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# Is cloud computing the digital solution to the future of banking?

Maoyong Cheng[a], Yang Qu[a], Chunxia Jiang[b,*], Chenchen Zhao[b]

[a] School of Economics and Finance, Xi'an Jiaotong University, Xi'an, China
[b] University of Aberdeen, Business School, Aberdeen AB24 3QY, UK

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ABSTRACT

This study investigates the impact of banks' strategic move to cloud computing on bank performance and risk-taking. Based on a novel index of banks' exposure to cloud computing, we find that banks' adoption of cloud computing is associated with lower cost efficiency, higher profit efficiency, and greater operational risk using data on Chinese banks over the period 2008–2019. We also find that cloud computing interacts with other newly emerging technologies, leading to synergy gains in cost efficiency and operational risk control but with a substitutive effect on profit efficiency from blockchain. The findings are of timely policy importance and practical relevance for regulators, policy-makers, and bank managers.

## 1. Introduction

Banks face constant challenges on several fronts, such as daunting data handling and storage that consume massive resources, weak cybersecurity that undermines the ability to protect key customer data, and strong competition from high-tech giants that offer more appealing customer experiences. In 2018, approximately 14% of retail and commercial banking revenues were taken by cloud and agile technology-based new entrants.[1]

Cloud computing offers an unrivaled level of agility, security, and scalability and significantly increases data handling capacity.[2] Banks have turned to cloud computing not only for cheaper and quicker solutions to the challenges they face but also for business transformation—a potential game changer to their modernization strategy. Across the global financial services industry, financial institutions started their cloud technology journey approximately five years ago. Deloitte Global reports a threefold increase in the number of financial institutions that adopted cloud computing between 2016 and 2018. Some banks have moved heavily into cloud computing. For instance, Barclays uses Salesforce to streamline mortgage processing, and Capital One takes advantage of Amazon Web Services for faster development of new applications.

The tremendous acceleration of cloud computing applications in banking is expected to have significant implications for banks' business efficiency and operational control (i.e., system security and fraud detection); however, little research has empirically examined these impacts. This paper attempts to fill this gap by providing the first evidence on the following fundamental question: How does banks' strategic move toward cloud computing affect bank efficiency and banks' control over their operational risk?

We conduct the research in the context of the world's largest banking system – the Chinese banking sector – which offers an ideal setting for answering the abovementioned research question.[3] The Chinese government has made considerable efforts in technological upgrading over the past decade. "Internet Plus" was launched in November 2012 as an integral part of the national strategy, in which cloud computing plays a pivotal role.[4] "Internet Plus" combines the internet and traditional industries, i.e., FinTech, which uses technology to enhance financial

* Corresponding author.
*E-mail addresses:* mcheng.1986@mail.xjtu.edu.cn (M. Cheng), quyang@stu.xjtu.edu.cn (Y. Qu), chunxia.jiang@abdn.ac.uk (C. Jiang), c.zhao.20@abdn.ac.uk (C. Zhao).

[1] https://www.accenture.com/_acnmedia/pdf-85/accenture-technology-advisory-cloud-readiness-banking.pdf.

[2] The cloud services include SaaS (Software as a service) to deliver software applications on subscription basis, IaaS (Infrastructure as a service) to provide IT infrastructure, data storage, operating systems with IP connectivity, and PaaS (Platform as a service) to provide on-demand environment for developing, delivering, and managing applications.

[3] https://www.ft.com/content/14f929de-ffc5–11e6–96f8–3700c5664d30.

[4] The State Council issued the "Opinions of the State Council on Promoting the Innovative Development of Cloud Computing and Cultivating New Formats of the Information Industry" in January 2015 and the "Three-year Plan for Cloud Computing Development" in March 2017.

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services. Commercial banks are eager to gain a competitive edge by embracing new technologies. According to a survey by the China Academy of Information and Communications Technology in 2018, 41% of 391 surveyed financial institutions have applied cloud computing, and 47% have plans to do so (www.caict.ac.cn).

As a preview, we find that the application of cloud computing in banking is associated with lower cost efficiency, higher profit efficiency, and greater operational risk in China over the period 2008–2019. We also find that cloud computing interacts with other newly emerging technologies, leading to synergy gains in cost efficiency and operational risk control but producing a substitutive effect on profit efficiency from blockchain. Our results are robust to alternative model specifications, measurements, estimation techniques, and subsamples. The findings from this research have important policy implications and are of practical relevance by providing useful information for regulators and policy-makers to formulate industrial policy on cloud computing and for bank managers to control operational risk.

This study contributes to the literature in three ways. *First,* it extends the sparse literature on cloud computing. Existing research on cloud computing mainly relates to patents, technical characteristics, and application platforms (Velte et al., 2009; Mell and Grance, 2011; Mahmud et al., 2020). As a new research field, one challenge is the paucity of data and systematic measures of cloud computing applications in banking. Following the literature (John and Li, 2021; Hou et al., 2016), we apply text-based filtering methods to a large amount of unstructured data obtained from web crawler technology and construct a novel index to measure the strength of banks' strategic move to cloud computing. This allows us to empirically examine the impact of cloud computing in banking. *Second*, this study extends the bank efficiency literature from a new technological perspective. Research on bank efficiency is extensive (e.g., Berger et al., 2009; Barth et al., 2013; Peng et al., 2017; Shamshur and Weill, 2019; Mutarindwa et al., 2021), while little research examines the impact of cloud computing. *Third*, this study enriches the literature on bank operational risk. Due to the unique nature of operational risk, it is challenging to accurately estimate bank operational risk, resulting in a scarcity of related empirical research. We employ a new indicator proposed by the Basel Committee on Banking Supervision (BCBS) in 2017 and provide empirical evidence on the impact of cloud computing on bank operational risk.

The paper proceeds as follows. Section 2 reviews the literature and develops hypotheses. Section 3 outlines the sample and estimation strategy. Section 4 analyzes the empirical results. Section 5 presents a battery of robustness tests. Section 6 extends the analysis to the interaction between cloud computing and other newly emerging technologies. Section 7 concludes.

## 2. Literature review and hypothesis development

### *2.1. Cloud computing in the banking industry*

Cloud computing has emerged since the 1960s for the management of virtual data resources. However, not until the early 21st century was it popularized when Amazon Web Services was launched in 2006, followed by IBM's enterprise cloud solutions in 2007, Google's App Engine in 2008, Alibaba Cloud in 2009, and Microsoft's Azure in 2010. The global market value of cloud computing has grown by more than 20% per year since 2014, reaching more than $100 billion in 2019[5] and is projected to reach $266 billion in 2020.[6] The banking sector has been slow in adopting new technologies due to concerns over reliability and regulatory issues. As Amazon demonstrated, hundreds of millions of customers operate safely online simultaneously, and financial sector regulators worldwide have welcomed cloud computing.

Cloud computing opens a new frontier to banks with applications such as hosting servers, payment gateways, enterprise resource planning, and customer relationships. Cloud computing elevates how banks function; for example, it provides banks with a multichannel relationship with customers at many different levels to maintain and improve customer service. Depending on the needs for performance, security, compliance, and costs, banks can choose from different types of cloud computing, namely, public clouds, private clouds, hybrid clouds, and industry clouds.[7] Large banks usually use hybrid cloud solutions. While taking advantage of the public cloud's numerous benefits in terms of costs and deployment, they maintain controls on critical business in the private cloud. In the past five years, cloud computing has been widely adopted in the financial services industry for noncore activities, i.e., 88% of banks in Europe, 100% of large banks and more than 80% of tier 1 regional banks in Japan, and more than 90% of mega banks and joint-stock commercial banks in China (SandP Global, 2021).

There are also challenges for banks to move to cloud computing at a full scale. First, security and privacy issues related to the control of data locality and compliance with customer-privacy laws, such as the General Data Protection Regulation and data back-ups. These issues are particularly relevant to small and regional banks that do not use top leading cloud providers. Second, associated cyber risks could include fraud, hacks, and data breaches. Third, it can be challenging to comply with different regulatory frameworks, requirements, and guidelines. Finally, systemic risks become high if the global banking sector relies on a few mainly US-based providers that dominate the highly concentrated cloud computing market (SandP Global, 2021).

Cloud computing has experienced rapid development in the Chinese banking industry. Motivated by the national "Internet Plus" strategy and competition from financial services provided by tech giants (i.e., WeChat Pay and Alipay), Chinese banks embraced cloud computing as their new development strategy. Cloud computing has been employed to offer a wide range of services, including infrastructure services, platform services, business services, and communication channel services.[8] The top state-controlled banks lead the race to adopt emerging new technologies.[9]

Despite challenges and concerns, banks have begun to move toward cloud computing within different jurisdictions. Cloud products and systems have sprung up, which has effectively changed the structure and business of traditional banking. The application of cloud computing

[5] https://www.gartner.com/en.

[6] https://www.fintechfutures.com/files/2020/03/Cloud_Transformation_in_Banking_The-_2020_State_of_Play_V6.pdf.

[7] A public cloud is provided by a third-party service provider that makes computing resources available to users over the public internet, including a wide range of services from ready-to-use software applications, to individual virtual machines (VMs), and to complete enterprise-grade infrastructures and development platforms. The private cloud refers to cloud infrastructure operated exclusively for the client company that has private, isolated access to the infrastructure. It is typically hosted on the premises, but it can also be hosted on dedicated cloud provider or third-party infrastructure. It provides client greater controls over resources, data security, and regulatory compliance. The hybrid cloud combines private cloud and public cloud, allowing a client to move workloads seamlessly between them to optimize performance, security, compliance at low costs. The industry cloud is a customized system to fit a specific industry and accommodate the business, operational, legal, regulatory, security, and other considerations. The focus is vertical integration solutions (https://www.ibm.com/cloud/learn/public-cloud).

[8] Infrastructure services include servers, storage, and networking, especially inside and outside services for banks' data center. A data center is the core technology department responsible for the production and operation of all financial data, data management and transaction monitoring.

[9] For example, the China Construction Bank advanced a FinTech strategy and started to provide cloud services to its peers from the second half of 2018. The Industrial and Commercial Bank of China has become the industry leader in providing platform services with independently developed visual management of network resources. In 2017, the Bank of China and Tencent Technology Company began to cooperate.

helps banks upgrade their outdated risk management practices and optimize diversification and operational efficiency. At present, cloud computing in banking is mainly for noncritical activities, and banks are at a trial phase for more critical functions involving personally sensitive data and the development of transformational cloud infrastructure and strategy. This study is motivated by both the rapid initial development and future prospects of cloud computing in banking.

### 2.2. Research on bank efficiency

The literature on bank efficiency is extensive, and existing research mainly explains the variations in bank efficiency in terms of the macroeconomic environment, industrial market conditions, and bank characteristics. Bank efficiency can be affected by the macroeconomic environment. For instance, Sturm and Williams (2010) find that a favorable macroeconomic environment (i.e., high GDP growth) tends to lead to a more efficient banking industry. Chortareas et al. (2012) and Barth et al. (2013) argue that a more restrictive regulatory environment can reduce bank cost and profit efficiency, while Ayadi et al. (2016) find that compliance with regulations (i.e., the Basel Core Principles for Effective Bank Supervision) has no significant impact on bank efficiency.

Industrial market conditions can exert strong influences on bank efficiency, especially market competitive conditions. Yildirim and Philippatos (2007) investigate commercial banks in Latin America, reporting improved efficiency under a higher degree of competition. Duygun et al. (2013) indicate an important role of the Schumpeterian competition model in affecting the relationship between efficiency and competition, and the net impact of intensified competition through innovation in the banking sector is negative. Peng et al. (2017) find evidence for economies of scope that diversification into the insurance industry improves bank efficiency.

There is voluminous research focusing on how bank efficiency varies with bank-specific characteristics, such as size, risk-taking, product diversification, cultural background, and ownership structure. In general, banks tend to be more efficient if they are small (Berger et al., 2005), take a lower level of risks (Fiordelisi et al., 2011), have a high level of product diversification (Saghi-Zedek, 2016), and if their chairmen and CEOs share similar cultural characteristics (Bian et al., 2019). Ownership structure has been a popular topic in banking efficiency studies, which mainly discuss whether state-owned banks or foreign banks are more efficient, and empirical results are mixed (Bonin et al., 2005; Berger et al., 2009; Shaban and James, 2018).

Technological advancement is the key driving factor of productivity and efficiency. Despite increasingly pervasive applications of new emerging technologies, their impact on bank productivity and efficiency is under-researched. This study attempts to fill this gap by examining the impact of cloud computing on bank cost and profit efficiency.

### 2.3. Research on bank operational risk

Banks, with complex operational businesses dealing with money, constantly face a wide range of operational risks “from inadequate or failed internal processes, people and systems or from external events” (BCBS, 2006). Operational risk is one of the three main risks requiring a bank’s dedicated equity capital against the consequences of risk events under the Basel capital accord. However, due to the unique nature (i.e., pure losses, no risk-return trade-off) and complexity (a wide range of causes) of operational risk, it has received much less academic attention than the other two main bank risks—credit and market risk.

Early research focused on characterizing and quantifying operational risk. Building on the corporate finance literature framework, operational risk is divided into the risk of a loss due to operating technology or agency costs (Jarrow, 2008). Chavez-Demoulin et al. (2006) propose probability and statistical techniques for quantitatively analyzing some operational loss data. This effort continues with the proposal of a single nonmodel-based method for quantifying bank operational risk to calculate capital requirements by the Basel Committee on Banking Supervision in December 2017.

More recent studies primarily focus on the contributing factors of operational risk events and the determinants of operational risk. In terms of macroeconomic conditions and regulatory characteristics, Aldasoro et al. (2020) find that operational losses are larger after credit booms and excessively accommodative monetary policy but smaller under better supervision. Abdymomunov et al. (2020) find that banks suffer from greater operational losses in adverse macroeconomic conditions, which are largely driven by high frequency and severity tail events. The operational risk of larger and more leveraged banks is more sensitive to macroeconomic conditions. Operational risk is also found to be strongly linked with firm-specific covariates. Using data on US financial institutions, Chernobai et al. (2021) find that firms face higher operational risk if they are younger, more complex, take greater credit risk and financial distress risk and if their CEOs have higher stock option holdings and bonuses relative to salary. Size also matters, as reported in Curti et al. (2020); the largest banks are exposed to a higher level of operational risk among large U.S. bank holding companies.

