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The impact of fintech on the efficiency of urban commercial banks in China-based on super slacks-based measures with undesirable output

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Abstract

This study endeavours to elucidate the influence of financial technology (fintech) on the operational efficiency of urban commercial banks in China. By scrutinizing the integration of Internet-based fintech solutions, it seeks to illuminate their potential for streamlining banking processes, elevating customer experiences and augmenting the precision of credit assessments and lending decisions through sophisticated data analytics and risk management tools. This research evaluates the efficiency of Chinese urban commercial banks employing the Super Slacks-Based Measure (Super-SBM) which incorporates undesirable output. Furthermore, it leverages the System Generalized Method of Moments (System GMM) to investigate fintech's specific impact on urban commercial bank efficiency across various Chinese regions. The findings underscore fintech's pivotal role in catalyzing digital transformation within banks, thereby bolstering operational efficiency and customer satisfaction. Moreover, this study highlights the critical importance of fintech in fortifying risk management capabilities within the banking sector. The insights gleaned from this research contribute to the banking industry's sustainable growth and competitive resilience. Additionally, the findings furnish policymakers with empirical evidence to support the strategic integration of fintech and the optimization of banking service processes. Urban commercial banks can streamline operations, enhance customer experiences, refine credit assessments and ultimately attain higher efficiency and long-term sustainability levels in the rapidly evolving financial landscape by harnessing the transformative potential of fintech.

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1. Introduction

Fintech is an organic combination of financial services and information technology (Aysan & Nanaeva, 2022; Mhlanga, 2022; Milian, Spinola, & de Carvalho, 2019; Wilson Jr, 2017). Fintech significantly impacts the further optimisation and development of financial businesses, prompting the transformation of traditional financial companies into new financial innovation services (Chang et al., 2020). Since the rapid development of Internet finance and frequent emergencies, the concept of fintech has gradually emerged. In 1993, Citibank put forward the meaning of fintech. With the advancement of science and technology, fintech has developed rapidly and has a far-reaching impact on China's economy and society. Fintech has significantly impacted the way China's commercial banking sector works. It has gradually affected various financial services fields such as the processes of some traditional financial institutions like banks, securities, insurance, etc. with its rapid growth worldwide (Kumari & Devi, 2022). With the advent of the 21st century, the landscape of global technology has witnessed an unprecedented surge in the evolution of novel scientific and technological domains, heralding an era of accelerated innovation cycles and fostering a synergistic confluence between science, technology and the financial sector, thereby revitalizing the domain of financial innovation with novel insights and methodologies (Lee & Shin, 2018). In the contemporary context, the fintech sector in China has notably benefitted from the robust backing of governmental policies aligned with contemporary global trends. Notably, in January 2022, the People's Bank of China revealed the "Financial Technology Development Plan (2022-2025)" marking the initiation of the second phase of fintech developmental strategies after the inaugural framework established in August 2019, thereby delineating an expansive trajectory for the fintech sector within both national and international arenas in response to the evolving global dynamics (Zhang & Chen, 2022). Third-party payment platforms have attracted numerous customers due to their convenient payment methods and low payment costs gradually eroding the market share of the traditional banking industry (Guo & Bouwman, 2016). Fintech tools such as Ant Gold and WeChat Pay have changed the way people manage their finances (Lai & Langley, 2023). The public's access to more prosperous, flexible and convenient investment channels through online financial management puts commercial banks' deposit businesses at risk (Jameaba, 2020). In addition, the application of artificial intelligence has led to an increasing shift away from over-the-counter services resulting in the closure of many bank branches and unsustainable over-the-counter business, increasing the pressure on bank operations. However, as a technology-driven financial innovation, fintech not only improves the efficiency of financial operations, expands the boundaries of traditional finance and accelerates the technological change of commercial banks but also brings a broader development space for the banking industry (Murinde, Rizopoulos, & Zachariadis, 2022). At present, fintech not only plays a significant role in the application of technology in the banking field but also adds a new ecological model to the business and mode of traditional banks (Sánchez, 2022). In China's huge financial system, commercial banks especially urban commercial banks occupy an important position in the financial market and have a profound impact on the financial industry (Koroleva, Jigeer, Miao, & Skhvediani, 2021). Urban commercial banks originated in the 1980s aiming to support the financial development of the local real economy and small and medium-sized enterprises. Urban commercial banks are facing greater challenges especially the absorption of residential deposits, their core source of deposits by Internet wealth management platforms and their high reliance on loan interest which makes the impact of fintech on China's urban commercial banks more significant with the development of fintech.

