employment and Technology Spending

This table reports the results from panel regressions where the dependent variables are residual employment and the independent variables are their previous-year residual technology spending as well as other firm characteristics. The coefficients on variables of years are suppressed from reporting. The standard errors are clustered at the firm-level and reported in parentheses. *t*-statistics based on robust standard errors are in brackets.

Variables	(1) Number of Employees	(2) Staff Expense	(3) Number of Employees	(4) Staff Expense
Technology Spending, *t-1*	0.348***	0.380***	0.196***	0.202***
	(0.017)	(0.018)	(0.023)	(0.021)
	[19.93]	[21.28]	[8.49]	[9.65]
Market to Book, *t-1*			-0.196***	-0.227***
			(0.022)	(0.021)
			[-9.00]	[-10.73]
Leverage, *t-1*			0.015***	0.019***
			(0.004)	(0.003)
			[4.19]	[5.70]
Return on Assets, *t-1*			-6.813***	-7.910***
			(1.180)	(1.212)
			[-5.77]	[-6.53]
Non-Interest Income, *t-1*			0.499***	0.636***
			(0.108)	(0.107)
			[4.63]	[5.94]
Tier 1 Capital Ratio, *t-1*			-0.536*	-0.267
			(0.310)	(0.287)
			[-1.73]	[-0.93]
Constant	-0.036*	-0.029	0.095	0.042
	(0.022)	(0.021)	(0.072)	(0.069)
	[-1.65]	[-1.42]	[1.31]	[0.61]
Observations	6,302	6,892	5,570	6,078
Firms	742	780	708	743
R-squared	0.233	0.253	0.318	0.364
Size *t* Effects	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 6. Tasks and Technology Spending

This table reports the results from panel regressions where the dependent variables are the residual tasks and the independent variables are their previous-year residual technology spending as well as other firm characteristics. The coefficients on variables of years are suppressed from reporting. The standard errors are clustered at the firm-level and reported in parentheses. *t*-statistics based on robust standard errors are in brackets.

Variables	(1) **Loans & Deposits**	(2) **Net Output**	(3) **Number of Branches**	(4) **Loans & Deposits**	(5) **Net Output**	(6) **Number of Branches**
Technology Spending, *t-1*	0.308***	0.301***	0.324***	0.137***	0.161***	0.191***
	(0.016)	(0.016)	(0.017)	(0.019)	(0.020)	(0.022)
	[19.77]	[18.90]	[18.74]	[7.19]	[7.92]	[8.56]
Market to Book, *t-1*				-0.230***	-0.199***	-0.171***
				(0.019)	(0.019)	(0.021)
				[-12.40]	[-10.30]	[-8.04]
Leverage, *t-1*				0.020***	0.019***	0.014***
				(0.003)	(0.004)	(0.003)
				[5.83]	[5.12]	[4.96]
Return on Assets, *t-1*				-5.412***	-3.430***	-6.028***
				(1.105)	(1.153)	(1.084)
				[-4.90]	[-2.97]	[-5.56]
Non-Interest Income, *t-1*				-0.208**	-0.307***	-0.046
				(0.087)	(0.090)	(0.100)
				[-2.39]	[-3.40]	[-0.46]
Tier 1 Capital Ratio, *t-1*				-1.313***	-1.054***	-0.337
				(0.277)	(0.303)	(0.285)
				[-4.75]	[-3.48]	[-1.18]
Constant	-0.034*	-0.023	-0.023	0.284***	0.243***	0.134**
	(0.018)	(0.017)	(0.022)	(0.069)	(0.072)	(0.061)
	[-1.87]	[-1.35]	[-1.04]	[4.11]	[3.37]	[2.19]
Observations	6,903	6,903	6,753	6,086	6,086	5,974
Firms	780	780	774	743	743	737
R-squared	0.203	0.196	0.228	0.323	0.287	0.303
Size *t* Effects	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 7. Employment, Tasks and Technology Spending in Rural Banks and Urban Banks

This table reports the results from panel regressions where the dependent variables are residual employment or residual tasks and the independent variables are their previous-year residual technology spending as well as other firm characteristics, in rural banks and urban banks, respectively. The coefficients on variables of years are suppressed from reporting. The standard errors are reported in parentheses. *t*-statistics based on standard errors are in brackets. Significance at the 1%, 5% or 10% levels is shown with 3, 2, or 1 asterisks, respectively. Panel A keeps the sample in the post financial crisis period (2010-2017). Panel B drops too-big-to-fail banks from sample. Panel C keeps banks that are not involved with mergers and acquisitions activities (Non-M&A banks) in our sample during 2000-2017.Panel D keeps banks in our sample that recorded technology and communication expense in each year during 2000-2017.