Another strand of literature addresses the consequences of operational risk, for instance, posing threats to financial stability. Berger et al. (2017) find a statistically and economically significant positive link between operational risk and bank systemic risk at large US bank-holding companies. Operational losses affect bank returns (Gillet et al., 2010; Cummins et al., 2006), consuming approximately 18% of financial institutions’ returns (Allen and Bali, 2007). The market reacts negatively and faster to operational loss announcements caused by internal fraud (Biell and Muller, 2013). Köster and Pelster (2017) investigate the impact of financial penalties due to bank misconduct, reporting a negative relation with pretax profitability but a positive relation with buy-and-hold returns.

Current research has gained some insights into the measurement, determinants, and impact of operational risk. To the best of our knowledge, there is very limited research that sheds light on the impact of the growing application of new technologies on operational risk. This omission is important in the literature, and this study attempts to fill this gap.

### 2.4. Hypotheses

Cost savings are considered one of the three key drivers of banks’ adoption of cloud-based services, as identified by the British Bankers’ Association (Springfield, 2018). First, banks may cut costs from the scalability of cloud computing and pay for what they use at the time the services are needed. Cloud computing assumes a pay-as-you-use billing model, and users only pay for the services they consume. This will promote more efficient capacity management to meet customer demand during peak periods while mitigating idle waste when data handling pressure is low. Second, banks may lower costs through economies of scale. Cloud computing completely reforms the traditional method of customer data management. It enables banks to process massive unstructured data from transactions and related records, which would otherwise result in huge personnel/labor costs to deal with business data to serve their customers. Third, banks may lower the costs associated with asymmetric information problems, i.e., borrowing screening costs. Cloud computing may equip banks with an information advantage at different levels and facilitate better business decisions at low costs.

On the other hand, banks’ switching to cloud computing can be costly, especially at the initial transition stage. Although it is argued that the adoption of public-based cloud services can save banks’ initial capital expenditure required for traditional IT infrastructure, such savings are not available for most banks, as banks’ operations have already, if not completely, heavily relied on traditional IT infrastructure. In fact, cloud computing involves infrastructures, such as the software-defined network, to manage cloud connections and distributed file systems (e.g., Hadoop), requiring a large amount of direct and indirect investment.

Moreover, the application of cloud computing also requires new management architectures/systems, such as the Service-Oriented Architecture (SOA) and Business Process Management (BPM) systems.[10] These new management paradigms require staff training, and training costs, perhaps ongoing, that can be substantial. Once (partially) moving onto cloud computing, banks also incur daily operating costs, such as the maintenance costs of the cloud computing data storage center and the security costs of the virtual local area network. Therefore, the impact of cloud computing on bank cost efficiency depends on whether cost savings outweigh the switching costs. As such, we formulate two competing hypotheses: *Cloud computing improves bank cost efficiency (Hypothesis 1a)* versus *Cloud computing worsens bank cost efficiency (Hypothesis 1b)*.

The application of cloud computing can have profound influences on bank profit efficiency. First, cloud computing equips banks with the capacity to offer a wider range of products and services, thereby benefiting from business diversification and the economy of scope. Research generally suggests that diversification improves profits (Stiroh and Rumble, 2006; Elsas et al., 2010; Sanya and Wolfe, 2011). Cloud computing, in addition to the provision of service platforms for traditional businesses, can also host advanced asset management software or applications to optimize performance. Second, a key potential benefit of cloud computing is the agility to innovate (SandP Global, 2021). Cloud computing enhances banks' ability to take advantage of emerging technologies (i.e., artificial intelligence, blockchain) to better capture business opportunities and boost revenue. This can speed up banks' expansion into new (global) markets. For instance, based on aggregated and intelligent analyses of supply chain information via cloud computing, banks can innovatively provide supply chain finance that coordinates and serves enterprises from upstream to downstream.

However, the rosy impact of cloud computing on profit efficiency can be complicated by the potential costs involved in the adoption of cloud computing. As mentioned above, it is unclear whether cloud computing leads to cost savings or higher expenditures. A report by Tencent Cloud shows a potential negative impact of cloud computing on corporate profitability due to the huge costs associated with the development of FinTech.[11] The short-term capital expenditure for the construction of supporting infrastructure of cloud computing can be tremendous, which may erode the profit efficiency. Moreover, cloud computing technology inherently has a life cycle— the investment, exploration, application, and re-improvement stages of emerging technologies. The payoff profile of each stage can vary significantly. Thus, the real impact of the adoption of cloud computing on profit efficiency becomes an empirical issue. As such, we formulate our second competing hypotheses: *Cloud computing improves bank profit efficiency (Hypothesis 2a)* versus *Cloud computing worsens bank profit efficiency (Hypothesis 2b)*.

The application of cloud computing has significant implications for banks' operational risk. Losses attributable to operational risk are related to the malfunction or breakdown of technology or support systems, including employee fraud or errors (Jarrow, 2008). Most operational losses among U.S. financial institutions from 1980 to 2005 can be traced to the breakdown of internal controls (Chernobai et al., 2021). The risk of cyberattacks, a subcomponent of operational risk, has emerged as a key threat to bank security (i.e., data breaches, fraud, and business disruption) (Kopp et al., 2017). While cyberattacks only cause a small fraction of banks' total operational losses, they account for a significant share of the total operational value-at-risk (Aldasoro et al., 2020).

Theoretically, the cloud infrastructure is more reliable, with better system security, privacy, and resiliency. Cloud computing may reduce the risk of system outages, enhance banks' control over system security and stability, and strengthen banks' internal control. With informational advantages, banks should perform better trade data surveillance to detect anti-money laundering and other fraud issues and better analyze data to identify risks and design more appropriate risk management strategies. However, in practice, the application of cloud computing introduces new systems, such as distributed file systems and business process management systems. This significantly increases the complexity of system management, which can be very challenging for banks, especially for small banks. Therefore, the application of cloud computing may lead to more operational errors and increase bank operational risk. Once again, it becomes an empirical issue whether cloud computing will increase or decrease operational risk, which largely depends on banks' ability to manage more advanced but complex systems. As such, we put forward our third competing hypotheses: *Cloud computing reduces bank operational risk exposure (Hypothesis 3a)* versus *Cloud computing increases bank operational risk exposure (Hypothesis 3b)*.

## 3. Methodology and sample

### 3.1. Cloud computing index

Due to the lack of data, the main challenge of studying the impact of newly emerging technologies is to quantify their application. Researchers have employed text-based filtering methods to exploit rich textual data and examine their implications in financial markets and banking. Recent studies have examined the impact of linguistic features on crowdfunding success (Rama et al., 2022), the effect of different types of COVID-19 information on price dynamics in stock markets (John and Li, 2021), the impact of internet finance development on banking (Hou et al., 2016), and the effect of bank FinTech on credit risk (Cheng and Qu, 2020). Extant research usually adopts crawler technology and a text analysis framework to quantify the development trend of newly emerging technologies. A large amount of unstructured data is obtained from the internet by a web crawler and then transformed into standard structured data with the help of text analysis. Inspired by this strand of research, we construct a novel index to measure the strength of banks' strategic move toward cloud computing at the bank-year level. We first generate related word frequency based on fuzzy search results to determine keywords related to the bank's cloud computing strategy (as shown in Table A1). Then, we logically combine cloud computing keywords, bank names, and years to perform a more precise search, which yields a textual database containing all related search results. Finally, by performing frequency statistics and panel factor analysis on the textual data database, we obtain a standardized index database. The larger the index value is, the greater the amount of network news containing defined keywords related to cloud computing, and hence the stronger the bank's intention to move to cloud computing.

Our text mining method has two innovative improvements. *First*, we obtain keywords related to cloud computing based on the word clouds from the fuzzy search results to enhance the technicality of our keyword setting method. The commonly used direct keyword setting method (e.g., Hou et al., 2016; Cheng and Qu, 2020) may lead to the loss of key information and undermine the rationality of the index. Using fuzzy search and related word frequency may help us intuitively understand the topics and know where relevant disclosures are, thereby setting better keywords. *Second*, we directly crawl search results from China's most popular search engine, the Baidu search engine (www.baidu.com), instead of reports on specific media websites. This helps overcome the limitations of reporting sources, reduces the probability of crawlers' bugs when opening specific websites, and avoids the inconsistency of streaming media information processing. Appendix A provides more details and shows how our textual data are constructed using a

[10] Service-Oriented Architecture is about how to use service interfaces to reuse software components where service interfaces based on common communication standards can be rapidly incorporated into new applications when needed without deep integration. BPM can help banks to automate standards procedures and processes and make necessary changes in business rules and processes without affecting other applications.

[11] https://cloud.tencent.com/developer.

**Table 1**
Estimation results of efficiency frontier.

| | |
|---|---|
| Panel A: The cost frontier | |
| Lambda ($\lambda \equiv \sigma_u/\sigma_v$) | 1.067*** |
| Log pseudo likelihood | 2514.716 |
| Mean cost efficiency | 0.983 |
| No. Observation | 1054 |
| Panel B: The profit frontier | |
| Lambda ($\lambda \equiv \sigma_u/\sigma_v$) | 2.01E+09 |
| Log pseudo likelihood | 186.768 |
| Mean profit efficiency | 0.781 |
| No. Observation | 1054 |

$$ln(TC_{it} or \quad TP_{it}) = \alpha + \sum_{j=1}^{3}\beta_i ln\left(y_{j,it}\right) + \sum_{m=1}^{3}\psi_m ln(w_{m,it}) \text{ -}$$
$$+\frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3}\beta_{jk}\times ln(y_{it})ln(y_{kt}) + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{3}\psi_{mn}\times ln(w_{m,it})ln(w_{n,it}) \text{ -}$$
$$+\sum_{j=1}^{3}\sum_{m=1}^{3}\varpi_{jm}ln\left(y_{j,it}\right)ln(w_{m,it}) + \tau_1 t + \tau_2 t^2 + \upsilon_{it} + u_{it} \quad (1)$$

This table reports estimated parameters and mean efficiency from the above equation for the cost frontier in Panel A and the alternative profit frontier in Panel B employing the true fixed effect SFA model (Greene, 2005a, 2005b). TC/TP is total costs/total profit; $y_i$ indicates three outputs – net loans ($y_1$), other earning assets ($y_2$), and non-interest income ($y_3$); $w_k$ indicates three input prices – the price of fund ($w_1$), the price of labor ($w_2$), and the price of capital ($w_3$); t is a time trend; $\upsilon_{it}$ are identical and independently distributed random errors, independent of $u_{it}$; $u_{it}$ are non-negative inefficiencies. All continuous variables are winsorized at the 2.5th and 97.5th percentiles. The standard error is corrected for heteroscedasticity (White, 1980).

commercial bank as an example.

### 3.2. Estimation of bank efficiency

We measure bank efficiency as how close a bank is to the best-practice bank(s) for producing identical output under the same conditions (Berger and Mester, 1997; Berger et al., 2009; Jiang et al., 2013). We prefer the stochastic frontier approach (SFA), which avoids a possible bias of efficiency estimates due to incomplete asset and liability coverage. Specifically, we employ the true fixed-effect SFA model proposed by Greene (2005a, 2005b), allowing for time-varying efficiency and multilevel fixed effects. SFA can better accommodate measurement errors and uncertain economic environments in transition economies when studying efficiency (Fries and Taci, 2005).

Following the literature (i.e., Barth et al., 2013; Jiang et al., 2013; Sun et al., 2013; Shamshur and Weill, 2019), we define three outputs—net loans ($y_1$), other earning assets ($y_2$), and non-interest income ($y_3$)—and three input prices—the price of fund ($w_1$) as the ratio to interest expense to total fund, the price of labor ($w_2$) as the ratio of personnel expenses to total assets,[12] and the price of capital ($w_3$) as the ratio of non-interest expenses (excluding personnel expense) to fixed assets. We include a time trend $t$ and its second-order term to capture the general catching up toward the best practice frontier over time. We employ a widely used translog function form, and the empirical specification of the cost frontier is shown in Eq. (1). The alternative profit frontier is estimated by replacing total costs with total profit with necessary adjustments to error terms. Cost efficiency ($CE_{it}$) and profit efficiency ($PE_{it}$) can be derived by estimating the cost and alternative profit frontiers.

[12] Ideally, price of labor should be defined as the ratio of personnel expenses to the number of employees. However, due to missing value in the number of employees, we would lose more than half of observations.

**Table 2**
Descriptive statistics.

| Variables | Obs | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| *HighTech Indices* | | | | | |
| $Cloud_{it}$ | 1054 | 0.101 | 0.192 | 0 | 1 |
| Techtype: $Bigdata_{it}$ | 1054 | 0.130 | 0.226 | 0 | 1 |
| $Blockchain_{it}$ | 1054 | 0.082 | 0.174 | 0 | 1 |
| $Internet_{it}$ | 1054 | 0.206 | 0.292 | 0 | 1 |
| $AI_{it}$ | 1054 | 0.034 | 0.090 | 0 | 1 |
| $HighTech_{it}$ | 1054 | 0.116 | 0.189 | 0 | 1 |
| *Bank Efficiency variables* | | | | | |
| $TC_{it}$ (total costs) | 1054 | 32.469 | 78.850 | 0.103 | 496.240 |
| $TP_{it}$ (total profit) | 1054 | 16.969 | 49.404 | 0.008 | 355.272 |
| $y1_{it}$ (net loan) | 1054 | 599.725 | 1702.538 | 2.098 | 12,800 |
| $y2_{it}$ (other earning asset) | 1054 | 432.474 | 1054.088 | 2.594 | 7565.485 |
| $y3_{it}$ (non-interest income) | 1054 | 7.780 | 21.864 | 0.000 | 144.906 |
| $w1_{it}$ (price of fund) | 1054 | 0.023 | 0.006 | 0.003 | 0.049 |
| $w2_{it}$ (price of labor) | 1054 | 0.005 | 0.002 | 0.002 | 0.012 |
| $w3_{it}$ (price of capital) | 1054 | 0.740 | 0.765 | 0.124 | 11.465 |
| $CE_{it}$ (est. cost efficiency) | 1054 | 0.983 | 0.015 | 0.841 | 0.998 |
| $PE_{it}$ (est. profit efficiency) | 1054 | 0.781 | 0.184 | 0.181 | 1 |
| *Operational Risk variables* | | | | | |
| $Dividend_{it}$ | 1054 | 0.032 | 0.275 | 0.000 | 7.205 |
| Net $Fee_{it}$ | 1054 | 6.169 | 18.146 | -0.597 | 125.613 |
| Net Gain Banking $book_{it}$ | 1054 | 0.189 | 1.346 | -8.740 | 15.507 |
| Net Gain Trading $book_{it}$ | 1054 | 0.780 | 2.191 | -7.366 | 22.491 |
| Net Interest $Income_{it}$ | 1054 | 25.501 | 69.791 | 0.032 | 477.828 |
| Other Operation $Income_{it}$ | 1054 | 1.249 | 3.642 | -1.187 | 55.655 |
| Other Operation $Expense_{it}$ | 1054 | 4.496 | 11.681 | 0.026 | 75.061 |
| $OR_{it}$ (est. operational risk) | 995 | 7.091 | 20.030 | 0.034 | 135.406 |
| *Control variables* | | | | | |
| $Size_{it}$ (total assets) | 1054 | 1209.078 | 3249.111 | 9.071 | 23,700 |
| $NPL_{it}$ (ratio) | 906 | 0.017 | 0.035 | 5.49E-07 | 0.988 |
| $Tier1_{it}$ | 941 | 10.760 | 2.884 | 3.25 | 58.56 |
| $EA_{it}$ (equity/total asset) | 1054 | 7.001 | 1.808 | 2.19 | 30.81 |
| $ROE_{it}$ | 976 | 15.203 | 10.782 | 0.27 | 292.91 |
| *Ownership variables* | | | | | |
| $SOCB_i$ | 1054 | 0.057 | 0.232 | 0 | 1 |
| $JSCB_i$ | 1054 | 0.121 | 0.327 | 0 | 1 |
| $CCB_i$ | 1054 | 0.611 | 0.488 | 0 | 1 |
| $RCB_i$ | 1054 | 0.211 | 0.408 | 0 | 1 |

This table reports descriptive statistics of variables used in our analysis over the period 2008–2019. All monetary variables are in billion Chinese Yuan at the price level in 2010.