Fintech is an emerging industry and China's urban commercial banks have actively catered to this change by upgrading their management level and staff's professional skills focusing on the introduction of fintech to carry out new business, obtaining a higher level of technology and broader coverage of customer groups. However, the risks brought by fintech should be considered such as how to guarantee security, avoid the possibility of reform failure and ensure its core position and business model in the reform, etc. Therefore, exploring the relationship between the development of fintech and the operational efficiency of urban commercial banks in China is of great theoretical and practical significance for promoting banks to use fintech to develop themselves and improve their operational efficiency as well as for the healthy development of China's banking industry.

In this study, we are committed to assess the impact of financial technology on the operational efficiency of Chinese urban commercial banks. This study aims to explore how it can streamline bank business processes, enhance the customer experience and improve the accuracy of credit assessment as well as the efficiency of lending decisions through powerful data analytics and risk management tools by introducing Internet-based Fintech. This study adopts the Super-Slack-Based Measurement (Super-SBM) model which incorporates non-performance outputs to measure the efficiency of urban commercial banks in China and analyzes in-depth the specific impact of fintech on the efficiency of urban commercial banks in various regions of China through the System Generalized Moment Estimation (System GMM) model. The findings reveal the positive role of fintech in facilitating banks' digital transformation and improving operational efficiency as well as customer experience while also emphasizing its importance in enhancing risk management capabilities. The findings of this study not only contribute to the sustainable development and competitiveness enhancement of the banking industry but also provide empirical support for policymakers to facilitate the integration of fintech and optimize banking service processes. After the first section, the second section contains the literature review, the third section is the methodology which contains the introduction of Super SBM with undesirable output and systematic GMM modeling and the fourth section contains the results of the study which include the introduction of the variables, descriptive analysis, a diagnostic checking report and empirical analysis. The fifth section includes conclusions and recommendations.

2. Literature Review

The concept of financial technology can be traced back to the 1990s when Citibank first mentioned "Financial Technology" in its "Financial Services Technology Alliance" program. However, it was not until 2011 that the term "fintech" was officially coined. The definition of fintech has been interpreted in many ways by different international organizations and scholars. Among them, the Financial Stability Board (FSB) first gave a more widely accepted definition in 2016 considering fintech as an area that can use cutting-edge technologies such as big data, cloud computing, blockchain, artificial intelligence, etc. and bring about a significant impact on the financial market and the financial industry's business models, technology applications and products and services (Yang & Li, 2018). Although China has not yet proposed an official definition, the People's Bank of China (PBOC) in its 2019 Financial Technology (FinTech) Development Plan (2019-2021) describes fintech as a type of technological innovation from a financial perspective with the core objective of pricing credit and reducing credit risk through science and technology (Fanusie & Jin, 2021). Other scholars have defined fintech from different perspectives. According to a technological perspective, fintech is the use of high technology to support the financial sector and improve the financial market's operational efficiency (Takeda & Ito, 2021). Therefore, fintech can be regarded as a financial innovation that deeply integrates technology and the financial field. Internationally, several organizations also provide different definitions. For example, the National Economic Council (NEC) defines fintech as a technological innovation that has the potential to disrupt the financial sector, the International Monetary Fund (IMF) and the World Bank Group (WBG) see it as an advanced technology that can lead to new business models, production processes and products as well as application scenarios and the International Organization of Securities Commissions (IOSCO) defines it as a wide range of innovative business models that may trigger changes in the financial sector.