Panel A. Employment and Technology Spending				
	Rural Banks		*Urban Banks*	
	(1)	(2)	(3)	(4)
Variables	**Number of Employees**	**Staff Expense**	**Number of Employees**	**Staff Expense**
Technology Spending, *t-1*	0.169***	0.163***	0.219***	0.231***
	(0.032)	(0.028)	(0.038)	(0.039)
	[5.27]	[5.87]	[5.79]	[5.97]
Market to Book, *t-1*	-0.258***	-0.321***	-0.153***	-0.173***
	(0.035)	(0.036)	(0.038)	(0.040)
	[-7.34]	[-8.91]	[-4.06]	[-4.38]
Leverage, *t-1*	0.015**	0.020***	0.018***	0.022***
	(0.006)	(0.005)	(0.007)	(0.006)
	[2.31]	[4.07]	[2.76]	[3.48]
Return on Assets, *t-1*	-4.747**	-6.258***	-4.606**	-5.530**
	(2.027)	(1.822)	(2.165)	(2.222)
	[-2.34]	[-3.44]	[-2.13]	[-2.49]
Non-Interest Income, *t-1*	0.323*	0.539***	0.744***	0.848***
	(0.180)	(0.183)	(0.240)	(0.203)
	[1.80]	[2.95]	[3.10]	[4.17]
Tier 1 Capital Ratio, *t-1*	-0.758	-0.557	-1.042*	-0.317
	(0.508)	(0.473)	(0.612)	(0.645)
	[-1.49]	[-1.18]	[-1.70]	[-0.49]
Constant	0.239*	0.147	-0.185	-0.164
	(0.142)	(0.113)	(0.125)	(0.126)
	[1.68]	[1.30]	[-1.48]	[-1.31]
Observations	1,425	1,664	1,280	1,409
Firms	186	201	178	189
R-squared	0.376	0.437	0.289	0.368
Size *t* Effects	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Panel B. Task and Technology Spending						
	Rural Banks			*Urban Banks*		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Loans & Deposits**	**Net Output**	**Number of Branches**	**Loans & Deposits**	**Net Output**	**Number of Branches**
Technology Spending, *t-1*	0.118***	0.138***	0.127***	0.152***	0.183***	0.223***
	(0.029)	(0.029)	(0.031)	(0.040)	(0.042)	(0.040)
	[4.13]	[4.70]	[4.10]	[3.82]	[4.34]	[5.52]
Market to Book, *t-1*	-0.288***	-0.274***	-0.232***	-0.211***	-0.173***	-0.158***
	(0.032)	(0.035)	(0.039)	(0.038)	(0.036)	(0.037)
	[-8.88]	[-7.93]	[-5.91]	[-5.51]	[-4.81]	[-4.28]
Leverage, *t-1*	0.019***	0.016**	0.013***	0.026***	0.027***	0.023***
	(0.007)	(0.006)	(0.005)	(0.007)	(0.007)	(0.006)
	[2.74]	[2.48]	[2.88]	[4.01]	[3.87]	[3.95]
Return on Assets, *t-1*	-5.669***	-3.453*	-5.985***	-1.916	-0.186	-3.429*
	(1.834)	(1.833)	(1.667)	(2.226)	(2.206)	(1.830)
	[-3.09]	[-1.88]	[-3.59]	[-0.86]	[-0.08]	[-1.87]
Non-Interest Income, *t-1*	-0.104	-0.292	0.295*	-0.376**	-0.368**	-0.012
	(0.194)	(0.207)	(0.173)	(0.175)	(0.173)	(0.161)
	[-0.54]	[-1.41]	[1.71]	[-2.14]	[-2.13]	[-0.08]
Tier 1 Capital Ratio, *t-1*	-1.250**	-1.428**	-0.959***	-1.969***	-1.232**	-0.259
	(0.492)	(0.621)	(0.342)	(0.594)	(0.606)	(0.575)
	[-2.54]	[-2.30]	[-2.81]	[-3.31]	[-2.03]	[-0.45]
Constant	0.353**	0.402***	0.290***	0.204	0.046	-0.323**
	(0.137)	(0.139)	(0.089)	(0.128)	(0.124)	(0.130)
	[2.58]	[2.89]	[3.25]	[1.59]	[0.38]	[-2.49]
Observations	1,668	1,668	1,655	1,410	1,410	1,384
Firms	201	201	200	189	189	185
R-squared	0.371	0.358	0.349	0.365	0.317	0.320
Size *t* Effects	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 8. Robustness Checks: Production Function Parameter Estimates

This table reports the production function parameter estimates with the natural log of net output as the dependent variable on the natural log of technology capital, which is estimated using a linear depreciation schedule and a linear depreciation schedule, conventional capital, and labor. The production variables are converted to 2017 dollars using the GDP deflator. The standard errors are reported in parentheses. *t*-statistics based on standard errors are in brackets. Significance at the 1%, 5% or 10% levels is shown with 3, 2, or 1 asterisks, respectively. Production function variables are converted to 2017 dollars using the GDP deflator. The estimation models, which are Olley and Pakes (OP), dynamic panel data (DPD), fixed-effects (FE) and ordinary least squares (OLS), are indicated in the column header. Panel A keeps the sample in the post financial crisis period (2010-2017). Panel B drops too-big-to-fail banks from sample. Panel C keeps banks that are not involved with mergers and acquisitions activities (Non-M&A banks) in our sample during 2000-2017.Panel D keeps banks in our sample that recorded technology and communication expense in each year during 2000-2017. Panel E uses the total income (net-interest income plus non-interest income) of banks as output.

Panel A. Post Financial Crisis Period (2010-2017)								
	Tech Capital - Perpetual Inventory Model				*Tech Capital - Linear Depreciation Schedule*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**DPD**	**FE**	**OLS**	**OP**	**DPD**	**FE**	**OLS**	**OP**
Technology Capital, t_t	0.239***	0.133***	0.107***	0.131***	0.189***	0.103***	0.085***	0.127***
	(0.060)	(0.014)	(0.010)	(0.044)	(0.050)	(0.012)	(0.009)	(0.040)
	[4.00]	[9.73]	[11.00]	[2.96]	[3.79]	[8.36]	[9.81]	[3.14]
Conventional Capital, k_t	0.357***	0.307***	0.422***	0.631***	0.359***	0.310***	0.424***	0.681***
	(0.042)	(0.015)	(0.014)	(0.051)	(0.042)	(0.015)	(0.014)	(0.050)
	[8.45]	[20.80]	[29.99]	[12.33]	[8.47]	[20.92]	[30.04]	[13.64]
Labor, l_t	0.461***	0.394***	0.463***	0.194***	0.478***	0.404***	0.473***	0.193***
	(0.060)	(0.017)	(0.015)	(0.030)	(0.061)	(0.017)	(0.015)	(0.030)
	[7.69]	[23.10]	[29.92]	[6.50]	[7.85]	[23.78]	[30.63]	[6.51]
ρ	0.863***	0.458***	0.926***	-	0.850***	0.451***	0.926***	-
	(0.053)	(0.014)	(0.006)	-	(0.053)	(0.014)	(0.006)	-
	[16.41]	[32.13]	[151.80]	-	[16.13]	[31.63]	[150.75]	-
Common factor	0.000	0.000	0.000	-	0.000	0.000	0.000	-
p-value: $\beta_{tk}+\beta_{ck}+\beta_l=1$	0.394	0.000	0.593	0.358	0.665	0.000	0.198	0.979
Observations	3,326	3,326	3,326	3,711	3,326	3,326	3,326	6,013
Firms	582	582	582	595	758	758	758	595