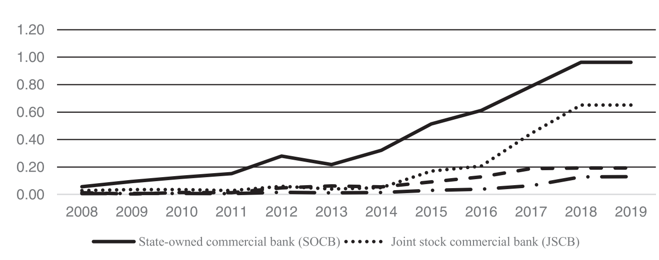


**Fig. 1.** Average cloud computing index by bank ownership in China (2008–2019).

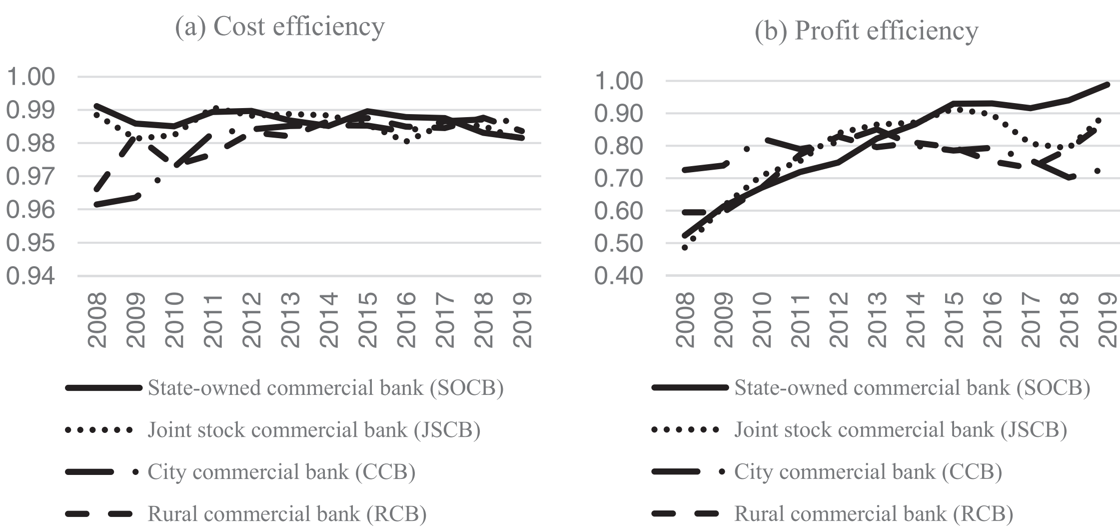


**Fig. 2.** Average bank efficiency by bank ownership in China (2008–2019).

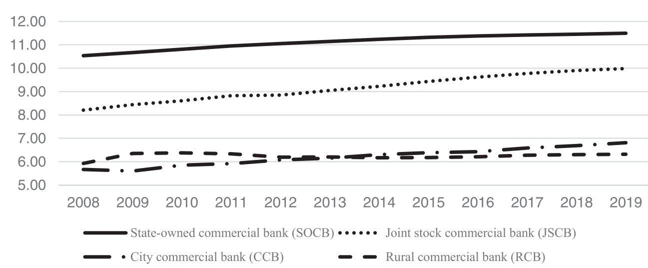


**Fig. 3.** Average operational risk by bank ownership in China (2008–2019).

$$
\begin{aligned}
ln(TC_{it}) = {} & \alpha + \sum_{j=1}^{3}\beta_i ln\left(y_{j,it}\right) + \sum_{m=1}^{3}\psi_m ln\left(w_{m,it}\right) + \frac{1}{2}\sum_{j=1}^{3} \\
& \times \sum_{k=1}^{3}\beta_{jk}\times ln(y_{it})ln(y_{kt}) + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{3}\psi_{mn} \\
& \times ln\left(w_{m,it}\right)ln\left(w_{n,it}\right) + \sum_{j=1}^{3} \\
& \times \sum_{m=1}^{3}\varpi_{jm} ln\left(y_{j,it}\right)ln\left(w_{m,it}\right) + \tau_1 t + \tau_2 t^2 + \upsilon_{it} + u_{it} \qquad (1)
\end{aligned}
$$

where $TC$ is the total costs of a bank in a given year; $y$ indicates three outputs—net loans ($y_1$), other earning assets ($y_2$), and non-interest income ($y_3$); $w$ indicates three input prices—the price of fund ($w_1$), the price of labor ($w_2$), and the price of capital ($w_3$); $t$ is a time trend; $\upsilon_{it}$ are identical and independently distributed random errors, independent of $u_{it}$; $u_{it}$ are non-negative inefficiencies; $j$, $k$, $m$, and $n$ in the summation are the units of count; and $\alpha$, $\beta$, $\psi$, $\tau_1$, and $\tau_2$ are the parameters to be estimated.

The standard restriction of linear homogeneity in input prices is imposed by normalizing total costs (profit), the price of labor ($w_2$), and the price of capital ($w_3$) using the price of fund ($w_1$). Total costs (profits) and output variables are normalized by total assets to control for scale biases and heteroskedasticity. All variables are demeaned to make the dimensions of all data centered at 0 (Petrova and Westerlund, 2020). Table 1 reports the estimation results from the stochastic frontier, and the parameters generally indicate a good fit of the true fixed effect model (Greene, 2005a, 2005b). The average estimate of profit efficiency (0.781) is lower than the average cost efficiency (0.983). The variation in profit efficiency (SD = 0.184) is greater than that in cost efficiency (SD = 0.015).

### 3.3. Operation risk indicator

The final Basel rules on operational risk capital requirements were released in December 2017 and will apply from January 1, 2022 (BCBS, 2017). A single non-model-based method for calculating operational risk capital—the Standardized Approach (SA)— has been introduced, replacing all three existing approaches under Basel III. This method is based on three components: (i) the Business Indicator (BI) as a proxy for operational risk based on financial statements; (ii) the Business Indicator Component (BIC) adjusting the BI by a set of regulatory determined marginal coefficients (αi); and (iii) the Internal Loss Multiplier (ILM) adjusting BIC for bank's average historical losses. Due to the lack of detailed data on internal operational risk losses with a ten-year history, we employ the BI as the measure of bank operational risk exposure.

The Business Indicator (*BI*), as defined in Eq. (2) comprises three components: the interest, leases, and dividend component (*ILDC*), the services component (*SC*), and the financial component (*FC*). Multiplying BI by the marginal coefficients ($\alpha_i$), we obtain BIC, our operational risk indicator.[13]

$$
\mathrm{BI}_{\mathrm{it}} = \mathrm{ILDC}_{\mathrm{it}} + \mathrm{SC}_{\mathrm{it}} + \mathrm{FC}_{\mathrm{it}} \qquad (2)
$$

where *ILDC*, *SC*, and *FC* are defined as follows:

*ILDC* = *Minimum [Absolute value (Interest Income – Interest Expense); 2.25%*Interest Earning Assets]* + *Dividend Income.*

*SC* = *Maximum [Other Operating Income; Other Operating Expense]* + *Maximum [Fee Income; Fee Expense].*

*FC* = *Absolute value (Net P&L on Trading Book)* + *Absolute value (Net P&L on Banking Book).*

The financial indicators on the right-hand side are three-year moving averages (*t*, *t-1*, and *t-2*). $OR_{it}$ is the natural logarithm of $BI_{it}$. The greater the $BI_{it\ is}$, the greater the operational risk ($OR_{it}$).

### 3.4. Empirical model

The empirical specification to examine the impact of cloud computing on bank efficiency is shown in Eq. (3). We also include a set of bank-specific control variables that have a proven effect on bank efficiency in the literature. Particularly, we control for the effect of bank

[13] The progressive marginal coefficient (αi) equals 12%, 15%, and 18% for BI smaller than €1billion, between €1 and €30 billion, and greater than €30billion, respectively. For instance, if BI = €35bn, the BIC = (1 ×12%) + (30−1) x 15% + (35−30) x 18% = €5.37bn (BCBS, 2017).

**Table 3**
The effect of cloud computing on cost efficiency.

| Variables | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | Cost efficiency | | | Cost efficiency rank | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Cloud_{it}$ | -0.010*** | -0.010*** | -0.013*** | -31.602*** | -31.602*** | -35.936*** |
| | (0.002) | (0.002) | (0.004) | (8.800) | (8.800) | (12.766) |
| $JSCB_i$ | | -0.004 | -0.009 | | -28.846 | -46.489 |
| | | (0.010) | (0.012) | | (30.591) | (33.913) |
| $CCB_i$ | | -0.004 | -0.010 | | -30.965 | -54.838 |
| | | (0.014) | (0.016) | | (38.880) | (43.175) |
| $RCB_i$ | | -0.004 | -0.013 | | -36.062 | -68.591 |
| | | (0.019) | (0.022) | | (62.919) | (67.893) |
| $JSCB_i \times Cloud_{it}$ | | | 0.001 | | | -1.854 |
| | | | (0.004) | | | (14.303) |
| $CCB_i \times Cloud_{it}$ | | | 0.010** | | | 36.624* |
| | | | (0.005) | | | (19.311) |
| $RCB_i \times Cloud_{it}$ | | | 0.008 | | | -13.669 |
| | | | (0.005) | | | (22.838) |
| *Control variables* | | | | | | |
| $Size_{it}$ | 0.001 | 0.001 | -0.001 | -2.199 | -2.199 | -7.094 |
| | (0.003) | (0.003) | (0.003) | (7.848) | (7.848) | (8.577) |
| $NPL_{it}$ | 0.012*** | 0.012*** | 0.012*** | 35.685** | 35.685** | 35.378** |
| | (0.004) | (0.004) | (0.004) | (15.737) | (15.737) | (15.929) |
| $Tier1_{it}$ | 0.001** | 0.001** | 0.001** | 2.170*** | 2.170*** | 2.252*** |
| | (0.000) | (0.000) | (0.000) | (0.582) | (0.582) | (0.580) |
| constant | 0.980*** | 0.980*** | 0.999*** | 57.710 | 57.710 | 134.645 |
| | (0.046) | (0.046) | (0.052) | (124.555) | (124.555) | (136.734) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 823 | 823 | 823 | 823 | 823 | 823 |
| Sigma/Adj.$R^2$ | 0.007*** | 0.007*** | 0.007*** | 0.099 | 0.099 | 0.103 |

$CE_{it} = \delta_0 + \delta_1 Cloud_{it} + \sum \delta_k Ownership_i + \sum \delta_l Cloud_{it} \times Ownership_i + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from above equation in columns (1)-(3) for cost efficiency using the truncated regression (Honoré and Powell, 1994) and (4)-(6) for cost efficiency rank using OLS. All continuous variables are winsorized at 2.5$^{th}$ and 97.5$^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. CE=cost efficiency. *Cloud* is the cloud computing index. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size* (the logarithm of total assets), non-performing loan ratio (*NPL*) for assets quality, and the core tier one capital ratio (*Tier1*) for capital adequacy. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

size ($Size_{it}$) proxied by the logarithm of total assets (Barth et al., 2013; Peng et al., 2017; Ahamed et al., 2021), asset quality ($NPL_{it}$) proxied by the non-performing loan ratio (Jiang et al., 2009; Fiordelisi et al., 2011), and capital adequacy ($Tierl_{it}$) measured by the core tier one capital ratio (Barth et al., 2013; Chortareas et al., 2013; Peng et al., 2017).

$$CE_{it}(or \quad PE_{it}) = \delta_0 + \delta_1 Cloud_{it} + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it} \tag{3}$$

where the dependent variable is the cost efficiency ($CE_{it}$) or profit efficiency ($PE_{it}$) of bank i in year *t*; $Cloud_{it}$ is the cloud computing index for bank *i* in year *t*; $Control_{it}$ is a set of control variables (size, asset quality, and capital adequacy); $Bank_i$ and $Year_t$ are bank and year fixed effects; and $\varepsilon_{it}$ is the error term.