In contrast, the UK Financial Conduct Authority (FCA) does not directly define fintech. However, it states that fintech innovations should positively impact financial services whether by providing better quality products, more convenient services or lower prices. These different definitions highlight the multidimensional and complex nature of fintech. Arner, Barberis, and Buckley (2017) delineated the evolutionary stages of financial technology identifying three key phases. The first phase (1866-1967) witnessed the popularisation of the telegraph which enabled basic calculations, replacing traditional methods of computation, giving rise to technologies such as point-of-sale (POS) machines and automated teller machines (ATMs) and facilitating global financial integration. The second phase (1967-2008) was characterized by the rapid development of networks and digital devices which accelerated the interconnection of a wide range of financial services and greatly expanded the information landscape of the financial industry. The third phase (2008-present) is characterized by the transformative impact of cloud computing, digitization and technological advances which have enhanced information gathering, risk assessment, pricing mechanisms, investment decisions and driven financial innovation. Ryu and Ko (2020) agree with this categorization as he divides fintech development into three phases: electronic, informatization and technologisation.

In contrast, China's fintech development is different. Scholars widely acknowledge that the evolution of China's fintech development has traversed three distinctive phases. From 1970 to 2008, the initial stage mostly involved the financial sector's first attempts to use information technology. During this period, the sector heavily relied on centralized computer systems for transaction processing alongside tentative forays into data-driven decision support. The subsequent phase occurring between 2008 and 2011 witnessed the advent of Internet finance signifying a disruptive transformation of the traditional financial business model. During this period, China strategically used the "Internet Plus" strategy to take advantage of the platform and user resources, pioneering innovative models such as peer-to-peer lending platforms, online payment systems and equity crowdfunding. In the third phase, from 2011 to the present, the fintech concept was formally introduced in 2011. Integrating state-of-the-art technologies, including big data, artificial intelligence, cloud computing and blockchain has catalysed technological advancements within China's conventional financial framework. This integration has become a pivotal driving force behind the nation's financial reform initiatives.

The ascent of financial technology has profoundly influenced the conventional landscape of commercial banking notably within critical domains such as the residential mortgage sector. This transformative trajectory has caused a gradual erosion of market presence for commercial banks, ceding ground to both shadow banks and fintech lenders, novel entities positioned distinctively within the regulatory framework and technological sphere. Fintech lenders display a heightened propensity to cater to borrowers with better creditworthiness than their shadow bank counterparts notwithstanding their relatively elevated interest rate structures. This phenomenon underscores a prevailing inclination among consumers to remunerate for an enhanced user experience and expedited loan adjudication processes. Furthermore, a salient disparity distinguishing fintech lenders from traditional participants in the mortgage market is their capacity to expedite application processing by approximately 20% while maintaining loan default risk at equilibrium (Fuster, Plosser, Schnabl, & Vickery, 2019).

Additionally, fintech lenders exhibit greater adaptability in response to market demands and show a proclivity for refinancing, particularly for borrowers poised to derive benefits. Consequently, the advent of fintech lenders has yielded a substantial enhancement in the efficiency of financial intermediation within the mortgage market, precipitating far-reaching transformations. Meanwhile, domestic and foreign scholars have paid extensive attention to the impact of fintech on banking. Studies have shown that the Internet financial technology spillover effect helps to reduce the operating costs of the financial system, thus improving the overall operational efficiency of banks (Srivastava, 2014). Internet financial platforms have a distinct advantage in terms of services that may generate knowledge spillover and economic impact compared to the traditional financial system (Shanmugam, Wang, Bugshan, & Hajli, 2015). Fintech has also disrupted the business model of traditional commercial banks forcing them to reformulate their high-quality development strategies to improve overall efficiency (Chen, Li, Wu, & Luo, 2017). In addition, fintech has contributed to the efficiency of banks by increasing the transparency of business processes and reducing misunderstandings and conflicts between customers and staff (Boubaker, Cellier, Manita, & Saeed, 2020). Fintech's data analytics enable banks to assess customers' credit online reducing the cost of field visits and increasing efficiency (Hafsal, Suvvari, & Durai, 2020). However, although fintech can help banks improve efficiency, it must be used carefully to avoid the possible adverse effects of inappropriate applications such as information system failures that can lead to data breaches and security issues which in turn can weaken a bank's operational efficiency (Le, Nguyen, & Schinckus, 2021).