Panel B. Too-Big-To-Fail Banks Excluded								
	Tech Capital - Perpetual Inventory Model				*Tech Capital - Linear Depreciation Schedule*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**DPD**	**FE**	**OLS**	**OP**	**DPD**	**FE**	**OLS**	**OP**
Technology Capital, t_t	0.114***	0.064***	0.070***	0.065**	0.087***	0.049***	0.056***	0.058**
	(0.033)	(0.009)	(0.007)	(0.031)	(0.025)	(0.008)	(0.006)	(0.027)
	[3.47]	[7.07]	[9.94]	[2.08]	[3.44]	[6.11]	[8.91]	[2.17]
Conventional Capital, k_t	0.443***	0.369***	0.443***	0.600***	0.444***	0.370***	0.445***	0.603***
	(0.025)	(0.011)	(0.011)	(0.046)	(0.025)	(0.011)	(0.011)	(0.040)
	[17.56]	[33.71]	[41.96]	[13.15]	[17.49]	[33.80]	[42.10]	[14.90]
Labor, l_t	0.435***	0.425***	0.440***	0.264***	0.439***	0.428***	0.445***	0.264***
	(0.034)	(0.012)	(0.011)	(0.024)	(0.034)	(0.011)	(0.011)	(0.025)
	[12.96]	[36.84]	[41.18]	[10.83]	[12.97]	[37.28]	[41.76]	[10.45]
ρ	0.872***	0.630***	0.915***		0.866***	0.628***	0.914***	
	(0.023)	(0.009)	(0.005)		(0.023)	(0.009)	(0.005)	
	[37.60]	[67.56]	[187.13]		[37.06]	[67.34]	[186.51]	
Common factor	0.000	0.000	0.000	-	0.000	0.000	0.000	-
p-value: $\beta_{tk}+\beta_{ck}+\beta_l=1$	0.809	0.000	0.000	0.085	0.353	0.000	0.231	0.057
Observations	6,922	6,922	6,922	6,013	6,922	6,922	6,922	6,013
Firms	758	758	758	749	758	758	758	749

Panel C. Non-M&A Banks								
	Tech Capital - Perpetual Inventory Model				*Tech Capital - Linear Depreciation Schedule*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**DPD**	**FE**	**OLS**	**OP**	**DPD**	**FE**	**OLS**	**OP**
Technology Capital, t_t	0.059**	0.050***	0.047***	0.040	0.053**	0.043***	0.039***	0.040
	(0.023)	(0.016)	(0.011)	(0.033)	(0.021)	(0.014)	(0.010)	(0.033)
	[2.52]	[3.12]	[4.25]	[1.22]	[2.50]	[3.03]	[4.03]	[1.24]
Conventional Capital, k_t	0.534***	0.451***	0.528***	0.633***	0.535***	0.452***	0.528***	0.719***
	(0.036)	(0.019)	(0.017)	(0.042)	(0.035)	(0.019)	(0.017)	(0.046)
	[15.03]	[23.48]	[30.18]	[15.17]	[15.08]	[23.55]	[30.29]	[15.66]
Labor, l_t	0.336***	0.327***	0.342***	0.294***	0.335***	0.327***	0.343***	0.294***
	(0.039)	(0.018)	(0.016)	(0.040)	(0.039)	(0.018)	(0.016)	(0.039)
	[8.51]	[18.28]	[21.21]	[7.41]	[8.53]	[18.30]	[21.28]	[7.58]
ρ	0.881***	0.690***	0.928***	-	0.878***	0.689***	0.928***	-
	(0.025)	(0.014)	(0.007)	-	(0.025)	(0.014)	(0.007)	-
	[34.83]	[47.95]	[128.16]	-	[35.23]	[47.85]	[127.81]	-
Common factor	0.000	0.410	0.000	-	0.000	0.295	0.000	-
p-value: $\beta_{tk} + \beta_{ck} + \beta_l = 1$	0.068	0.000	0.000	0.589	0.038	0.000	0.000	0.270
Observations	3,067	3,067	3,067	2,674	3,067	3,067	3,067	2,674
Firms	369	369	369	362	369	369	369	362

Panel D. Banks with Technology Spending Reported in All Sample Years								
	Tech Capital - Perpetual Inventory Model				*Tech Capital - Linear Depreciation Schedule*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**DPD**	**FE**	**OLS**	**OP**	**DPD**	**FE**	**OLS**	**OP**
Technology Capital, t_t	0.054**	0.061***	0.052***	0.010	0.043**	0.049***	0.043***	0.014
	(0.021)	(0.017)	(0.015)	(0.092)	(0.019)	(0.015)	(0.013)	(0.086)
	[2.52]	[3.49]	[3.46]	[0.11]	[2.34]	[3.23]	[3.22]	[0.17]
Conventional Capital, k_t	0.392***	0.340***	0.391***	0.400***	0.391***	0.340***	0.391***	0.402***
	(0.045)	(0.022)	(0.022)	(0.072)	(0.045)	(0.022)	(0.022)	(0.078)
	[8.76]	[15.71]	[18.13]	[5.52]	[8.74]	[15.71]	[18.13]	[5.14]
Labor, l_t	0.524***	0.538***	0.522***	0.320***	0.526***	0.540***	0.524***	0.319***
	(0.059)	(0.025)	(0.024)	(0.065)	(0.059)	(0.025)	(0.024)	(0.068)
	[8.96]	[21.46]	[21.86]	[4.93]	[8.90]	[21.62]	[21.95]	[4.66]
ρ	0.904***	0.711***	0.920***		0.905***	0.711***	0.920***	
	(0.018)	(0.017)	(0.010)		(0.017)	(0.017)	(0.010)	
	[51.08]	[41.32]	[94.81]		[51.85]	[41.32]	[94.72]	
Common factor	0.008	0.029	0.000	-	0.011	0.060	0.000	-
p-value: $\beta_{tk} + \beta_{ck} + \beta_l = 1$	0.459	0.021	0.143	0.009	0.306	0.006	0.070	0.016
Observations	1,648	1,648	1,648	1,275	1,648	1,648	1,648	1,275
Firms	97	97	97	96	97	97	97	96

Panel E. Output as Net Interest Income + Non-Interest Income								
	Tech Capital - Perpetual Inventory Model				*Tech Capital - Linear Depreciation Schedule*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**DPD**	**FE**	**OLS**	**OP**	**DPD**	**FE**	**OLS**	**OP**
Technology Capital, t_t	0.056**	0.058***	0.074***	0.056**	0.052**	0.060***	0.067***	0.040**
	(0.024)	(0.012)	(0.009)	(0.024)	(0.022)	(0.011)	(0.008)	(0.017)
	[2.38]	[4.81]	[7.94]	[2.30]	[2.41]	[5.59]	[8.04]	[2.32]
Conventional Capital, k_t	0.320***	0.285***	0.327***	0.398***	0.321***	0.286***	0.328***	0.377***
	(0.023)	(0.014)	(0.014)	(0.032)	(0.022)	(0.014)	(0.014)	(0.030)
	[14.20]	[19.68]	[23.20]	[12.53]	[14.39]	[19.80]	[23.28]	[12.72]
Labor, l_t	0.678***	0.631***	0.632***	0.567***	0.674***	0.629***	0.634***	0.568***
	(0.027)	(0.015)	(0.014)	(0.022)	(0.027)	(0.015)	(0.014)	(0.021)
	[24.95]	[41.35]	[44.35]	[25.61]	[25.19]	[41.41]	[44.69]	[27.36]
ρ	0.494***	0.350***	0.725***		0.497***	0.351***	0.724***	
	(0.045)	(0.012)	(0.008)		(0.045)	(0.012)	(0.008)	
	[10.96]	[30.17]	[89.34]		[11.02]	[30.28]	[89.11]	
Common factor	0.000	0.000	0.000	-	0.000	0.000	0.000	-
p-value: $\beta_{tk} + \beta_{ck} + \beta_l = 1$	0.059	0.136	0.017	0.541	0.099	0.145	0.043	0.628
Observations	7,151	7,151	7,151	6,149	7,151	7,151	7,151	6,149
Firms	781	781	781	770	781	781	781	770