Because bank ownership characteristics have a profound influence on bank efficiency (Bonin et al., 2005; Berger et al., 2009; Jiang et al., 2013; Shaban and James, 2018), we further investigate whether the impact of cloud computing varies with bank ownership. We introduce a set of ownership dummy variables and their interaction terms with cloud computing to the baseline model in Eq. (3), we obtain Eq. (4). Ownership variables include *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks, taking a value of 1 if a bank belongs to the ownership group and 0 otherwise.

$$CE_{it}(or \quad PE_{it}) = \delta_0 + \delta_1 Cloud_{it} + \sum \delta_k Ownership + \sum \delta_l Cloud \times Ownership + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it} \tag{4}$$

The empirical specification to examine the impact of cloud computing on bank operation risk is shown in Eq. (5). Based on the literature on operational risk, we include a set of bank-specific control variables. We control for the effect of bank size ($Size_{it}$). Some researchers argue that larger banks may face lower levels of operational risk due to economies of scale from information technology and risk management (Ellul and Yerramilli, 2013) or more supervisory attention (Hirtle et al., 2020), while other scholars posit that large banks have greater operational risk because of increased complexity (Chernobai et al., 2021), moral hazard risk-taking of being "too-big-to-fail" (Gropp et al., 2011), and a failure to assume professional obligations to clients and/or faulty product design (Curti et al., 2020). Chernobai et al. (2021) suggest that bank operational risk is closely linked to banks' credit risk and financial distress risk. Hence, we also control for the effect of credit risk ($NPL_{it}$), capital risk ($EA_{it}$) proxied by the ratio of equity to total assets, and profitability ($ROE_{it}$) measured by return on equity.

$$OR_{it} = \delta_0 + \delta_1 Cloud_{it} + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it} \tag{5}$$

where $OR_{it}$ is an operational risk indicator of bank *i* in year *t* (in logarithm); $Cloud_{it}$ is the cloud computing index for bank *i* in year *t*; $Control_{it}$ is a set of control variables (bank size, credit risk, capital risk,

**Table 4**
The effect of cloud computing on profit efficiency.

| Variables | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | Profit efficiency | | | Profit efficiency rank | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Cloud_{it}$ | 0.253*** | 0.253*** | 0.420*** | 44.103*** | 44.103*** | 78.617*** |
| | (0.037) | (0.037) | (0.046) | (7.392) | (7.392) | (8.586) |
| $JSCB_i$ | | 0.540*** | 0.818*** | | 82.624*** | 134.577*** |
| | | (0.135) | (0.150) | | (23.984) | (26.290) |
| $CCB_i$ | | 0.539** | 0.887*** | | 86.287** | 150.567*** |
| | | (0.229) | (0.244) | | (39.970) | (42.289) |
| $RCB_i$ | | 0.581* | 1.032*** | | 94.780 | 177.472*** |
| | | (0.350) | (0.364) | | (58.508) | (61.255) |
| $JSCB_i \times Cloud_{it}$ | | | -0.206*** | | | -46.008*** |
| | | | (0.043) | | | (9.003) |
| $CCB_i \times Cloud_{it}$ | | | -0.388*** | | | -66.793*** |
| | | | (0.076) | | | (15.401) |
| $RCB_i \times Cloud_{it}$ | | | -0.013 | | | -9.802 |
| | | | (0.115) | | | (21.807) |
| *Control variables* | | | | | | |
| $Size_{it}$ | 0.084** | 0.084** | 0.143*** | 12.000* | 12.000* | 22.482*** |
| | (0.038) | (0.038) | (0.040) | (6.386) | (6.386) | (6.891) |
| $NPL_{it}$ | -0.189 | -0.189 | -0.173 | -40.745* | -40.745* | -37.351* |
| | (0.128) | (0.128) | (0.115) | (22.348) | (22.348) | (19.751) |
| $Tier1_{it}$ | 0.018*** | 0.018*** | 0.017*** | 2.340*** | 2.340*** | 2.300*** |
| | (0.003) | (0.003) | (0.003) | (0.484) | (0.484) | (0.480) |
| constant | -0.992* | -0.992* | -1.978*** | -203.27** | -203.27** | -380.68*** |
| | (0.601) | (0.601) | (0.646) | (101.495) | (101.495) | (110.093) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 823 | 823 | 823 | 823 | 823 | 823 |
| Sigma/Adj.$R^2$ | 0.126*** | 0.126*** | 0.124*** | 0.349 | 0.349 | 0.365 |

$PE_{it} = \delta_0 + \delta_1 Cloud_{it} + \sum \delta_k Ownership_i + \sum \delta_l Cloud_{it} \times Ownership_i + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from above equation in columns (1)-(3) for profit efficiency using the truncated regression (Honoré and Powell, 1994) and (4)-(6) for profit efficiency rank using OLS. All continuous variables are winsorized at 2.5$^{th}$ and 97.5$^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. PE=profit efficiency. *Cloud* is the cloud computing index. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size* (the logarithm of total assets), non-performing loan ratio (*NPL*) for assets quality, and the core tier one capital ratio (*Tier1*) for capital adequacy. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

profitability); $Bank_i$ and $Year_t$ are bank and year fixed effects; and $\varepsilon_{it}$ refers to the error term.

Likewise, we introduce a set of ownership dummy variables and their interaction terms with cloud computing to Eq. (5), obtaining Eq. (6).

$$OR_{it} = \delta_0 + \delta_1 Cloud_{it} + \sum \delta_k Ownership + \sum \delta_l Cloud \times Ownership + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it} \tag{6}$$

### 3.5. Data sources and sample statistics

Our sample consists of data on 118 commercial banks in China over the period 2008–2019, including 5 state-owned commercial banks, 12 joint-stock commercial banks, 74 city commercial banks, and 27 rural commercial banks, accounting for more than 95% of the total assets of commercial banks in the market. The sample starts from 2008 as the application of cloud computing was gradually built up after 2008 (Velte et al., 2009). All banks have data for more than 3 consecutive years. All continuous variables have been winsorized at the 2.5% level to minimize the influence of data errors and outliers. Banks' financial data are collected from FitchSolution. Table 2 provides sample statistics, including our novel could computing index, estimated cost and profit efficiency, and calculated operation risk indicator based on Basel Committee's latest guidance.

Fig. 1 plots the average cloud computing index by ownership over the period 2008–2019. State-owned commercial banks (SOCBs) appear the industry leader in cloud computing applications, followed by joint-stock commercial banks (JSCBs), city commercial banks (CCBs), and rural commercial banks (RCBs). This is not surprising given that SOCBs are equipped with a better technical environment and human resources. Four SOCBs are among the top 10 largest banks in the world by market capitalization, and they have strong incentives to take advantage of newly emerging technologies to strengthen competitiveness.

Fig. 2 plots average cost and profit efficiency by ownership. Bank cost efficiency in Fig. 2(a) is relatively stable, while profit efficiency in Fig. 2(b) has improved. SOCBs performed better in terms of cost efficiency but have deteriorated in the recent few years. In contrast, SOCBs experienced the lowest profit efficiency in the first half of the sample period but became the most profit-efficient banks in the second half of the sample period. The results are in line with previous efficiency studies on Chinese banking (i.e., Jiang et al., 2013; Berger et al., 2009).

Fig. 3 shows the average operating risk of commercial banks with different ownership structures. Over the sample period, the operational risk of all banks has steadily increased, except for RCBs whose operational level is relatively stable. SOCBs face the highest operational risk, followed by JSCBs with CCBs and RCBs at the bottom. Overall, the operational risk indicator is in line with the Basel Committee's view that the scale of business is the core factor of operational risk.

## 4. Empirical results

In this section, we test our hypotheses developed in Section 2. In Sections 4.1 and 4.2, we examine the impact of cloud computing on bank cost and profit efficiency, respectively. Simar and Wilson (2007) suggest that truncated regression estimates are more accurate for cost/profit efficiency that is bounded between 0 and 1. Following the literature, Eq. (3) and Eq. (4) are estimated using the truncated regression, while the unreported results from the Least Square Dummy Variable (LSDV) estimator are consistent. In Section 4.3, we investigate how cloud

**Table 5**
The effects of cloud computing on operational risk.

| Variables | Dependent variable: Operational risk | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Cloud_{it}$ | 0.185*** | 0.185*** | -0.235*** | -0.214*** |
| | (0.064) | (0.064) | (0.069) | (0.069) |
| $JSCB_i$ | | -1.214*** | -1.873*** | -1.912*** |
| | | (0.282) | (0.303) | (0.276) |
| $CCB_i$ | | -2.149*** | -2.936*** | -2.905*** |
| | | (0.358) | (0.382) | (0.360) |
| $RCB_i$ | | -2.039*** | -3.067*** | -3.029*** |
| | | (0.477) | (0.512) | (0.481) |
| $JSCB_i \times Cloud_{it}$ | | | 0.535*** | 0.557*** |
| | | | (0.051) | (0.053) |
| $CCB_i \times Cloud_{it}$ | | | 0.750*** | 0.757*** |
| | | | (0.171) | (0.170) |
| $RCB_i \times Cloud_{it}$ | | | 0.435*** | 0.452*** |
| | | | (0.152) | (0.148) |
| *Control variables* | | | | |
| $Size_{it}$ | 0.673*** | 0.673*** | 0.542*** | 0.545*** |
| | (0.075) | (0.075) | (0.080) | (0.072) |
| $NPL_{it}$ | 0.558*** | 0.558*** | 0.516*** | 0.496** |
| | (0.212) | (0.212) | (0.197) | (0.202) |
| $EA_{it}$ | 0.015 | 0.015 | 0.010 | |
| | (0.012) | (0.012) | (0.013) | |
| $ROE_{it}$ | -0.003 | -0.003 | -0.002 | |
| | (0.003) | (0.003) | (0.003) | |
| constant | -0.326 | -0.326 | 1.898 | 1.889 |
| | (1.213) | (1.213) | (1.296) | (1.151) |
| Bank & Year FE | Yes | Yes | Yes | Yes |
| Observations | 827 | 827 | 827 | 871 |
| Adjusted-$R^2$ | 0.982 | 0.982 | 0.983 | 0.982 |

$OR_{it} = \delta_0 + \delta_1 Cloud_{it} + \sum \delta_k Ownership_i + \sum \delta_l Cloud_{it} \times Ownership_i + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from above equation. All continuous variables are winsorized at $2.5^{th}$ and $97.5^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. OR=operational risk. *Cloud* is the cloud computing index. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include bank size (the logarithm of total assets), non-performing loan ratio (NPL) for credit risk, the equity to capital ratio (EA) for capital risk, and profitability (ROE). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

computing affects bank operational risk. In all regressions, we control for bank and year fixed effects and consider heteroscedasticity and robust standard errors (White, 1980). Before proceeding with estimations, we first test the multicollinearity of our explanatory variables, and the variance inflation factors fairly suggest that our models in Eqs. (3)–(6) do not suffer from serious multicollinearity problems. We further employ the Fisher test (Im et al., 2003) and the residual cross-section dependence test (Pesaran, 2006) to determine whether our data are more suitable for panel estimation models. The unreported results (for brevity) lead to the choice of panel data estimations.

### 4.1. *The effect of cloud computing on bank cost efficiency*

Table 3 reports the estimation results for cost efficiency. The results from the baseline model in Eq. (3) are reported in Column (1). The negative and significant coefficient on $Cloud_{it}$ indicates that cloud computing application has a negative impact on cost efficiency. The impact is statistically significant, while its economic impact is small. For a one-standard-deviation increase in the cloud computing index, the decrease in cost efficiency is only approximately one-seventh of the standard deviation in cost efficiency ($(0.010 \times 0.192)/0.015 = 1/7$). It appears that the expected cost savings from cloud computing applications have yet to materialize. It is still the early transitional stage of cloud computing applications. While the transition incurs initial investment in R&D, infrastructure and human capital upfront, the traditional infrastructure is still running. The overall costs associated with cloud computing transition outweigh the expected benefits. After we introduce bank ownership to the baseline model in Column (2), where SOCBs are omitted from the regression as the control group, the coefficient on *Cloud* is negative and significant, consistent with that in Column (1). The coefficients on *JSCB*, *CCB*, and *RCB* are insignificant, suggesting that the performance of Chinese banks is not significantly different in terms of cost efficiency. The evidence supports *Hypothesis 1b that cloud computing worsens bank cost efficiency,* at least during our sample period.

We further investigate whether bank ownership affects the relationship between cloud computing and bank efficiency. The estimation results from Eq. (4) are reported in Column (3) of Table 3. Only the coefficient on $CCB_i \times Cloud_{it}$ is positive and significant, suggesting that the negative impact of cloud computing on cost efficiency is smaller for CCBs than for SOCBs. The impact of cloud computing on cost efficiency is null among other banks, as the coefficients on other interaction terms are insignificant. Moreover, the control variables also reveal interesting results. The positive coefficients on $NPL_{it}$ and $Tier1_{it}$ indicate that banks with more credit risk and better capitalization are more cost efficient.

This two-step approach in efficiency studies is widely used (Berger et al., 2009; Bonin et al., 2005; Shaban and James, 2018); nevertheless, it has been criticized for the contradictory assumptions in the two steps. To address the potential estimation bias, we follow the literature and use both efficiency scores and efficiency ranks (Berger et al., 2009; Shaban and James, 2018). As shown in Columns (4)–(6), the results from efficiency ranks are consistent with our main results in Columns (1)–(3). We further address this potential bias issue by employing the non-parametric method – data envelopment analysis (DEA)— to obtain cost efficiency based on the same set of inputs and outputs. The estimated average cost efficiency is 91%. The results from the second-stage regressions, as reported in Table B1 in the Appendix, suggest that cloud computing has a negative impact on bank cost efficiency in terms of both

**Table 6**
The effect of cloud computing on bank efficiency and operation risk: an alternative measure of cloud computing.

| Variables | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | Cost efficiency | | Profit efficiency | | Operational risk | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $HighTech_{it}$ | -0.015*** | -0.019*** | 0.386*** | 0.603*** | 0.337*** | -0.239** |
| | (0.003) | (0.005) | (0.052) | (0.060) | (0.093) | (0.098) |
| $JSCB_i$ | -0.007 | -0.013 | 0.641*** | 0.945*** | -1.074*** | -1.937*** |
| | (0.010) | (0.012) | (0.136) | (0.156) | (0.285) | (0.316) |
| $CCB_i$ | -0.008 | -0.015 | 0.667*** | 1.038*** | -1.961*** | -2.984*** |
| | (0.014) | (0.016) | (0.230) | (0.250) | (0.361) | (0.396) |
| $RCB_i$ | -0.009 | -0.018 | 0.725** | 1.199*** | -1.820*** | -3.140*** |
| | (0.019) | (0.023) | (0.351) | (0.371) | (0.480) | (0.529) |
| $JSCB_i\times HighTech_{it}$ | | 0.002 | | -0.258*** | | 0.738*** |
| | | (0.005) | | (0.053) | | (0.070) |
| $CCB_i\times HighTech_{it}$ | | 0.012* | | -0.467*** | | 1.102*** |
| | | (0.007) | | (0.093) | | (0.213) |
| $RCB_i\times HighTech_{it}$ | | 0.011* | | -0.186 | | 0.448*** |
| | | (0.006) | | (0.143) | | (0.163) |
| *Control variables* | | | | | | |
| $Size_{it}$ | 0.000 | -0.001 | 0.093** | 0.151*** | 0.691*** | 0.527*** |
| | (0.003) | (0.003) | (0.037) | (0.041) | (0.074) | (0.081) |
| $NPL_{it}$ | 0.012*** | 0.012*** | -0.191 | -0.175 | 0.555** | 0.498** |
| | (0.004) | (0.004) | (0.123) | (0.114) | (0.216) | (0.197) |
| $Tier1_{it}$ | 0.001** | 0.001*** | 0.017*** | 0.016*** | | |
| | (0.000) | (0.000) | (0.003) | (0.003) | | |
| $EA_{it}$ | | | | | 0.013 | 0.007 |
| | | | | | (0.012) | (0.013) |
| $ROE_{it}$ | | | | | -0.004 | -0.003 |
| | | | | | (0.003) | (0.003) |
| constant | 0.985*** | 1.004*** | -1.165* | -2.164*** | -0.636 | 2.195* |
| | (0.046) | (0.053) | (0.597) | (0.656) | (1.206) | (1.327) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 823 | 823 | 823 | 823 | 827 | 827 |
| Sigma/Adj.$R^2$ | 0.007*** | 0.007*** | 0.125*** | 0.124*** | 0.983 | 0.983 |

$Y_{it} = \delta_0 + \delta_1 HighTech_{it} + \sum \delta_k Ownership_i + \sum \delta_l HighTech_{it} \times Ownership_i + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from the above equation for cost efficiency in columns (1) – (2), profit efficiency in columns (3) – (4), and operational risk in columns (5)-(6). All continuous variables are winsorized at 2.5$^{th}$ and 97.5$^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. *HighTech* is an alternative measure of cloud computing. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size* (the logarithm of total assets), non-performing loan ratio (*NPL*) for assets quality/credit risk, and the core tier one capital ratio (*Tier1*) for capital adequacy, the equity to capital ratio (EA) for capital risk, and profitability (ROE). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

the cloud computing index and the alternative measure of the high-tech index. The evidence indicates that the potential estimation bias has a limited impact on our main results.