Although the existing literature has extensively explored the impact of fintech on banking efficiency, including improving the adaptability of loan markets and reducing operating costs, there is still a gap in the literature. Most research has focused on the impact of fintech on the short-term operational efficiency of the banking industry while its long-term impact and role in promoting the sustainable development of the banking industry have not been explored enough. Moreover, the measurement of bank efficiency is relatively simple and the measurement methods adopted are insufficient. When discussing the impact of fintech on the efficiency of commercial banks, the endogenous problem is also ignored.

3. Methodology

3.1. Data Sources

This study is based on secondary data mainly from the China Financial Yearbook, ESP database, Wind financial database, CSMAR database, CB sight database and listed commercial banks' corporate annual reports. By the end of 2021, there were 118 urban commercial banks in China. This study selected the panel data of 118 urban commercial banks from 2011 to 2021 as research samples.

3.2. Super SBM with Undesirable Output

3.2.1. Selection of Efficiency Measurement Methods

There are currently four methods for determining a commercial bank's efficiency. These are as follows:

In the modern academic field, the methods of assessing the operational efficiency of commercial banks are mainly divided into two categories: the financial indicator analysis method and the frontier analysis method. The financial indicator analysis method also known as factor analysis, estimates the overall operational efficiency of a bank by analyzing its financial data such as revenues, costs or profits to calculate key efficiency indicators (Dutta, Jain, & Gupta, 2020). This method can effectively reflect a bank's operating conditions in a specific period but it is weak in depicting its overall operating efficiency in a long-term dimension. In recent years, academic research has favoured frontier analysis which assesses the operational efficiency of a target bank by comparing it with banks on the efficiency frontier based on the actual degree of deviation. Frontier analysis methods are categorized as parametric and non-parametric. Parametric frontier analysis methods such as stochastic frontier analysis (SFA) and deterministic frontier analysis (DFA) require the predefinition of the form of the efficiency frontier function and the determination of the parameters in the production function based on the constructed input-output indicator system (Zhang, 2012).

In contrast, non-parametric frontier analysis methods such as Data Envelopment Analysis (DEA) and Free Disposal (FDH) do not require predefining the form of the efficiency frontier function providing higher flexibility and objectivity (Cunha Ferreira, Cunha Marques, Pedro, & Amaral, 2020; Esteve, Aparicio, Rabasa, & Rodriguez-Sala, 2020). DEA models not only avoid errors in the setting of the production function but also handle multiple input and output indicators for a more comprehensive analysis. However, traditional DEA models have limitations in measuring the operational efficiency of decision-making units such as the inability to compare multiple efficient decision-making units and the failure to take into account slack variables thus not being able to consider inputs and outputs at the same time (Tone, Toloo, & Izadikhah, 2020).

In this study, we adopt the improved Super SBM (Slacks-Based Measure) model especially the Super-SBM model that considers non-expected outputs to assess commercial banks' efficiency more accurately. This approach provides a more comprehensive and accurate efficiency assessment than traditional Data Envelopment Analysis (DEA) (Mardani, Zavadskas, Streimikiene, Jusoh, & Khoshnoudi, 2017). The core strength of the Super SBM model lies in its comprehensive consideration of slack variables. This feature enables the model to identify the specific sources of efficiency losses in detail. In addition, it can handle multiple types of inputs and outputs simultaneously, including undesired outputs commonly found in the financial industry such as non-performing loans and operational risk (Preeti & Roy, 2021). This comprehensiveness and flexibility are particularly critical when fintech is rapidly evolving.