Table 9. Robustness Checks: Employment, Tasks and Technology Spending

This table reports the results from panel regressions where the dependent variables are residual employment or residual tasks and the independent variables are their previous-year residual technology spending as well as other firm characteristics. The coefficients on control variables are suppressed from reporting. The standard errors are reported in parentheses. *t*-statistics based on standard errors are in brackets. Significance at the 1%, 5% or 10% levels is shown with 3, 2, or 1 asterisks, respectively. Panel A keeps the sample in the post financial crisis period (2010-2017). Panel B drops too-big-to-fail banks from sample. Panel C keeps banks that are not involved with mergers and acquisitions activities (Non-M&A banks) in our sample during 2000-2017.Panel D keeps banks in our sample that recorded technology and communication expense in each year during 2000-2017.

Panel A. Employment and Technology Spending

	Post Financial Crisis Period (2010-2017)		*TBTF Banks Excluded*		*Non-M&A Banks*		*Banks with Technology Spending Reported in All Sample Years*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**Number of Employees**	**Staff Expense**	**Number of Employees**	**Staff Expense**	**Number of Employees**	**Staff Expense**	**Number of Employees**	**Staff Expense**
Tech Spending, *t-1*	0.174***	0.206***	0.183***	0.190***	0.210***	0.222***	0.195***	0.199***
	(0.030)	(0.029)	(0.023)	(0.021)	(0.043)	(0.038)	(0.034)	(0.028)
	[5.82]	[7.18]	[7.86]	[8.97]	[4.92]	[5.83]	[5.75]	[7.02]
Observations	2,585	2,947	5,393	5,899	2,242	2,588	1,394	1,455
Firms	490	543	687	722	326	353	94	94
R-squared	0.200	0.237	0.325	0.368	0.334	0.368	0.364	0.385
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Size *t* Effects	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B. Tasks and Technology Spending

	Post Financial Crisis Period (2010-2017)			*TBTF Banks Excluded*			*Non-M&A Banks*			*Banks with Technology Spending Reported in All Sample Years*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	**Loans & Deposits**	**Net Output**	**# of Branches**	**Loans & Deposits**	**Net Output**	**# of Branches**	**Loans & Deposits**	**Net Output**	**# of Branches**	**Loans & Deposits**	**Net Output**	**# of Branches**
Tech Spending, *t-1*	0.186***	0.201***	0.180***	0.121***	0.148***	0.182***	0.135***	0.165***	0.188***	0.120***	0.154***	0.175***
	(0.030)	(0.032)	(0.027)	(0.019)	(0.020)	(0.022)	(0.034)	(0.038)	(0.037)	(0.029)	(0.028)	(0.036)
	[6.20]	[6.33]	[6.75]	[6.43]	[7.21]	[8.10]	[3.97]	[4.38]	[5.02]	[4.20]	[5.44]	[4.91]
Observations	2,953	2,953	2,900	5,907	5,907	5,834	2,595	2,595	2,586	1,455	1,455	1,413
Firms	543	543	533	722	722	717	353	353	353	94	94	94
R-squared	0.209	0.211	0.191	0.333	0.295	0.311	0.339	0.301	0.333	0.335	0.297	0.303
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Size *t* Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

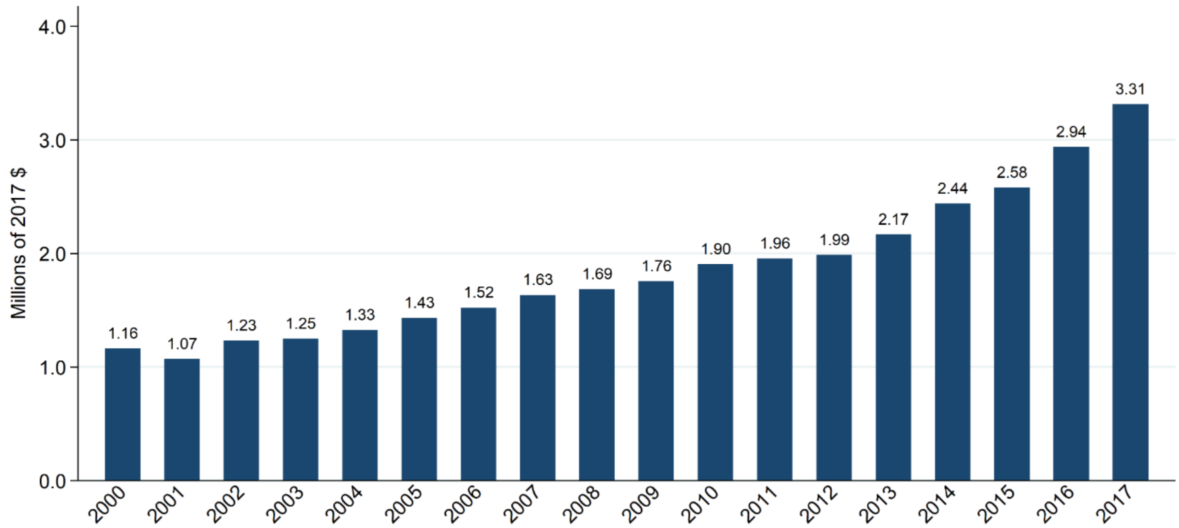


Figure 1. Technology Spending Trends

This figure illustrates the trends (medians) of technology and communication expense of banks in our sample during 2000-2017. Technology and communication expense is converted to 2017 dollars using the GDP deflator.