### 4.2. The effect of cloud computing on bank profit efficiency

Turning to profit efficiency, estimation results appear much rosier, as reported in Table 4. The coefficient on $Cloud_{it}$ is positive and statistically significant in Column (1), providing strong evidence for gains in profit efficiency from cloud technology. For a one-standard-deviation increase in the cloud computing index, bank profit efficiency, on average, increases by nearly 5% points (=0.253 ×0.192). Although banks incur greater costs, they tend to enjoy gains in profit efficiency, likely driven by faster revenue growth. Cloud computing can deliver immediate benefits of boosting revenues through innovative products and services, business diversification, informational advantages, and optimization. In Column (2), after the inclusion of bank ownership variables, the main effect of cloud computing on profit efficiency remains positive and significant. The coefficients on all ownership variables (JSCB, CCB, and RCB) are positive and statistically significant, implying that these banks outperform SOCBs in terms of profit efficiency. The results are generally consistent with the literature that SOCBs are less profit efficient than other types of banks (Jiang et al., 2013). The results provide evidence supporting *Hypothesis 2a: Cloud computing improves bank profit efficiency*. For control variables, the results show that larger banks and better-capitalized banks are more efficient, as the coefficients on $Size_{it}$ and $Tier1_{it}$ are positive and statistically significant, consistent with the extant research (Barth et al., 2013; Peng et al., 2017).

After introducing bank ownership and the interaction terms between ownership and cloud computing in Columns (3), the interaction term $JSCB_i \times Cloud_{it}$ enters the regression with a negative and statistically significant coefficient. The impact of cloud computing on profit efficiency is smaller for JSCB and much smaller for CCBs than for SOCBs. In other words, holding other things constant, for the same level of cloud computing application, SOCBs attain greater profit efficiency gains than JSCBs and CCBs. For an increase in the cloud computing index by one standard deviation, profit efficiency increases by 8 (=0.420 ×0.192) percentage points for SOCBs, 4.1 (= (0.420–0.206) × 0.192) percentage points for JSCBs, and 0.6 (= (0.420–0.388) × 0.192) percentage points for CCBs. In short, in terms of profit efficiency, SOCBs benefit the most from cloud computing technology, and CCBs are on the other end of the spectrum with the lowest gains in profit efficiency. The results from profit efficiency ranked in Columns (4)–(6) are consistent with our main results.

### 4.3. The effect of cloud computing on bank operational risk

The estimation results from Eq. (5) and Eq. (6) are reported in Table 5. The coefficient on $Cloud_{it}$ is positive and statistically significant in Columns (1)–(2), implying that cloud computing application increases bank operational risk. For a one-standard-deviation increase in the cloud computing index, operational risk exposure, on average,

**Table 7**
The effect of cloud computing on bank efficiency and operation risk: an alternative information source for cloud computing index.

| Variables | Dependent variables | | | | | |
|---|---|---|---|---|---|---|
| | Cost efficiency | | Profit efficiency | | Operational risk | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $CloudAR_{it}$ | -0.003** | | 0.074*** | | -0.083*** | |
| | (0.001) | | (0.013) | | (0.013) | |
| $JSCB_i$ | 0.004 | -0.000 | 0.342** | 0.391*** | -1.575*** | -1.723*** |
| | (0.010) | (0.010) | (0.135) | (0.139) | (0.263) | (0.273) |
| $CCB_i$ | 0.008 | 0.000 | 0.261 | 0.315 | -2.626*** | -2.899*** |
| | (0.013) | (0.014) | (0.229) | (0.232) | (0.331) | (0.351) |
| $RCB_i$ | 0.010 | 0.002 | 0.233 | 0.314 | -2.627*** | -2.870*** |
| | (0.019) | (0.020) | (0.349) | (0.353) | (0.445) | (0.458) |
| $JSCB_i \times CloudAR_{it}$ | 0.000 | | -0.052*** | | 0.118*** | |
| | (0.001) | | (0.014) | | (0.013) | |
| $CCB_i \times CloudAR_{it}$ | 0.003* | | -0.074*** | | 0.086*** | |
| | (0.002) | | (0.017) | | (0.030) | |
| $RCB_i \times CloudAR_{it}$ | 0.002 | | -0.024 | | 0.048 | |
| | (0.002) | | (0.026) | | (0.037) | |
| $HighTechAR_{it}$ | | -0.000*** | | 0.003*** | | -0.003*** |
| | | (0.000) | | (0.001) | | (0.001) |
| $JSCB_i \times HighTechAR_{it}$ | | 0.000 | | -0.002*** | | 0.006*** |
| | | (0.000) | | (0.001) | | (0.001) |
| $CCB_i \times HighTechAR_{it}$ | | 0.000*** | | -0.003*** | | 0.005*** |
| | | (0.000) | | (0.001) | | (0.001) |
| $RCB_i \times HighTechAR_{it}$ | | 0.000*** | | -0.001 | | 0.004** |
| | | (0.000) | | (0.001) | | (0.002) |
| *Control variables* | | | | | | |
| $Size_{it}$ | 0.002 | 0.001 | 0.048 | 0.057 | 0.605*** | 0.562*** |
| | (0.003) | (0.003) | (0.039) | (0.039) | (0.073) | (0.074) |
| $NPL_{it}$ | 0.012*** | 0.014*** | -0.190 | -0.181 | 0.544*** | 0.566*** |
| | (0.005) | (0.005) | (0.141) | (0.135) | (0.199) | (0.193) |
| $Tier1_{it}$ | 0.001** | 0.001** | 0.020*** | 0.020*** | | |
| | (0.000) | (0.000) | (0.003) | (0.003) | | |
| $EA_{it}$ | | | | | 0.015 | 0.009 |
| | | | | | (0.012) | (0.013) |
| $ROE_{it}$ | | | | | -0.002 | -0.002 |
| | | | | | (0.003) | (0.003) |
| constant | 0.954*** | 0.971*** | -0.415 | -0.551 | 0.804 | 1.545 |
| | (0.046) | (0.047) | (0.618) | (0.630) | (1.186) | (1.217) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 823 | 823 | 823 | 823 | 827 | 827 |
| Sigma/Adj.$R^2$ | 0.007*** | 0.007*** | 0.128*** | 0.127*** | 0.982 | 0.983 |

$Y_{it} = \delta_0 + \delta_1 CloudAR_{it} \quad (or \quad HighTechAR_{it}) + \sum \delta_k Onwership_i + \sum \delta_l \quad CloudAR_{it}(or \quad HighTechAR_{it}) \times Ownership_i + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from the above equation for cost efficiency in columns (1) – (2), profit efficiency in columns (3) – (4), and operational risk in columns (5)-(6). All continuous variables are winsorized at 2.5$^{th}$ and 97.5$^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. *CloudAR* and *HighTechAR* are alternative measures of cloud computing using information from banks' annual reports. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size* (the logarithm of total assets), non-performing loan ratio (*NPL*) for assets quality/credit risk, and the core tier one capital ratio (*Tier1*) for capital adequacy, the equity to capital ratio (*EA*) for capital risk, and profitability (*ROE*). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

increases by 3.6% (=0.185 ×0.192). The results show that the practical burden from the more complex systems associated with cloud computing outweighs the potential benefits during the early stage of the transition period. The empirical evidence supports *Hypothesis 3b: cloud computing increases bank operational risk exposure*.

We find that bank operational risk varies significantly with ownership. As shown in Column (2) of Table 5, the coefficients on *JSCB, CCB,* and *RCB* are all negative, and their magnitudes indicate that these banks have substantially lower operational risk than SOCBs. The operational risk exposure of JSCBs is 121% lower than that of SOCBs, and the figure for CCBs and RCBs is more than 200%, consistent with Fig. 3.

The coefficients on the interaction terms between the cloud computing index and ownership capture the differential impact of cloud computing on operational risk depending on bank ownership. In Column (3), we include a full set of control variables, while in Column (4), we drop two insignificant control variables. The coefficient on $Cloud_{it}$ turns negative, indicating that cloud computing application lowers operational risk for SOCBs. For example, in Column (3), for a one-standard-deviation increase in the cloud computing index, SOCBs' operational risk decreases by 4.5% (=(−0.235)× 0.192). The coefficients on all interaction terms ($JSCB_i \times Cloud_{it}$, $CCB_i \times Cloud_{it}$, $RCB_i \times Cloud_{it}$) are positive and larger than the negative coefficient on $Cloud_{it}$; that is, the net impact of cloud computing leads to an increase in operational risk for these banks. For a one-standard-deviation increase in the cloud computing index, operational risk increases by 9.9% for CCBs (= (−0.235 +0.750) × 0.192), followed by 5.7% for JSCBs (= (−0.235 +0.535) × 0.192), and 3.84% for RCBs (= (−0.235 +0.435) × 0.192). Cloud computing increases bank operational risk exposure in the banking sector, and this effect varies significantly with bank ownership. Only SOCBs enjoy the reduction in operational risk brought about by cloud computing, and all other banks have experienced an increase in operational risk exposure.

Moreover, bank size and credit risk are associated with higher operational risk, consistent with the literature (Curti et al., 2020;

**Table 8**
The effect of cloud computing on bank performance.

| Variables | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | Overhead to equity ratio | | Return on assets | | Return on equity | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Cloud_{it}$ | 0.130*** | 0.152** | 0.173*** | 0.184*** | 3.305*** | 5.357*** |
| | (0.004) | (0.028) | (0.060) | (0.073) | (0.915) | (1.079) |
| $JSCB_i$ | 0.026 | 0.051 | 0.238 | 0.266 | 12.488*** | 15.492*** |
| | (0.909) | (0.850) | (0.235) | (0.274) | (3.886) | (4.344) |
| $CCB_i$ | -0.260 | -0.230 | 0.641* | 0.679* | 18.178*** | 21.860*** |
| | (0.406) | (0.527) | (0.354) | (0.415) | (5.743) | (6.471) |
| $RCB_i$ | 0.118 | 0.155 | 1.243** | 1.295** | 26.835*** | 31.573*** |
| | (0.797) | (0.766) | (0.364) | (0.416) | (5.998) | (6.601) |
| $JSCB_i\times Cloud_{it}$ | | -0.024 | | 0.007 | | -2.763*** |
| | | (0.723) | | (0.058) | | (0.910) |
| $CCB_i\times Cloud_{it}$ | | -0.034 | | -0.062 | | -3.442** |
| | | (0.753) | | (0.119) | | (1.921) |
| $RCB_i\times Cloud_{it}$ | | -0.056 | | -0.042 | | -1.143 |
| | | (0.631) | | (0.157) | | (2.221) |
| *Control variables* | | | | | | |
| $Size_{it}$ | 0.006 | 0.006 | 0.084 | 0.091 | 3.512*** | 4.097*** |
| | (0.923) | (0.923) | (0.066) | (0.075) | (1.124) | (1.224) |
| $NPL_{it}$ | 0.108* | 0.108* | -0.055 | -0.056 | -1.738 | -1.577 |
| | (0.093) | (0.093) | (0.154) | (0.155) | (3.136) | (3.011) |
| $Tier1_{it}$ | -0.064*** | -0.064*** | 0.029*** | 0.028*** | -0.395*** | -0.405*** |
| | (0.000) | (0.000) | (0.008) | (0.008) | (0.138) | (0.141) |
| constant | -0.903 | -0.903 | -0.591 | -0.707 | -31.888* | -41.784** |
| | (0.385) | (0.385) | (1.070) | (1.206) | (18.550) | (20.081) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 823 | 823 | 778 | 778 | 777 | 777 |
| Adjusted-$R^2$ | 0.832 | 0.832 | 0.733 | 0.732 | 0.746 | 0.747 |

$Y_{it} = \delta_0 + \delta_1 Cloud_{it} + \sum\delta_k Ownership_i + \sum\delta_l Cloud_{it} \times Ownership_i + \sum\delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from the above equation for overhead to equity ratio in columns (1) – (2), return on assets in columns (3) – (4), and return on equity in columns (5) – (6). All continuous variables are winsorized at 2.5$^{th}$ and 97.5$^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. *Cloud* is a measure of cloud computing. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size* (the logarithm of total assets), non-performing loan ratio (*NPL*) for assets quality/credit risk, and the core tier one capital ratio (*Tier1*) for capital adequacy. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Chernobai et al., 2021). For an increase in bank total assets by 1%, bank operational risk increases by 0.54%. When a bank's NPL ratio increases by a one-standard deviation, bank operational risk rises by 1.8% (=0.516 × 0.035).

## 5. Robustness tests

In this section, we carry out a battery of robustness tests. We first employ alternative measures, estimation techniques, and a subsample in Section 5.1. We address the potential endogeneity problems in Section 5.2. The results suggest that our main conclusions are robust.