3.2.2. Super SBM-Undesirable Model with Undesirable Output

This study fully considers the commercial bank operating process such as non-performing assets and other non-expected outputs as well as the effective edge of the commercial bank for further analysis and research. This study decided to choose the super-efficient SBM-undesirable model to measure and analyse the operating efficiency of commercial banks specifically. The commercial bank operating efficiency measurement model is designed as follows: Under the condition of certain inputs, the more desired outputs and the fewer non-desired outputs, the greater the value of operational efficiency and vice versa.

$$min\rho = \left(1+\frac{1}{m}\sum_{z=1}^{m}\frac{S^-}{x_{zj_0}}\right)\Big/\left(1-\frac{1}{q_1-q_2}\left(\sum_{i=1}^{q_1}\frac{S_1^+}{y_{ij_0}}+\sum_{t=1}^{q_2}\frac{S_t^{b-}}{b_{tj_0}}\right)\right) \quad (1)$$

$$st.x_{zj_0} \geq \sum_{j=1}^{n}\gamma_j x_{zj} + S_z^-, \forall z \quad (2)$$

$$y_{ij_0} \geq \sum_{j=1}^{n}\gamma_j y_{ij} - S_t^+, \forall i \quad (3)$$

$$b_{tj_0} \geq \sum_{j=1}^{n}\gamma_j b_{tj} + S_t^{b-}, \forall t \quad (4)$$

$$\frac{1}{q_1-q_2}\left(\sum_{i=1}^{q_1}\frac{S_1^+}{y_{ij_0}}+\sum_{t=1}^{q_2}\frac{S_t^{b-}}{b_{tj_0}}\right) < 1 \quad (5)$$

$$\gamma_j > 0$$

$$S_z^-, S_t^+, S_t^{b-} \geq 0, \forall z, \forall i, \forall t \quad (6)$$

$$1 \leq i \leq q_1 \leq s, 1 \leq t \leq q_2 \leq s, q_1 + q_2 = s \quad (7)$$

$$1 \leq j_0 \leq n \quad (8)$$

Where it is assumed that there are n commercial banks as decision-making units in the model (denoted as DMU_j, j=1,....,n) and each DMU will have m inputs (denoted as x_z, z=1,.....,m), q_1 expected outputs (denoted as y_i, i=1,....., q_1), and q_2 denotes unintended outputs (denoted as bt, i=1,.....,q_2) while the slack variables denoting the zth input, the ith denotes expected output and the tth denotes unintended output and various inputs and expected output denote the operational efficiency of commercial banks and the weights of the various input, expected output and unintended output variables where returns to scale are constant (CRS) if ≥0 and variable (VRS) if ≥0 and =1.

3.2.3. Construction of the Indicator System

In Super SBM with undesirable output, the number of employees, total deposits and operating expenses are selected as input variables, total interest and total loans are selected as desired output variables and the non-performing loan ratio is selected as a non-desired output variable. Firstly, Table 1 presents the choice of the number of employees as an input variable that reflects the importance of human resources in bank operations. Employees are the key factors in bank services and operations and their quantity and quality directly affect the efficiency and quality of bank services (Lebdaoui & Chetioui, 2020). Total deposits as another input variable represent the ability to absorb bank funds and are the basis of bank capital operations (Wang, Liu, & Luo, 2021). Operating expenses as the third input variable include the costs of daily operations of the bank and are an important indicator for assessing the bank's cost efficiency (Antunes, Hadi-Vencheh, Jamshidi, Tan, & Wanke, 2022). In terms of expected output variables, Table 1 presents total interest as one of the main sources of income for banks and reflects their profitability (Dsouza, Rabbani, Hawaldar, & Jain, 2022). On the other hand, total loans indicate the credit scale of the bank which is an important part of the bank's asset operation and its scale and quality are directly related to the bank's performance and risk level (Sahiti Ramushi & Sahiti, 2021). Finally, Table 1 presents the non-performing loan ratio chosen as an unintended output variable because it is a key indicator of a bank's credit risk. The level of non-performing loan ratio (NPL) directly affects banks' asset quality and future profitability (Chen, Chiu, Jan, Chen, & Liu, 2015; Wang, Huang, Wu, & Liu, 2014). In the context of the rapid development of fintech, controlling the NPL ratio is crucial to maintain the stable operation of banks.