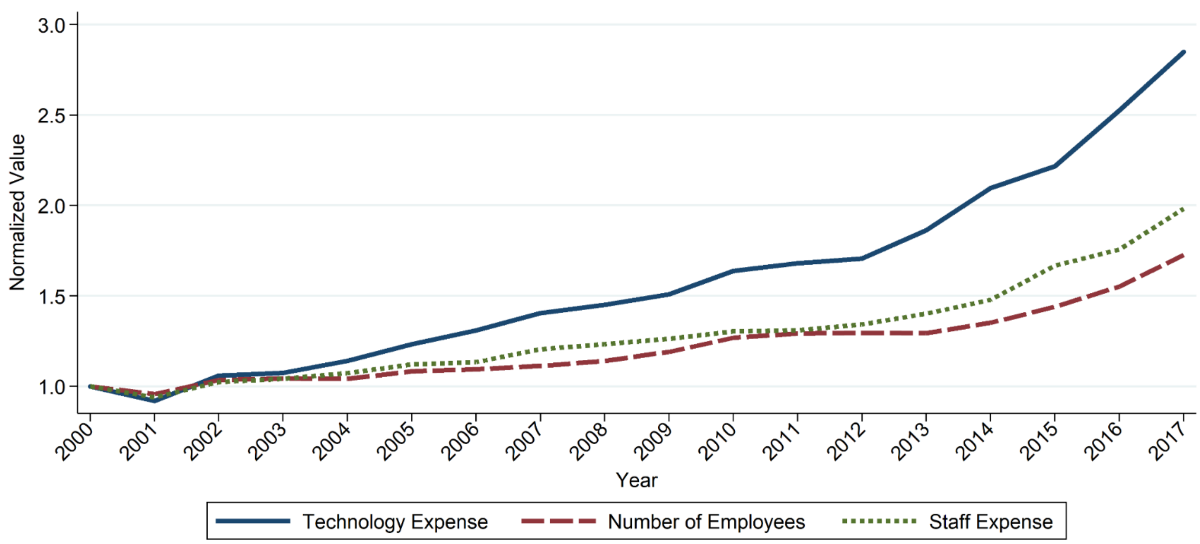


Figure 2. Employment and Technology Spending Over Time

This figure illustrates the evolution of the median of technology and communication expense, the number of employees and staff expense of banks in our sample during 2000-2017. All values are normalized to equal one in the year 2000. Monetary variables are converted to 2017 dollars using the GDP deflator.

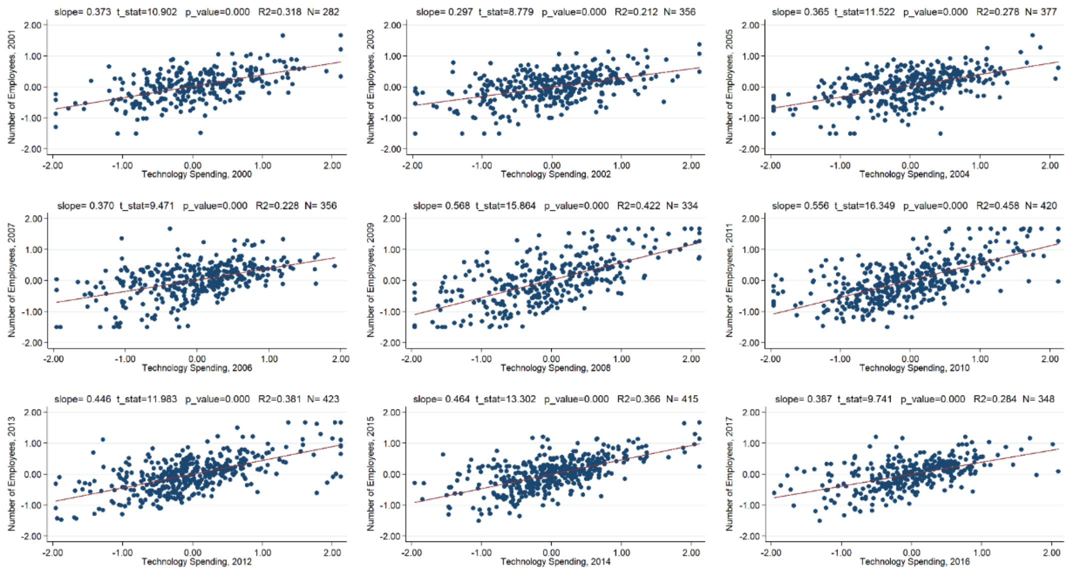


Figure 3. Number of Employees and Technology Spending in the Cross-Section

This figure plots residual number of employees on the vertical axis against residual technology spending on the horizontal axis for nine sample years. The *t*-statistics are calculated using HC3-robust standard errors with an adjustment to account for the degrees of freedom absorbed by computing residuals.

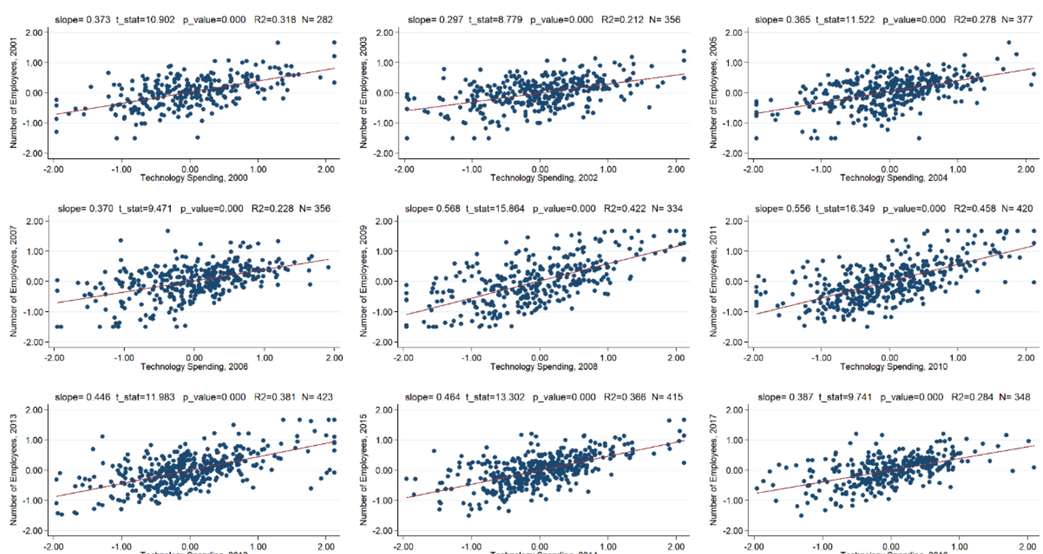


Figure 4. Staff Expense and Technology Spending in the Cross-Section

This figure plots residual staff expense on the vertical axis against residual technology spending on the horizontal axis for nine sample years. The *t*-statistics are calculated using HC3-robust standard errors with an adjustment to account for the degrees of freedom absorbed by computing residuals.