### 5.1. Alternative measurement, estimator, and subsamples

We start with an alternative measure of cloud computing based on the same information sources. Our main cloud computing index is constructed based on an initial three-dimensional lexicon for crawling keywords, which may omit other key information related to cloud computing (i.e., collaborative financial products of cloud computing and big data). To address the potential bias due to incomplete search information, we broaden the initial lexicon to cover the most popular and prominent emerging high-tech technologies (Nicoletti et al., 2017; Chen et al., 2019) and obtain a high-tech index—$HighTech_{it}$—to replace $Cloud_{it}$ in Eqs. (3)–(6). The estimation results are reported in Table 6: Columns (1)–(2) for cost efficiency, Columns (3)–(4) for profit efficiency, and Columns (5)–(6) for operational risk. These results are consistent with those in Tables 3–5.

Then, we use banks' annual reports as an alternative information source and employ Python to search for the keyword "cloud computing" and define *CloudAR* as the frequency count of "cloud computing". Given the close connections among different newly emerging technologies, banks' annual reports may not separate them clearly and use high-tech-related words interchangeably. To address this possibility, we also search for key words–"Fintech", "cloud computing", "information technology", "big data", "artificial intelligence", and "blockchain", and define *HighTechAR* as the total frequency count of these words. We replace *Cloud* in Eqs. (4) and (6) with *CloudAR* and *HighTechAR*, respectively, and the regression results, as reported in Table 7, are consistent with our main results in Tables 3–5.

To test the potential selection bias of bank performance measures, we use three financial indicators as alternative bank performance measures, namely, the overhead-to-equity ratio, return on assets (ROA), and return on equity (ROE). We focus on overhead (normalized by equity) because a large proportion of the costs of cloud computing development (i.e., the depreciation of related capital investment and personnel expenses of related human capital) is included in non-interest overhead expenses, while ROA and ROE are widely used profitability measures. As shown in Table 8, the cloud computing index is associated with a higher overhead-to-equity ratio and banks' profitability in terms of both ROA and ROE. Coefficients on ownership variables and control variables are all in line with expectations. The results are generally consistent with our main results that the application of cloud computing increases costs but

**Table 9**
The effect of cloud computing on bank efficiency based on the OLS regression.

| Variables | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | Cost efficiency | | | Profit efficiency | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Cloud_{it}$ | -0.010*** | -0.010*** | -0.013*** | 0.253*** | 0.253*** | 0.420*** |
| | (0.003) | (0.003) | (0.004) | (0.041) | (0.041) | (0.050) |
| $JSCB_i$ | | -0.004 | -0.009 | | 0.540*** | 0.818*** |
| | | (0.011) | (0.013) | | (0.147) | (0.163) |
| $CCB_i$ | | -0.004 | -0.010 | | 0.539** | 0.887*** |
| | | (0.015) | (0.017) | | (0.249) | (0.266) |
| $RCB_i$ | | -0.004 | -0.013 | | 0.581 | 1.032*** |
| | | (0.021) | (0.024) | | (0.380) | (0.397) |
| $JSCB_i \times Cloud_{it}$ | | | 0.001 | | | -0.206*** |
| | | | (0.004) | | | (0.047) |
| $CCB_i \times Cloud_{it}$ | | | 0.010* | | | -0.388*** |
| | | | (0.005) | | | (0.083) |
| $RCB_i \times Cloud_{it}$ | | | 0.008 | | | -0.013 |
| | | | (0.005) | | | (0.125) |
| *Control variables* | | | | | | |
| $Size_{it}$ | 0.000 | 0.000 | -0.001 | 0.084** | 0.084** | 0.143*** |
| | (0.003) | (0.003) | (0.004) | (0.041) | (0.041) | (0.044) |
| $NPL_{it}$ | 0.012** | 0.012** | 0.012** | -0.189 | -0.189 | -0.173 |
| | (0.005) | (0.005) | (0.005) | (0.139) | (0.139) | (0.125) |
| $Tier1_{it}$ | 0.001** | 0.001** | 0.001** | 0.018*** | 0.018*** | 0.017*** |
| | (0.000) | (0.000) | (0.000) | (0.003) | (0.003) | (0.003) |
| constant | 0.980*** | 0.980*** | 0.999*** | -0.992 | -0.992 | -1.978*** |
| | (0.050) | (0.050) | (0.056) | (0.653) | (0.653) | (0.705) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 823 | 823 | 823 | 823 | 823 | 823 |
| Adjusted-$R^2$ | 0.129 | 0.129 | 0.130 | 0.357 | 0.357 | 0.372 |

$Y_{it} = \delta_0 + \delta_1 Cloud_{it} + \sum \delta_k Ownership_i + \sum \delta_l Cloud_{it} \times Ownership_i + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from the above equation for cost efficiency in columns (1) – (3) and profit efficiency in columns (4) – (6). All continuous variables are winsorized at $2.5^{th}$ and $97.5^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. *Cloud* is the cloud computing index. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size* (the logarithm of total assets), non-performing loan ratio (*NPL*) for assets quality/credit risk, and the core tier one capital ratio (*Tier1*) for capital adequacy. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

results in high profitability, largely due to a faster increase in revenue.[14]

Our main results on the cost efficiency and profit efficiency in Table 3 and Table 4 are estimated using the truncated regression (Honoré and Powell, 1994), as suggested by Simar and Wilson (2007) that other estimators may yield biased results because cost/profit efficiency is bounded between 0 and 1. To check the robustness of our results, we employ standard OLS, in particular, least squares dummy variable (LSDV) regression, to re-estimate the model. As shown in Table 9, the results in Columns (1)–(3) are consistent with those in Table 3 for cost efficiency, while the results in Columns (4)–(6) are consistent with those in Table 4 for profit efficiency.

It could be argued that our results are biased, driven by large SOCBs since we observe in Fig. 1 that the cloud computing index mostly captures SOCBs. We drop SOCBs and re-estimate using the subsamples of JSCBs, CCBs, and RCBs. As shown in Table 10, the coefficient on *Cloud* is negative for cost efficiency and positive for profit efficiency and operational risk, consistent with our main results in Tables 3–5. The results provide strong evidence that our main results are robust and not driven by large SOCBs.

### 5.2. Endogeneity

To address the potential endogeneity problem, we carry out two tests. We first test for potential two-way causality. The adoption of cloud computing generally goes through different stages, from theoretical justification, framework discussion, and policy guidance to the launch of the dedicated technical department related to cloud computing. The department launch is a milestone, indicating banks' commitment to the transition to cloud computing. When compiling the crawler's raw data, we notice that cloud computing-induced innovative financial services generally appear after the launch of the technical department. Therefore, we examine whether bank efficiency and operational risk are driving factors for banks' strategic move to cloud computing proxied by the launch of the cloud computing-related technical department. We manually collect news disclosure and policy documents from 118 banks' websites that confirm the official launch of their cloud computing-related technical departments. We define *TechBank* as a dummy variable taking a value of 1 for banks having established the technical department and 0 otherwise. We drop all observations after the launch of technical departments (176 observations are dropped), which allows us to test whether banks' prior cost efficiency, profit efficiency, and operational risk can predict the launch of the technical departments. The empirical binary choice model is specified in Eq. (7).

$$TechBank_{it} = \delta_0 + \delta_1 CE_{it} + \delta_2 PE_{it} + \delta_3 OR_{it} + \sum \delta_j Control_{it} + Year_t + \varepsilon_{it} \quad (7)$$

where $CE_{it}$ is cost efficiency, $PE_{it}$ is profit efficiency, and $OR_{it}$ is operational risk. $Control_{it}$ includes the most important bank characteristics of $Size_{it}$ and $NPL_{it}$. $Year_t$ is a series of dummy variables used to control year

[14] Our finding of deteriorating cost efficiency but increasing profit efficiency is also confirmed by the unreported results from a commonly employed accounting ratio of cost efficiency – the cost-to-income ratio. If profit (income) increases faster than costs, the cost-to-income ratio decreases. We regress cloud computing index against cost-to-income ratio. As expected, it loads negatively that a higher cloud computing index is associated with lower cost-to-income ratio. This result, nevertheless, reveals the deficiency of accounting ratio as a measure of cost efficiency because the decreasing cost-to-income ratio does not necessarily suggest improved cost efficiency but is becasue revenues (income) increase at a faster speed than costs.

**Table 10**
The effect of cloud computing on bank efficiency and operation risk: a subsample excluding large state banks.

| Variables | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | Cost efficiency | | Profit efficiency | | Operational risk | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Cloud_{it}$ | -0.010*** | -0.010*** | 0.205*** | 0.205*** | 0.331*** | 0.331*** |
| | (0.003) | (0.003) | (0.040) | (0.040) | (0.068) | (0.068) |
| $CCB_i$ | | -0.002 | | 0.371** | | -1.823*** |
| | | (0.009) | | (0.188) | | (0.233) |
| $RCB_i$ | | -0.004 | | 0.497 | | -1.913*** |
| | | (0.016) | | (0.319) | | (0.359) |
| *Control variables* | | | | | | |
| $Size_{it}$ | -0.000 | -0.000 | 0.135*** | 0.135*** | 0.562*** | 0.562*** |
| | (0.003) | (0.003) | (0.041) | (0.041) | (0.079) | (0.079) |
| $NPL_{it}$ | 0.012*** | 0.012*** | -0.168 | -0.168 | 0.514*** | 0.514*** |
| | (0.004) | (0.004) | (0.116) | (0.116) | (0.197) | (0.197) |
| $Tier1_{it}$ | 0.001** | 0.001** | 0.017*** | 0.017*** | | |
| | (0.000) | (0.000) | (0.003) | (0.003) | | |
| $EA_{it}$ | | | | | 0.011 | 0.011 |
| | | | | | (0.012) | (0.012) |
| $ROE_{it}$ | | | | | -0.002 | -0.002 |
| | | | | | (0.003) | (0.003) |
| constant | 0.986*** | 0.986*** | -1.372** | -1.372** | 0.524 | 0.524 |
| | (0.044) | (0.044) | (0.576) | (0.576) | (1.131) | (1.131) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 763 | 763 | 763 | 763 | 768 | 768 |
| Sigma/Adj.$R^2$ | 0.008*** | 0.008*** | 0.131*** | 0.131*** | 0.971 | 0.971 |

$Y_{it} = \delta_0 + \delta_1 Cloud_{it} + \sum \delta_k Ownership_i + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from the above equation for cost efficiency in columns (1) – (2), profit efficiency in columns (3) – (4), and operational risk in columns (5)-(6). All continuous variables are winsorized at 2.5$^{th}$ and 97.5$^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. *Cloud* is a measure of cloud computing. Ownership includes *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size* (the logarithm of total assets), non-performing loan ratio (*NPL*) for assets quality/credit risk, and the core tier one capital ratio (*Tier1*) for capital adequacy, the equity to capital ratio (EA) for capital risk, and profitability (ROE). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

**Table 11**
The predictive power of bank efficiency and operational risk for the cloud computing adoption.

| Variables | Dependent variable: $TechBank_{it}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $CE_{it}$ | -6.067 | | | -15.404 |
| | (67.136) | | | (68.949) |
| $PE_{it}$ | | 1.845 | | -0.585 |
| | | (6.870) | | (4.847) |
| $OR_{it}$ | | | 0.361 | 0.656 |
| | | | (1.336) | (0.915) |
| *Control variables* | | | | |
| $Size_{it}$ | 0.012 | 0.009 | -0.044 | -0.008 |
| | (0.069) | (0.183) | (0.158) | (0.080) |
| $NPL_{it}$ | -1.858 | -5.864 | -5.762 | -0.784 |
| | (17.874) | (10.578) | (29.944) | (16.933) |
| constant | 19.842 | 24.637*** | 14.107 | 24.108 |
| | (66.529) | (7.895) | (16.500) | (67.068) |
| Year FE | Yes | Yes | Yes | Yes |
| Observations | 579 | 579 | 579 | 579 |
| Ln Sig2u | 6.563*** | 7.363*** | 6.611*** | 6.251*** |
| LR test of Rho | 551.340*** | 561.440*** | 547.280*** | 545.740*** |

$TechBank_{it} = \delta_0 + \delta_1 CE_{it} + \delta_2 PE_{it} + \delta_3 OR_{it} + \sum \delta_j Control_{it} + Year_t + \varepsilon_{it}$

This table reports results from the above binary choice model equation. All continuous variables are winsorized at 2.5th and 97.5th percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. *TechBank* is a dummy variable for banks with a dedicated cloud-computing related department, *CE* is cost efficiency, *PE* is profit efficiency, and *OR* is operational risk. $Control_{it}$ includes bank *Size* and *NPL* for asset quality. $Year_t$ is a series of dummy variables used to control year fixed effects. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

fixed effects.

As shown in Table 11, the coefficients on $CE_{it}$, $PE_{it}$, and $OR_{it}$ are insignificant in all specifications, indicating that banks' efficiency and operational risk have no predictive power for the launch of their cloud computing-related technical departments. The results provide strong evidence that banks' strategic move to cloud computing is not driven by poor performance and/or high operational risks. Moreover, we check the robustness of the numerical integration, and our results remain unchanged. In short, our baseline results do not suffer from potential two-way causality.

It is helpful to resolve the endogeneity issue using a difference-in-differences analysis. While our sample does not meet the strict assumptions for the difference-in-differences analysis, we design two settings to provide further evidence supporting our main results. In July 2016, the central bank of China, the People's Bank of China, promulgated *Supervision and Guidance Opinions on the 13th Five-Year Development Plan of Information Technology in Chinese Banking (hereafter Opinions)*. This *Opinions* document clearly points out the mission of promoting emerging high-tech in the banking industry. We consider this to be an exogenous policy shock to banks and define $Shock_t$, which equals 1 for years after 2016 and 0 otherwise.