Table 1. Selection variables for super-SBM with undesirable output

Inputs	Desirable outputs	Undesirable outputs
Total number of staff	Total loans	Non-performing loan ratio
Total deposits	Total interest	-
Operating expenses	-	-

3.3. System GMM Model

Two prevailing methodologies have been employed concerning the modelling of fintech's impact on urban commercial banks in various Chinese provinces. The first approach involves cross-sectional data regression. In contrast, the second entails the construction and analysis of panel data. It is essential to acknowledge certain inherent limitations associated with cross-sectional data analysis. First, cross-sectional regression needs to account for the endogeneity of variables, thereby potentially introducing bias into the analysis. Secondly, this method overlooks individual characteristics that remain unaffected by changes over time. Moreover, the utilisation of cross-sectional data is primarily constrained by its inability to effectively capture the dynamic interplay among yearly observations within the sample database.

On the contrary, panel data commonly referred to as longitudinal data, integrates multiple sets of cross-sectional datasets chronologically aiming to amalgamate information across both temporal and spatial dimensions. Panel data analysis has been a focal point of scholarly inquiry since the 1960s and has evolved into an indispensable component of econometric analysis. Panel data incorporates attributes of both cross-sectional and time series data which augment the number of sample observations and bolster the robustness of estimation outcomes. Consequently, this study adopts the panel data modelling approach to explore relevant issues comprehensively. In general, the dynamic panel model can be expressed as follows:

$$Y_{i,t} = \alpha + \rho Y_{i,t-1} + x'_{i,t}\beta + z'_{i,t}\eta + \mu_i + \varepsilon_{i,t}(t = 2,3,\cdots,T) \qquad (9)$$

Where $Y_{i,t}$ is the explanatory variable lagged by one period, $x_{i,t}$ is the explanatory variable and $z_{i,}$ is an individual characteristic. $\mu_i + \varepsilon_{i,t}$ is a composite disturbance term where μ_i is an unobservable random variable representing individual heterogeneity and $\varepsilon_{i,t}$ is a random disturbance term.

The dynamic panel data model includes the lagged dependent variable from the previous period as an independent variable introducing additional factors not previously considered by the model. This augmentation serves to enhance the model's contextual relevance. Nonetheless, the explanatory variables may exhibit associations with random disturbance terms posing considerable challenges. Dynamic panel data models are employed to achieve unbiased and efficient parameter estimation to address these issues, thereby mitigating potential distortions from parameter biases. Dynamic panel data models typically contend with heteroscedasticity, autocorrelation and individual effects. Two primary approaches are commonly employed for estimation within this framework.

One approach entails correcting estimation results derived from conventional static models to mitigate estimation errors and enhance precision. Diverse correction methods elucidated in Kiviet (1995) and Hansen and Sargent (2001) are applied for this purpose. Alternatively, the generalised method of moment estimation (GMM) is employed to appraise the model directly. GMM holds particular scholarly interest due to its capability to yield consistent estimation results. Accordingly, this study adopts the SYS-GMM estimation method delineated by Arellano and Bond (1991) and Blundell and Bond (2000). SYS-GMM integrates differential GMM and horizontal GMM estimation methodologies to reinforce the efficacy of parameter estimation. To provide a succinct overview, this paper furnishes a comprehensive tabulation of the Sys-GMM model:

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t} \qquad (10)$$

Where $y_{i,t}$ is the explanatory variable, $y_{i,t-1}$ is the lagged term, $X_{i,t}$ is the explanatory variable, β' is the vector of coefficients to be estimated, μ_i is the individual effect and $\varepsilon_{i,t}$ the random disturbance term.

3.4. Variable Selection

3.4.1. Explained Variables

Urban Commercial Bank Efficiency (UCBE): This study comprehensively evaluates urban commercial bank efficiency considering multiple input and output factors along with non-expected outputs. These non-expected outputs such as non-performing loans and defaults, introduce complexities compared to traditional DEA models. This research draws upon the findings of Tone (2002) and Tone and Tsutsui (2010) to enhance accuracy in efficiency assessment. It employs an advanced super-efficient SBM model that accommodates non-expected outputs. This model represents an enhancement of Tone's (2002) original proposal amalgamating the strengths of super-efficient DEA and SBM models. It addresses comparability issues among efficient decision-making units and tackles non-desired outputs enabling a more effective, precise and objective measurement of urban commercial bank decision-making unit efficiency.