Appendix A1. Definition of Variables

Variable	Abb.	Definition
Technology and Communication Expense	Technology Expense or Technology Spending, or Tech Spending	Expenses paid for communications, data processing and technology such as computers, software, information systems and telecommunications, as defined by S&P Global Market Intelligence (SNL Financial). (SNL Keyfield: 132659, tech_comm_exp)
Net Output	Net Output	Net interest income (Compustat: niint)
Technology Capital	Technology capital	Technology capital is constructed using a perpetual inventory model with a depreciation rate of 35% or a four-year linear depreciation schedule.
Conventional Capital	Conventional capital	Total assets (Compustat: at) minus intangible assets (Compustat: intan) and technology capital
Labor	Labor	Staff expense (Compustat: xlr). It represents salaries, wages, pension costs, profit sharing and incentive compensation, payroll taxes, and other employee benefits.
Investment Expenditure	Investment	Capital expenditure (Compustat: capx) minus sale of property (Compustat: sppe). Sppe is set to zero if missing.
Number of Automatic Teller Machines	ATMs	The number of automatic teller machines operated. [SNL Keyfield: 131225, num_atms]
Residual	Res	Residuals obtained from the regression model: $Variable_{i,t} = \alpha + \beta_1 LnSize_{i,t} + \varepsilon_i$.Where $Variable$ are the natural log of technology and communication expense, employment measures, tasks measures, respectively, and $LnSize$ is the natural log of market capitalization at the end of the fiscal year.
Number of Employees	Number of Employees	The number of people employed by the company (Compustat: emp)
Staff Expense	Staff Expense	Staff expense of the company (Compustat: xlr)
Total Loans and Deposits	Loans and Deposits	The sum of total loans (Compustat: lntal) and total deposits (Compustat: dptc).
Number of Branches	Number of Branches	For banks and thrifts, the number of offices a company operates within the United States, updated for completed M&A activity. A branch/office is any location, or facility, of a financial institution, including its main office, where deposit accounts are opened, deposits are accepted, checks paid, and loans granted. A branch does not include Automated Teller Machines (ATM), Consumer Credit Offices, Contractual Offices, Customer Bank Communication Terminals (CBCT), Electronic Fund Transfer Units (EFTU), and Loan Production Offices. As a result, this figure may differ from what a company reports in its earnings releases or SEC filings. For Specialty Lenders, it is the number of retail branch offices. [SNL KeyField: 131227, total_numfices]
Firm Size	Firm Size	The natural log of market capitalization at the end of the fiscal year (Compustat: prcc_f*csho).
Market to Book	Market to Book	The ratio of the market capitalization of equity (Compustat: prcc_f*csho) to book value of equity (Compustat: ceq+txdb). txdb is set to zero if missing.
Leverage	Leverage	The ratio of total assets (Compustat: at) to book value of equity (Compustat: ceq+txdb). Txdb is set to zero if missing.
Return on Assets	ROA	Earnings before extraordinary items (Compustat: ib) plus depreciation and amortization (Compustat: dp) to total assets (Compustat: at).
Non-Interest Income	Non-Interest Income	The ratio of banks' Non-Interest Income (Compustat: tnii) to the sum of Net Interest Income (Compustat: niint) and Non-Interest Income (Compustat: tnii)
Tier 1 Capital Ratio	Tier 1 Capital Ratio	Risk-adjusted capital ratio – Tier1 (Compustat: capr1)
Rural banks	Rural Banks	Banks whose average urban deposit concentration in the bottom 30 percentiles. The urban deposit concentration of each bank is calculated as its deposits in the top 100 Metropolitan Statistical Area (MSA) in population divided by its total deposits.
Urban banks	Urban banks	Banks whose average urban deposit concentration in the top 70 percentiles. The urban deposit concentration of each bank is calculated as its deposits in the top 100 Metropolitan Statistical Area (MSA) in population divided by its total deposits.
Too-big-to-fail banks	TBTF Banks	Banks whose average gross total assets exceed \$50 billion in 2017 dollars. Gross total assets are the sum of total assets (Compustat: at) and provision for loan losses (Compustat: pclc). pclc is set to zero if missing.
No Mergers and Acquisitions Banks	Non-M&A Banks	Banks did not involve in mergers and acquisitions during the sample period of 2000-2017.

Appendix A2. Correlations of Residual Technology Spending and Residual Employment Measures

This table reports the correlations of residual technology spending and residual employment measures. Significance at the 1%, 5% or 10% levels is shown with 3, 2, or 1 asterisks, respectively.

Panel C. Residual Correlations						
Variables	**Residual Technology Spending**, *t*	**Residual Technology Spending**, *t-1*	**Residual Number of Employees**, *t*	**Residual Number of Employees**, *t-1*	**Residual Staff Expense**, *t*	**Residual Staff Expense**, *t-1*
Residual Technology Spending, *t*	1					
Residual Technology Spending, *t-1*	0.908***	1				
Residual Number of Employees, *t*	0.648***	0.579***	1			
Residual Number of Employees, *t-1*	0.584***	0.644***	0.900***	1		
Residual Staff Expense, *t*	0.672***	0.599***	0.898***	0.808***	1	
Residual Staff Expense, *t-1*	0.599***	0.671***	0.798***	0.897***	0.888***	1

Appendix A3. Residual Employment and Tasks

This table report results from cross-sectional regressions of bank employment and tasks, respectively, as the dependent variable on the natural log of their market capitalization (Firm Size) for four sample years, as well as a pooled panel regression with year fixed effects. The standard errors are reported in parentheses. *t*-statistics are in brackets. The standard errors are computing using HC3 robust standard errors for the four sample years and are clustered at the firm-level at the pooled panel regressions. Significance at the 1%, 5% or 10% levels is shown with 3, 2, or 1 asterisks, respectively.