We consider two quasi-natural experiment settings and apply a difference-in-differences framework to verify the impact of could computing on bank efficiency and operational risk. First, large commercial banks with better infrastructure systems and R&D capability (i.e., human capital) are implicitly expected to lead the race of new technology application. Hence, the policy shock is expected to have a more profound impact on large banks. Following the literature (Berger et al., 2017; Vallascas et al., 2017; Lorenc and Zhang, 2020), we define $BigBank_i$ as taking a value of 1 if a bank's total assets are greater than the sample median and 0 otherwise. Second, we expect the policy shock to be more profound for banks that have embraced cloud computing than

**Table 12**
Endogeneity Test: Policy shocks.

| Variables | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | Cost efficiency | | Profit efficiency | | Operational risk | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $BigBank_i$ | -0.001 | | 0.040** | | 0.206*** | |
| | (0.002) | | (0.038) | | (0.044) | |
| $CloudD_i$ | | 0.000 | | 0.035 | | -0.439*** |
| | | (0.002) | | (0.068) | | (0.143) |
| $Shock_t$ | 0.002** | 0.002** | -0.052* | -0.052** | -0.014 | 0.041* |
| | (0.001) | (0.001) | (0.045) | (0.050) | (0.052) | (0.024) |
| $BigBank_i \times Shock_t$ | -0.003*** | | 0.048*** | | 0.068* | |
| | (0.001) | | (0.042) | | (0.065) | |
| $CloudD_i \times Shock_t$ | | -0.002*** | | 0.032** | | -0.055 |
| | | (0.001) | | (0.044) | | (0.050) |
| $JSCB_i$ | 0.004 | 0.003 | 0.276* | 0.300* | -0.301 | -0.416 |
| | (0.005) | (0.005) | (0.134) | (0.135) | (0.208) | (0.231) |
| $CCB_i$ | 0.006 | 0.006 | 0.128 | 0.207 | -1.003*** | -1.548*** |
| | (0.005) | (0.005) | (0.226) | (0.257) | (0.222) | (0.242) |
| $RCB_i$ | 0.006 | 0.006 | 0.123 | 0.165 | -0.575 | -1.095*** |
| | (0.008) | (0.008) | (0.326) | (0.318) | (0.298) | (0.261) |
| *Control variables* | | | | | | |
| $Size_{it}$ | 0.001 | 0.001 | 0.030 | 0.039 | 0.889*** | 0.917*** |
| | (0.001) | (0.001) | (0.031) | (0.030) | (0.043) | (0.043) |
| $NPL_{it}$ | 0.013*** | 0.013*** | -0.190 | -0.182 | 0.514*** | 0.547*** |
| | (0.005) | (0.005) | (0.140) | (0.142) | (0.133) | (0.180) |
| $Tier1_{it}$ | 0.000 | 0.000 | 0.025*** | 0.024*** | | |
| | (0.000) | (0.000) | (0.005) | (0.005) | | |
| $EA_{it}$ | | | | | 0.036*** | 0.046*** |
| | | | | | (0.010) | (0.011) |
| $ROE_{it}$ | | | | | -0.006** | -0.005 |
| | | | | | (0.003) | (0.003) |
| constant | 0.963*** | 0.965*** | -0.019 | -0.140 | -3.760*** | -3.643*** |
| | (0.020) | (0.018) | (0.549) | (0.555) | (0.756) | (0.760) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 823 | 823 | 823 | 823 | 827 | 827 |
| Sigma/Adj.$R^2$ | 0.008*** | 0.008*** | 0.138*** | 0.138*** | 0.981 | 0.980 |

$Y_{it} = \delta_0 + \delta_1 Shock_t + \delta_2 BigBank_i(or \quad CloudD_i) + \delta_3 Shock_t \times BigBank_i(or \quad CloudD_i) + \sum\delta_k Ownership_i + \sum\delta_j Control_{it} + Bank_i + \varepsilon_{it}$
This table reports results from the above equation for cost efficiency in columns (1)-(2), profit efficiency in columns (3)-(4), and operational risk in columns (5)-(6). All continuous variables are winsorized at $2.5^{th}$ and $97.5^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. *Shock* is a dummy variable for policy in 2016 promoting Information Technology in Chinese Banking. *BigBank* is a dummy for banks with total assets greater than the sample median, and *CloudD* is a dummy for banks already adopted cloud computing. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size* (the logarithm of total assets), non-performing loan ratio (*NPL*) for assets quality/credit risk, and the core tier one capital ratio (*Tier1*) for capital adequacy, the equity to capital ratio (*EA*) for capital risk, and profitability (*ROE*). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

for those that have yet to apply new technologies. We define $CloudD_i$ that takes a value of 1 for banks that have applied cloud technology and 0 otherwise. The empirical specifications are shown in Eq. (8). As $Shock_t$ is a time dummy, we follow Petersen (2009) and exclude year fixed effects in the models but with standard errors clustered by year.

$$Y_{it} = \delta_0 + \delta_1 Shock_t + \delta_2 BigBank_i(or \quad CloudD_i) + \delta_3 Shock_t \times BigBank_i(or \quad CloudD_i) + \sum\delta_k Ownership + \sum\delta_j Control_{it} + Bank_i + \varepsilon_{it} \tag{8}$$

where the dependent variables are cost efficiency, profit efficiency, and operational risk.

The estimation results are reported in Table 12. The coefficients on the two interaction terms—$Shock_t \times BigBank_i$ and $Shock_t \times CloudD_i$—are negative and significant in Columns (1)–(2) but positive and statistically significant in Columns (3)–(4). The results suggest that after the policy shock—the promulgation of the *Opinions* to promote new technologies (such as cloud computing) in banking—large banks (unofficially pressurized to promote new technology) and banks that had already adopted cloud computing are associated with lower cost efficiency but higher profit efficiency relative to small banks and banks without applying cloud computing. In terms of operational risk, only the coefficient on $Shock_t \times BigBank_i$ is positive and significant in Column (5). Larger banks expected to advance new technologies experience higher operational risk than their counterparts. Overall, the results are consistent with those from our baseline models, providing evidence for the causal impact of cloud computing on bank efficiency and operational risks.

## 6. Extended study: cloud computing and newly emerging technologies

Cloud computing is one of the newly emerging technologies, along with big data, blockchain, internet, and artificial intelligence. The development of technology is never isolated but interconnected; some of them can be complementary with synergy gains, while others may be substitutive. In this section, we explore how cloud computing interacts with other newly emerging technologies and jointly affects bank efficiency and operational risk. Using the same method in Section 3.1, we construct an index for big data: $Bigdata_{it}$, blockchain-$Blockchain_{it}$, internet-$internet_{it}$, and artificial intelligence-$AI_{it}$. The empirical model is shown in Eq. (9).

$$Y_{it} = \delta_0 + \delta_1 Cloud_{it} + \delta_2 Techtype_{it} + \sum\delta_l Cloud \times Techtype + \sum\delta_k Ownership + \sum\delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it} \tag{9}$$

where $Y_{it}$ is the cost efficiency $CE_{it}$, profit efficiency $PE_{it}$, or operational risk ($OR_{it}$ in logarithm) of bank $i$ in year $t$; $Cloud_{it}$ is the cloud computing

**Table 13**
The effect of cloud computing on cost efficiency: the interaction with other new emerging technologies.

| Variables | $Techtype_{it}$ =*Bigdata* | | $Techtype_{it}$ =*Blockchain* | | $Techtype_{it}$ =*Internet* | | $Techtype_{it}$ =*AI* | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $Cloud_{it}$ | -0.018*** | -0.018*** | -0.001 | -0.001 | -0.013*** | -0.013*** | -0.007** | -0.007** |
| | (0.007) | (0.007) | (0.003) | (0.003) | (0.005) | (0.005) | (0.003) | (0.003) |
| $Techtype_{it}$ | 0.003 | 0.003 | -0.021*** | -0.021*** | -0.001 | -0.001 | -0.041*** | -0.041*** |
| | (0.003) | (0.003) | (0.005) | (0.005) | (0.003) | (0.003) | (0.011) | (0.011) |
| $Cloud_{it}\times Techtype_{it}$ | 0.006 | 0.006 | 0.006 | 0.006 | 0.004 | 0.004 | 0.031*** | 0.031*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.011) | (0.011) |
| $JSCB_i$ | | -0.004 | | -0.011 | | -0.004 | | -0.010 |
| | | (0.010) | | (0.011) | | (0.010) | | (0.011) |
| $CCB_i$ | | -0.003 | | -0.013 | | -0.003 | | -0.011 |
| | | (0.014) | | (0.014) | | (0.014) | | (0.014) |
| $RCB_i$ | | -0.004 | | -0.016 | | -0.003 | | -0.013 |
| | | (0.020) | | (0.020) | | (0.020) | | (0.020) |
| *Control variables* | | | | | | | | |
| $Size_{it}$ | 0.000 | 0.000 | -0.001 | -0.001 | 0.001 | 0.001 | -0.000 | -0.000 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| $NPL_{it}$ | 0.012*** | 0.012*** | 0.012*** | 0.012*** | 0.012*** | 0.012*** | 0.012*** | 0.012*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $Tier1_{it}$ | 0.001** | 0.001** | 0.001*** | 0.001*** | 0.001** | 0.001** | 0.001** | 0.001** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| constant | 0.978*** | 0.978*** | 1.003*** | 1.003*** | 0.976*** | 0.976*** | 0.994*** | 0.994*** |
| | (0.047) | (0.047) | (0.047) | (0.047) | (0.048) | (0.048) | (0.047) | (0.047) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 823 | 823 | 823 | 823 | 823 | 823 | 823 | 823 |
| Sigma | 0.007*** | 0.007*** | 0.007*** | 0.007*** | 0.007*** | 0.007*** | 0.007*** | 0.007*** |

$CE_{it} = \delta_0 + \delta_1 Cloud_{it} + \delta_2 Techtype_{it} + \sum \delta_l Cloud_{it} \times Techtype_{it} + \sum \delta_k Ownership_i + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from the above model. All continuous variables are winsorized at 2.5$^{th}$ and 97.5$^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. CE=cost efficiency. $Cloud_{it}$ is cloud computing index. $Techtype_{it}$ refers to $Bigdata_{it}$, $Blockchain_{it}$, $Internet_{it}$, and $AI_{it}$. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size*, non-performing loan ratio (*NPL*), and the core tier one capital ratio (*Tier1*). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

**Table 14**
The effect of cloud computing on profit efficiency: the interaction with other new emerging technologies.

| Variables | $Techtype_{it}$ =*Bigdata* | | $Techtype_{it}$ =*Blockchain* | | $Techtype_{it}$ =*Internet* | | $Techtype_{it}$ =*AI* | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $Cloud_{it}$ | 0.140 | 0.140 | 0.080 | 0.080 | 0.055 | 0.055 | 0.157*** | 0.157*** |
| | (0.100) | (0.100) | (0.067) | (0.067) | (0.093) | (0.093) | (0.043) | (0.043) |
| $Techtype_{it}$ | -0.009 | -0.009 | 0.346*** | 0.346*** | 0.057 | 0.057 | 0.413 | 0.413 |
| | (0.053) | (0.053) | (0.090) | (0.090) | (0.044) | (0.044) | (0.281) | (0.281) |
| $Cloud_{it}\times Techtype_{it}$ | 0.132 | 0.132 | -0.075 | -0.075 | 0.209** | 0.209** | -0.125 | -0.125 |
| | (0.100) | (0.100) | (0.100) | (0.100) | (0.099) | (0.099) | (0.258) | (0.258) |
| $JSCB_i$ | | 0.548*** | | 0.655*** | | 0.613*** | | 0.650*** |
| | | (0.135) | | (0.136) | | (0.137) | | (0.141) |
| $CCB_i$ | | 0.544** | | 0.693*** | | 0.618*** | | 0.675*** |
| | | (0.228) | | (0.230) | | (0.231) | | (0.234) |
| $RCB_i$ | | 0.594* | | 0.785** | | 0.674* | | 0.752** |
| | | (0.350) | | (0.349) | | (0.351) | | (0.354) |
| *Control variables* | | | | | | | | |
| $Size_{it}$ | 0.089** | 0.089** | 0.112*** | 0.112*** | 0.092** | 0.092** | 0.104*** | 0.104*** |
| | (0.038) | (0.038) | (0.038) | (0.038) | (0.039) | (0.039) | (0.038) | (0.038) |
| $NPL_{it}$ | -0.189 | -0.189 | -0.182 | -0.182 | -0.192 | -0.192 | -0.187 | -0.187 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| $Tier1_{it}$ | 0.018*** | 0.018*** | 0.016*** | 0.016*** | 0.018*** | 0.018*** | 0.017*** | 0.017*** |
| | (0.127) | (0.127) | (0.122) | (0.122) | (0.127) | (0.127) | (0.124) | (0.124) |
| constant | -1.059* | -1.059* | -1.406** | -1.406** | -1.149* | -1.149* | -1.323** | -1.323** |
| | (0.609) | (0.609) | (0.605) | (0.605) | (0.624) | (0.624) | (0.609) | (0.609) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 823 | 823 | 823 | 823 | 823 | 823 | 823 | 823 |
| Sigma | 0.126*** | 0.126*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** | 0.125*** |

$PE_{it} = \delta_0 + \delta_1 Cloud_{it} + \delta_2 Techtype_{it} + \sum \delta_l Cloud_{it} \times Techtype_{it} + \sum \delta_k Ownership_i + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from the above model. All continuous variables are winsorized at 2.5$^{th}$ and 97.5$^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. PE=profit efficiency. $Cloud_{it}$ is cloud computing index. $Techtype_{it}$ refers to $Bigdata_{it}$, $Blockchain_{it}$, $Internet_{it}$, and $AI_{it}$. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size*, non-performing loan ratio (*NPL*), and the core tier one capital ratio (*Tier1*). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