3.4.2. Explanatory Variables

This study adopts the "Digital Financial Inclusion Index" ("FinTech Index") to measure the development of fintech in China's provinces developed by the Institute of Digital Finance at Peking University in cooperation with Ant Financial Services Group. The index covers three major elements: breadth of coverage, depth of utilisation and level of digitization. The breadth of coverage reflects the role of modern digital technology in breaking through traditional financial boundaries. Depth of utilisation assesses the actual use of financial services covering a wide range of financial products such as payment transactions, credit, insurance, investment and money funds. Digitization is the central factor which is assessed on criteria including mobility, affordability and convenience.

The Digital Financial Inclusion Index is based on Ant Financial Services Group's provincial transaction account data from 2011 to 2021 which is highly representative and credible. Therefore, this paper uses the provincial digital financial inclusion index as a proxy variable for fintech and as a core explanatory variable for research and analysis.

3.4.3. Control Variables

Based on some previous pieces of literature, we chose the following control variables first: Asset size (Asset), Cost-income ratio (CIR), Capital Adequacy Ratio (CAR) and Loan-to-deposit Ratio (LDR) are chosen to measure the internal influences of commercial banks and the growth rate of gross domestic product growth rate (GDPg) is chosen to measure the external influences of commercial banks. Table 2 shows the specific definitions and calculations of these variables.

Table 2. Description of variables.

Variables	Symbol	Measurement
Efficiency of urban commercial banks	UCBE	Calculated from the super-efficient SBM model containing non-desired outputs.
Level of financial technology development	Fin	Digital inclusive finance index
Asset size	Asset	Logarithm of the total asset size of commercial banks
Cost-income ratio	CIR	Ratio of commercial bank operating expenses to operating income
Capital adequacy ratio	CAR	Capital to risk-weighted assets
GDP growth rate	GDPg	GDP growth rate
Non-interest income	NIC	Non-interest income of banks

4. Results

The presented descriptive statistics in Table 3 furnish valuable insights into various critical variables. Notably, the average efficiency of urban commercial banks in China is registered at 0.430 signalling a suboptimal overall efficiency level. In this context, efficiency spans from a minimum of 0 to a maximum of 3.190 underscoring discernible variations among regions and urban commercial banks.

Furthermore, the average degree of financial technology development is quantified at 2.340, encompassing values ranging from a minimum of 0.160 to a maximum of 4.590. These statistics accentuate significant disparities not only between provinces but also across different years. Concerning the control variables, the average asset size of banks stands at 2.220 exhibiting a range from 0 to 30.59. Similarly, the average cost-return ratio is recorded at 35.42 fluctuating between 0 and 153 while the capital adequacy ratio demonstrates an average of 13.61 extending from 0 to 59.61. Non-interest income exhibits an average value of 1.120 from -1.01 to 20.08. Lastly, the GDP growth rate presents a mean of 7.8 with values oscillating between -5.4 and 16.40. This statistical insight offers a comprehensive overview of the considered variables, highlighting their diversity and significance within the analytical framework.

Table 3. Descriptive analysis.

Index	Number of samples	Mean	Standard deviation
UCBE	1298	0.430	0.250
Fin	1298	2.340	1.030
Cir	1298	35.42	12.52
Car	1298	13.61	3.790
Gdp	1298	7.800	2.730
Asset	1298	2.220	3.470
Nic	1298	1.120	2.100

4.1. Regression Analysis

Firstly, the Wooldridge test is used to test for the presence of autocorrelation in the regression model. The White test is used for heteroscedasticity and its robustness in the regression model. Unlike the Wooldridge test, the White test is based on the residuals from the original regression model and does not rely on the auxiliary regression model. The White test adds the independent variables and their squares, cross-terms, etc. to the auxiliary regression model and then tests to see if these variables significantly affect the variance of the residuals. If heteroscedasticity exists, a robust heteroscedasticity estimator may need to be used. Secondly, the Variance Inflation Factor (VIF) is used to analyse multicollinearity between variables. VIF is a statistic of linear correlation of independent variables in a regression model and is used to identify multicollinearity. A high degree of correlation between independent variables is known as multicollinearity and can affect the stability and explanatory power of parameter estimates.