Panel A. Employment and Firm Size

	Number of Employees					**Staff Expense**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	**2000**	**2005**	**2010**	**2015**	**Pooled**	**2000**	**2005**	**2010**	**2015**	**Pooled**
Firm Size	0.788***	0.858***	0.636***	0.764***	0.758***	0.818***	0.899***	0.684***	0.818***	0.799***
	(0.018)	(0.016)	(0.024)	(0.022)	(0.015)	(0.018)	(0.016)	(0.023)	(0.017)	(0.014)
	[44.21]	[53.40]	[26.73]	[35.14]	[50.95]	[45.09]	[56.34]	[30.10]	[48.33]	[55.90]
Constant	2.080***	1.229***	2.867***	1.743***	2.220***	-1.186***	-1.882***	-0.132	-1.121***	-1.097***
	(0.092)	(0.088)	(0.119)	(0.121)	(0.071)	(0.093)	(0.086)	(0.112)	(0.092)	(0.069)
	[22.57]	[13.97]	[24.09]	[14.40]	[31.04]	[-12.71]	[-21.86]	[-1.18]	[-12.18]	[-15.87]
Observations	277	404	438	425	7,052	300	425	474	499	7,744
Firms	277	404	438	425	747	300	425	474	499	780
R-squared	0.889	0.885	0.730	0.847	0.827	0.900	0.913	0.768	0.893	0.858
Year FE	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES

Panel B. Tasks and Firm Size

	Loans and Deposits					**Net Output**					**Number of Branches**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Variables	**2000**	**2005**	**2010**	**2015**	**Pooled**	**2000**	**2005**	**2010**	**2015**	**Pooled**	**2000**	**2005**	**2010**	**2015**	**Pooled**
Firm Size	0.800***	0.881***	0.665***	0.847***	0.793***	0.812***	0.895***	0.687***	0.834***	0.805***	0.655***	0.727***	0.554***	0.680***	0.657***
	(0.015)	(0.011)	(0.020)	(0.013)	(0.010)	(0.016)	(0.012)	(0.019)	(0.012)	(0.010)	(0.047)	(0.024)	(0.023)	(0.024)	(0.017)
	[52.10]	[80.21]	[33.10]	[65.76]	[75.74]	[50.08]	[75.53]	[36.62]	[67.57]	[78.02]	[14.08]	[29.82]	[23.60]	[28.69]	[39.31]
Constant	3.481***	2.821***	4.540***	3.326***	3.511***	-0.288***	-1.037***	0.660***	-0.481***	-0.257***	-0.247	-0.941***	0.499***	-0.564***	-0.255***
	(0.074)	(0.059)	(0.102)	(0.073)	(0.051)	(0.075)	(0.063)	(0.097)	(0.070)	(0.050)	(0.189)	(0.122)	(0.114)	(0.124)	(0.079)
	[47.23]	[47.44]	[44.43]	[45.43]	[68.44]	[-3.81]	[-16.46]	[6.84]	[-6.89]	[-5.18]	[-1.31]	[-7.69]	[4.39]	[-4.55]	[-3.22]
Observations	301	426	474	500	7,758	301	426	474	500	7,757	283	417	468	489	7,579
Firms	301	426	474	500	780	301	426	474	500	780	283	417	468	489	775
R-squared	0.929	0.950	0.782	0.941	0.893	0.937	0.955	0.807	0.939	0.902	0.686	0.724	0.605	0.695	0.686
Year FE	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES

Appendix A4. Employment and Technology Spending - Firm Size Based on Total Assets

Panel A report results from cross-sectional regressions of the natural log of technology and communication expense of banks as the dependent variable on the natural log of their total assets (Firm Size) for four sample years, as well as a pooled panel regression with year fixed effects. The standard errors are computing using HC3 robust standard errors for the first four columns and are clustered at the firm-level at the last column. The standard errors are reported in parentheses. *t*-statistics based on standard errors are in brackets. Panel B reports the results from panel regressions where the dependent variables are residual of bank employment and the independent variables are their previous-year residual technology spending as well as other firm characteristics. The coefficients on variables of years are suppressed from reporting. The standard errors are clustered at the firm-level and reported in parentheses. *t*-statistics based on robust standard errors are in brackets.

Panel A. Technology Spending and Firm Size

	(1)	(2)	(3)	(4)	(5)
Variables	**2000**	**2005**	**2010**	**2015**	**Pooled**
Firm Size	0.828***	0.855***	0.658***	0.782***	0.767***
	(0.027)	(0.027)	(0.029)	(0.024)	(0.022)
	[31.10]	[31.52]	[22.35]	[32.26]	[35.14]
Constant	-3.576***	-4.035***	-2.213***	-3.053***	-3.294***
	(0.126)	(0.140)	(0.138)	(0.130)	(0.097)
	[-28.28]	[-28.91]	[-16.03]	[-23.41]	[-34.13]
Observations	301	426	474	500	7,758
Firms	301	426	474	500	780
R-squared	0.818	0.800	0.655	0.777	0.760
Year FE	NO	NO	NO	NO	YES

Panel B. Firm Size Employment and Technology Spending

	(1)	(2)	(3)	(4)
Variables	**Number of Employees**	**Staff Expense**	**Number of Employees**	**Staff Expense**
Technology Spending, *t-1*	0.124***	0.123***	0.109***	0.110***
	(0.017)	(0.014)	(0.018)	(0.015)
	[7.32]	[8.85]	[5.95]	[7.36]
Market to Book, *t-1*			-0.008	-0.006
			(0.009)	(0.009)
			[-0.83]	[-0.61]
Leverage, *t-1*			-0.002	-0.001
			(0.002)	(0.002)
			[-0.83]	[-0.66]
Return on Assets, *t-1*			-1.647***	-1.859***
			(0.436)	(0.471)
			[-3.78]	[-3.95]
Non-Interest Income, *t-1*			0.592***	0.623***
			(0.086)	(0.085)
			[6.85]	[7.31]
Tier 1 Capital Ratio, *t-1*			0.060	0.272
			(0.212)	(0.194)
			[0.28]	[1.40]
Constant	-0.004	0.002	-0.072	-0.097**
	(0.014)	(0.013)	(0.051)	(0.043)
	[-0.27]	[0.13]	[-1.40]	[-2.26]
Observations	6,526	7,162	5,573	6,084
Firms	745	781	708	743
R-squared	0.069	0.064	0.135	0.141
Size *t* Effects	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Appendix A5. Employment and Technology Spending – Firm Size Based on Total Loans and Deposits