**Table 15**
The effect of cloud computing on operational risk: the interaction with other new emerging technologies.

| Variables | $Techtype_{it}$ =*Bigdata* | | $Techtype_{it}$ =*Blockchain* | | $Techtype_{it}$ =*Internet* | | $Techtype_{it}$ =*AI* | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $Cloud_{it}$ | 0.546*** | 0.546*** | 0.546*** | 0.546*** | 0.377** | 0.377** | 0.417*** | 0.417*** |
| | (0.187) | (0.187) | (0.133) | (0.133) | (0.183) | (0.183) | (0.083) | (0.083) |
| $Techtype_{it}$ | 0.386*** | 0.386*** | 0.517*** | 0.517*** | 0.347*** | 0.347*** | 0.819** | 0.819** |
| | (0.111) | (0.111) | (0.155) | (0.155) | (0.076) | (0.076) | (0.342) | (0.342) |
| $Cloud_{it}\times Techtype_{it}$ | -0.774*** | -0.774*** | -0.991*** | -0.991*** | -0.376* | -0.376* | -1.424*** | -1.424*** |
| | (0.168) | (0.168) | (0.157) | (0.157) | (0.201) | (0.201) | (0.314) | (0.314) |
| $JSCB_i$ | | -1.313*** | | -1.239*** | | -1.187*** | | -1.345*** |
| | | (0.277) | | (0.279) | | (0.283) | | (0.283) |
| $CCB_i$ | | -2.218*** | | -2.155*** | | -2.101*** | | -2.284*** |
| | | (0.353) | | (0.354) | | (0.357) | | (0.360) |
| $RCB_i$ | | -2.207*** | | -2.100*** | | -2.076*** | | -2.237*** |
| | | (0.474) | | (0.476) | | (0.481) | | (0.480) |
| *Control variables* | | | | | | | | |
| $Size_{it}$ | 0.624*** | 0.624*** | 0.641*** | 0.641*** | 0.627*** | 0.627*** | 0.637*** | 0.637*** |
| | (0.076) | (0.076) | (0.075) | (0.075) | (0.077) | (0.077) | (0.075) | (0.075) |
| $NPL_{it}$ | 0.554** | 0.554** | 0.569** | 0.569** | 0.544** | 0.544** | 0.556** | 0.556** |
| | (0.217) | (0.217) | (0.221) | (0.221) | (0.220) | (0.220) | (0.216) | (0.216) |
| $EA_{it}$ | 0.010 | 0.010 | 0.011 | 0.011 | 0.012 | 0.012 | 0.012 | 0.012 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| $ROE_{it}$ | -0.003 | -0.003 | -0.004 | -0.004 | -0.004 | -0.004 | -0.003 | -0.003 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| constant | 0.402 | 0.402 | 0.139 | 0.139 | 0.251 | 0.251 | 0.262 | 0.262 |
| | (1.220) | (1.220) | (1.209) | (1.209) | (1.244) | (1.244) | (1.218) | (1.218) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 827 | 827 | 827 | 827 | 827 | 827 | 827 | 827 |
| Adjusted-$R^2$ | 0.983 | 0.983 | 0.983 | 0.983 | 0.983 | 0.983 | 0.983 | 0.983 |

$OR_{it} = \delta_0 + \delta_1 Cloud_{it} + \delta_2 Techtype_{it} + \sum \delta_l Cloud_{it} \times Techtype_{it} + \sum \delta_k Ownership_i + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$

This table reports results from the above model. All continuous variables are winsorized at 2.5$^{th}$ and 97.5$^{th}$ percentiles. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. OR=operational risk. $Cloud_{it}$ is cloud computing index. $Techtype_{it}$ refers to $Bigdata_{it}$, $Blockchain_{it}$, $Internet_{it}$, and $AI_{it}$. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size*, non-performing loan ratio (*NPL*), equity to asset ratio (*EA*), and profitability (*ROE*). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

index; $Techtype_{it}$ refers to $Bigdata_{it}$, $Blockchain_{it}$, $internet_{it}$, and $AI_{it}$; $Control_{it}$ is a set of control variables (bank size, credit risk, capital risk, profitability); $Bank_i$ and $Year_t$ are bank and year fixed effects; and $\varepsilon_{it}$ refers to the error term.

Table 13 reports the results from Eq. (9) for cost efficiency. In Columns (1)–(2), the coefficient on $Cloud_{it}$ remains significant and negative, while the coefficients on $Bigdata_{it}$ and $Cloud_{it}\times HighTech_{it}$ are both insignificant. The evidence suggests that the application of big data technology has no influence on cost efficiency. Big data and cloud computing are closely linked. Big data refers to the large datasets collected, while cloud computing is the means of remotely analyzing and taking action on the data. Their effect on cost efficiency is captured by cloud computing. In Columns (3)–(4), cloud computing renders its explanatory power to blockchain and becomes insignificant. Both blockchain and cloud computing change banks' work environments. While cloud computing mostly runs on a traditional database structure, blockchain guarantees data transparency based on a core principle of decentralization without any third-party trusted centralized authority. Our result suggests that blockchain appears to have a substitute effect on the cloud. In Columns (5)–(6), we find that internet technology has no impact on cost efficiency and does not interact with cloud computing. Columns (7)–(8) show interesting results. While the coefficient on $Cloud_{it}$ remains negative and statistically significant, the coefficient on $Cloud_{it}\times AI_{it}$ is positive and statistically significant. The application of artificial intelligence improves the effect of cloud computing on cost efficiency. Banks adopting both cloud computing and artificial intelligence technologies are more cost efficient than banks adopting only cloud computing. Cloud computing and artificial intelligence appear to be complementary and lead to synergy gains in cost efficiency.

Table 14 reports the results from Eq. (9) for profit efficiency. In Columns (1)–(2), the coefficients on $Cloud_{it}$, $Bigdata_{it}$, and their interaction term $Cloud_{it}\times Bigdata_{it}$ are all insignificant. This is probably due to the multicollinearity problem, as the variance inflation factor for the big data model is 5.48.[14] The result in Columns (3)–(4) is consistent with that in Table 13, that cloud computing becomes insignificant. Blockchain is positively associated with profit efficiency, indicating a dominant substitute effect of blockchain with respect to cloud computing. In Columns (5)–(6), both cloud computing and internet technology are insignificant, but their interaction term is significant. The combination of cloud computing and the internet tends to improve bank profit efficiency. In Columns (7)–(8), the impact of cloud computing on profit efficiency is not affected by the bank's application of artificial intelligence. The coefficient on $Cloud_{it}$ remains positive and statistically significant.

Moving on to bank operational risk, the estimation results from Eq. (9) is reported in Table 15. The coefficients on all emerging technology indices are statistically significant, suggesting strong influences on banks' operational risk. The coefficients on the interaction terms between cloud computing and other new technologies are negative and statistically significant in all regressions. As in Column (2), for a one-standard-deviation increase in the big data index, holding other things constant, banks' operational risk on average decreases by 17.5% (=0.774 ×0.226). The corresponding figures for blockchain, internet, and artificial intelligence are 22.4%, 8.5%, and 32%, respectively. The results provide strong evidence that cloud computing interacts with other new technologies and jointly lowers banks' operational risk. Banks gain more from the joint application of new technologies in controlling operational risk, perhaps due to the diversifying and complementary

[14] The variance inflation factors (VIFs) for other new technologies are all below 5.

effect of different technologies. They are all based on the infrastructure construction of internet technology, cloud computing, big data, and artificial intelligence, which have become very powerful in risk identification, while blockchain enhances the security protocol.

## 7. Conclusion

Applying information crawling technology and text-based filtering methods, we construct a novel cloud computing index and examine the impact of cloud computing on bank efficiency and operational risk. We also explore how this effect varies with bank ownership and the application of other new emerging technologies. Our main findings are as follows. *First*, banks that adopt cloud computing are found to have lower cost efficiency but higher profit efficiency. *Second*, the application of cloud computing, on average, increases bank operational risk. However, this effect varies significantly with bank ownership: state-owned banks reduce operational risk, while all other banks experience increased operational risk. *Third,* we find tentative evidence suggesting that cloud computing interacts with other newly emerging technologies and jointly affects bank efficiency and operational risk. We find evidence for pervasive synergy gains in controlling operational risk. The findings are of timely policy importance and practical relevance for regulators, policy-makers, and bank managers. Cloud computing in banking is still at the early transitional stage, and its effects remain to be seen. Future research should follow up on the impact of cloud computing and other emerging technologies in the banking sector.

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## Appendix A. The cloud computing index

The cloud computing index is constructed in three steps. In the first step, we perform a fuzzy search on the application of cloud computing in the financial and banking industry. We conduct two series of fuzzy search on "*cloud computing* + *banking*" and "*cloud computing* + *finance*" without many restrictions. Table A1 shows the list of key words used in the fuzzy search and their frequencies. Next, we perform text segmentation on the homepage text content of the first 10,000 search results of every fuzzy search and generate two word-clouds. Based on the two word-clouds, we define the initial identifying information that contains three parts (year, bank name, and cloud computing keywords) and establish the lexicons of keywords, as shown in Table A2. We locate banks' media disclosure from three aspects of cloud computing – specific applications, service models, and service types, which covers public media disclosure that do not involve too many technical details.[15]

The second step is to obtain the frequency of the keywords in the search results. We target news releases containing the keywords for each bank each year over the period 2008–2019 through the Baidu search engine. Web crawler crawls all search results and keeps information in terms of time, search items, and relevant web contents. In total, we crawled more than 2 million news items and we eliminate duplicates and derive the frequency of the could computing keywords. For example, we obtain the total number of search results of the Industrial and Commercial Bank of China from 2008 to 2019 in the three dimensions (as shown in Table A2) as 25,138, 13,447, and 24,585, respectively. In comparison, the corresponding search results of the Shanghai Pudong Development Bank are 15,491, 8221, and 13,082. Fig. A1 shows a significant difference in the number of search results for these two banks, indicating the variation in their effort toward moving to cloud computing.

In the third step, we apply the factor analysis to construct yearly cloud computing index for 118 banks. Pretests are carried out to determine whether there are shared elements among the original keywords in each dimension. The KMO tests (Kaiser, 1974) and the approximate chi-square values of the Bartlett test of sphericity (Bartlett, 1938) reject the null hypothesis that the correlation coefficient matrix is a unit matrix. The test results indicate that the original keywords contain shared factors, and they are appropriate for factor analysis. Moreover, the common factors are extracted following the principle that the eigenvalue should be greater than 1. The results show that the variance

[15] In the original data obtained by our crawler, each bank's disclosure of each relevant keyword in each year has more than ten pages of search results under the Baidu search standard mode, which ensures the universality of each disclosure.

**Table A1**
The fuzzy search results of cloud computing in finance and banking industry.

| Name | Frequency |
|---|---|
| Cloud computing | 15,872 |
| Cloud business | 14,764 |
| Public cloud | 9379 |
| Cloud bank | 8914 |
| Cloud industry | 6609 |
| Cloud management | 5907 |
| Cloud finance | 5303 |
| Architecture | 5210 |
| Private cloud | 4209 |
| Platform service | 4172 |
| Cloud software | 3871 |
| Infrastructure | 3719 |
| Cloud data | 3641 |
| Cloud resource | 3108 |
| Cloud process | 2807 |
| Cloud application | 2765 |
| Cloud risk | 2674 |
| Cloud model | 2107 |
| Cloud strategy | 1907 |
| Clouding | 998 |

This table reports the key words and their frequency of fuzzy search results about cloud computing in finance and banking industry. We list the word frequency of the top 20 words with the highest frequency and these words are the basis for our initial lexicons for cloud computing index.

**Table A2**
Initial lexicons for cloud computing index.

| Dimensions | Application | Model | Type |
|---|---|---|---|
| Detailed keywords | Cloud computing | PaaS (Platform-as-a-Service) | Public cloud |
| | Cloud architecture | SaaS (Software-as-a-Service) | Private cloud |
| | Cloud service | IaaS (Infrastructure-as-a-Service) | Industry cloud |
| | Cloud finance | BPaaS (Business Process-as-a-Service) | Hybrid cloud |

This table reports the keywords used in the first step of the cloud computing index construction. We establish a three-dimensional initial lexicon in terms of cloud computing application, type, and model. Each dimension contains four high frequency representative keywords.

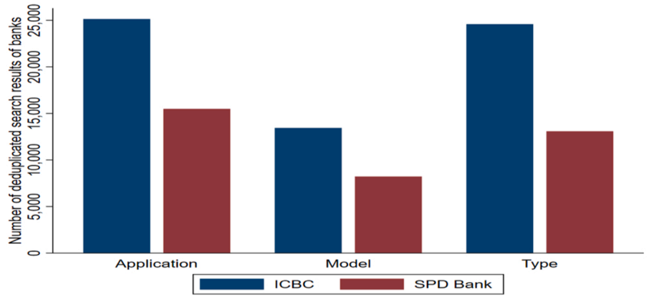


**Fig. A1.** The number of search results for the Industrial and Commercial Bank of China and the Shanghai Pudong Development Bank over the period 2008–2019.

contribution rate of the extracted common factors exceeds 60%, indicating that the extracted factors can reflect the information contained in the keywords. To ensure that the values of the index are positive, the maximum-minimum processing is applied to standardize data between 0 and 1.

## Appendix B

See Table B1.

**Table B1**
The effect of cloud computing on bank cost efficiency: data envelopment analysis (DEA) approach.

| Variables | Dependent variable: Cost efficiency | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Cloud_{it}$ | -0.035*** | -0.034*** | -0.034*** | | | |
| | -0.009 | (0.010) | (0.010) | | | |
| $HighTech_{it}$ | | | | -0.050*** | -0.059*** | -0.059*** |
| | | | | -0.013 | (0.015) | (0.015) |
| $JSCB_i$ | | | 0.061 | | | 0.040 |
| | | | (0.042) | | | (0.044) |
| $CCB_i$ | | | 0.034 | | | 0.007 |
| | | | (0.053) | | | (0.055) |
| $RCB_i$ | | | 0.088 | | | 0.057 |
| | | | (0.074) | | | (0.076) |
| *Control variables* | | | | | | |
| $Size_{it}$ | | 0.029*** | 0.029*** | | 0.027** | 0.027** |
| | | (0.011) | (0.011) | | (0.011) | (0.011) |
| $NPL_{it}$ | | 0.017 | 0.017 | | 0.017 | 0.017 |
| | | (0.015) | (0.015) | | (0.015) | (0.015) |
| $Tier1_{it}$ | | 0.002* | 0.002* | | 0.002** | 0.002** |
| | | (0.001) | (0.001) | | (0.001) | (0.001) |
| constant | 0.983*** | 0.506*** | 0.506*** | 0.989*** | 0.548*** | 0.548*** |
| | -0.014 | (0.169) | (0.169) | -0.014 | (0.170) | (0.170) |
| Bank & Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1083 | 822 | 822 | 1053 | 822 | 822 |
| Sigma | 0.041*** | 0.032*** | 0.032*** | 0.041*** | 0.032*** | 0.032*** |

$CE_{it} = \delta_0 + \delta_1 Cloud_{it} + \sum \delta_j Control_{it} + Bank_i + Year_t + \varepsilon_{it}$
This table reports results from the above equation for cost efficiency scores obtained from the Data envelopment analysis (DEA) approach. Using the truncated regression (Honoré and Powell, 1994), columns (1)-(3) report results from cloud computing index and (4)-(6) for an alternative high-tech index. All continuous variables are winsorized at $2.5^{th}$ and $97.5^{th}$ percentiles. The standard error is corrected for heteroscedasticity (White, 1980). $Cloud_{it}$ is the cloud computing index. $HighTech_{it}$ is an alternative measure of cloud computing. Ownership includes *SOCB* for state-owned commercial banks, *JSCB* for joint-stock commercial banks, *CCB* for city commercial banks, and *RCB* for rural commercial banks. Control variables include *Size* (the logarithm of total assets), non-performing loan ratio (*NPL*) for assets quality, and the core tier one capital ratio (*Tier1*) for capital adequacy. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

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