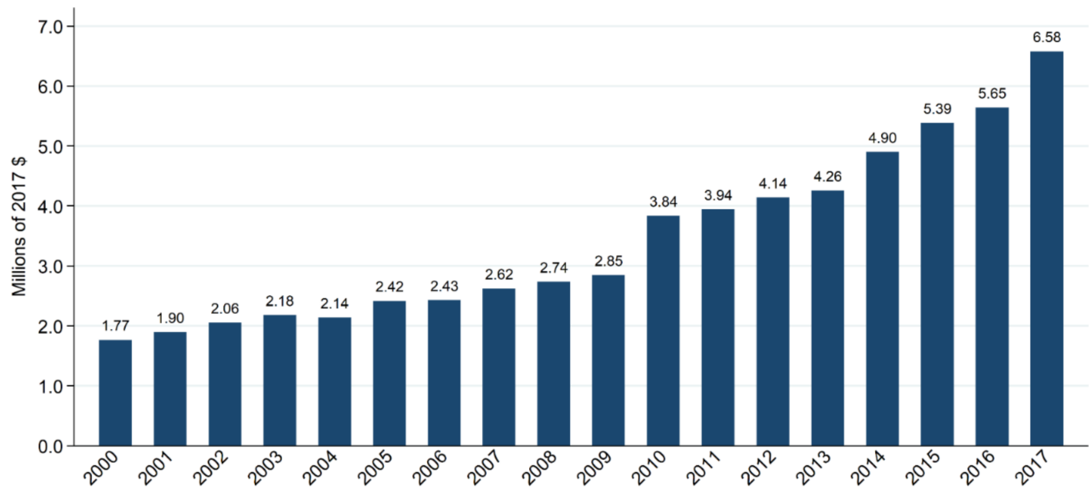
Panel A report results from cross-sectional regressions of the natural log of technology and communication expense of banks as the dependent variable on the natural log of their total loans and deposits (Firm Size) for four sample years, as well as a pooled panel regression with year fixed effects. The standard errors are computing using HC3 robust standard errors for the first four columns and are clustered at the firm-level at the last column. The standard errors are reported in parentheses. *t*-statistics based on standard errors are in brackets. Panel B reports the results from panel regressions where the dependent variables are residual of bank employment and the independent variables are their previous-year residual technology spending as well as other firm characteristics. The coefficients on variables of years are suppressed from reporting. The standard errors are clustered at the firm-level and reported in parentheses. *t*-statistics based on robust standard errors are in brackets.

Panel A. Technology Spending and Firm Size

	(1)	(2)	(3)	(4)	(5)
Variables	**2000**	**2005**	**2010**	**2015**	**Pooled**
Firm Size	1.029***	0.966***	0.988***	0.930***	0.963***
	(0.023)	(0.026)	(0.023)	(0.023)	(0.019)
	[45.57]	[36.98]	[43.23]	[41.19]	[49.52]
Constant	-7.131***	-6.739***	-6.701***	-6.173***	-6.657***
	(0.157)	(0.186)	(0.170)	(0.175)	(0.130)
	[-45.32]	[-36.22]	[-39.39]	[-35.31]	[-51.27]
Observations	318	447	491	500	8,030
Firms	318	447	491	500	781
R-squared	0.881	0.835	0.834	0.837	0.845
Year FE	NO	NO	NO	NO	YES

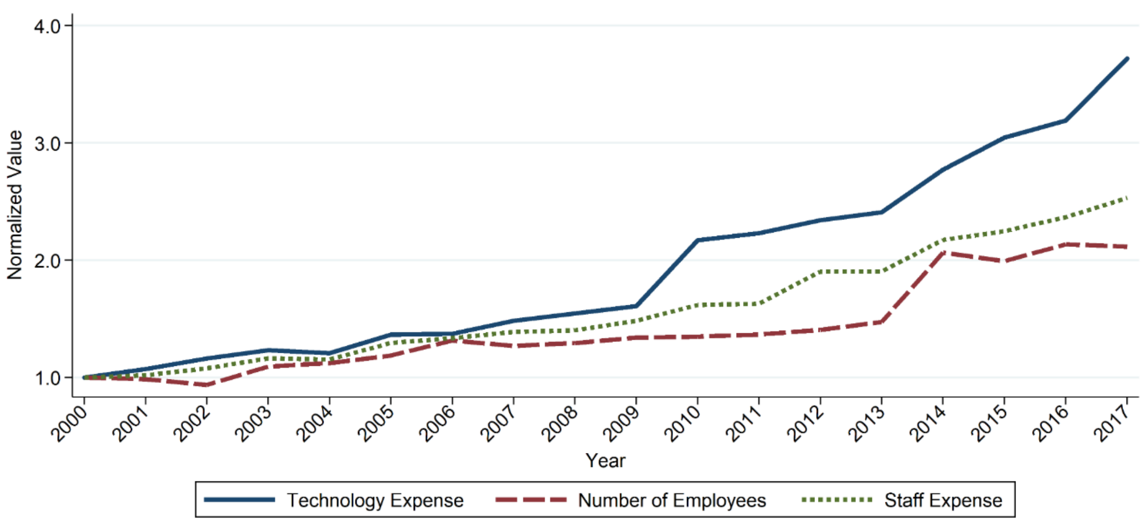
Panel B. Firm Size Employment and Technology Spending

	(1)	(2)	(3)	(4)
Variables	**Number of Employees**	**Staff Expense**	**Number of Employees**	**Staff Expense**
Technology Spending, *t-1*	0.134***	0.136***	0.110***	0.112***
	(0.016)	(0.014)	(0.016)	(0.014)
	[8.36]	[9.82]	[6.69]	[8.04]
Market to Book, *t-1*			-0.010	-0.014
			(0.009)	(0.009)
			[-1.04]	[-1.58]
Leverage, *t-1*			0.000	0.001
			(0.001)	(0.001)
			[0.18]	[0.59]
Return on Assets, *t-1*			-2.073***	-2.216***
			(0.478)	(0.505)
			[-4.34]	[-4.39]
Non-Interest Income, *t-1*			0.699***	0.749***
			(0.088)	(0.089)
			[7.90]	[8.38]
Tier 1 Capital Ratio, *t-1*			0.614***	0.850***
			(0.178)	(0.175)
			[3.45]	[4.84]
Constant	-0.012	-0.009	-0.177***	-0.203***
	(0.014)	(0.014)	(0.038)	(0.035)
	[-0.83]	[-0.66]	[-4.72]	[-5.73]
Observations	6,526	7,162	5,573	6,084
Firms	745	781	708	743
R-squared	0.076	0.069	0.167	0.180
Size *t* Effects	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES



Appendix B1. Technology Spending Trends

This figure illustrates the trends (medians) of technology and communication expense of banks in our sample that recorded technology and communication expense in each year during 2000-2017. There is a total of 97 firms. Technology and communication expense is converted to 2017 dollars using the GDP deflator.



Appendix B2. Employment and Technology Spending Over Time

This figure illustrates the evolution of the median of technology and communication expense, the number of employees and staff expense of banks in our sample that recorded technology and communication expense in each year during 2000-2017. There is a total of 97 firms. All values are normalized to equal one in the year 2000. Monetary variables are converted to 2017 dollars using the GDP deflator.