Table 4. Diagnostic checking report.

Wooldridge test	41.354	0.0000
White test	66.62	0.0010
VIF	1.12~4.44	-

Table 4 presents the outcomes of rigorous statistical tests encompassing autocorrelation, heteroscedasticity and multiple covariance analyses. The Woolridge test was initially employed to assess the presence of autocorrelation issues revealing the presence of autocorrelation problems across all models. Furthermore, White's test predicated on the original hypothesis scrutinised potential heteroscedasticity problems, unearthing heteroscedasticity issues within all models. An examination of Variance Inflation Factor (VIF) values indicated that most of them remained below the threshold of 5 signifying an absence of significant covariance within the dataset. These comprehensive tests provide a robust foundation for the subsequent analyses highlighting key statistical aspects that warrant consideration.

The regression outcomes are meticulously presented in Table 5. The result exhibited in Table 5 unveils a statistically significant positive coefficient denoting the influence of financial technology on the efficiency of China's urban commercial banks attaining a noteworthy significance level of 1%. This unequivocally indicates that financial technology exerts a conspicuous effect on these banking institutions.

Table 5. System GMM regression results.

Index	SYS-GMM model
$UCBE_{i,\,t-1}$	0.2549*** (18.5641)
Fin	1.4759*** (3.3705)
CIR	-0.1544*** (-3.0665)
CAR	0.7006*** (5.0697)
GDP	0.3667*** (4.0785)
Asset	-0.1642* (-1.7145)
NIC	0.0165 (0.4760)
C	0.2134*** (5.2109)
AR (1)	0.0000
AR (2)	0.1601
Sargan test	0.1093

Note: t statistics in parentheses
$^{*}p < 0.1$, $^{***}p < 0.01$.

Table 6. Systematic GMM regression results for east, central and west regions.

Index	East	Central	West
UCBEi,t-1	0.1562*** (47.1065)	0.4025*** (2.9245)	0.3952*** (35.4493)
Fin	1.3388*** (6.6368)	-6.1105* (-1.6498)	-1.6574*** (-2.7294)
CIR	-0.1698*** (-9.0019)	-0.7617*** (-3.3211)	-0.3843*** (-15.6554)
CAR	0.4517*** (5.8433)	2.7594*** (4.6421)	0.4091*** (6.3804)
GDP	0.1680*** (4.2113)	0.6685** (2.2247)	-0.5862*** (-10.0260)
Asset	-0.1654*** (-3.0253)	24.4697** (2.0315)	-0.2244*** (-3.4453)
NIC	0.0744*** (3.7820)	-0.4274*** (-2.7041)	-0.1376*** (-6.1757)
C	0.3252*** (17.2424)	-6.1154** (-1.9921)	0.4552*** (15.7141)
AR(1)	0.0020	0.0455	0.0479
AR(2)	0.1325	0.4790	0.8420
Sargan test	0.3380	1.0000	0.9996

Note: t statistics in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Given the vast expanse of China with pronounced regional economic disparities, the evolution of fintech adoption exhibits regional discrepancies, inevitably exerting varying influences on the interrelationships among pertinent variables across distinct regions. This study stratifies data from 31 provinces into three geographic regions: eastern, central and western China to scrutinise the repercussions of divergent fintech development levels on urban commercial banks in distinct regional contexts. Subsequently, a system GMM model performs regression analyses on the three segregated datasets. The result of these regression analyses is elaborated in Table 6 providing valuable insights into the regional dynamics of fintech impact on urban commercial banks.

Table 6 presents compelling evidence regarding the impact of fintech on the efficiency of urban commercial banks across various Chinese regions. Notably, fintech exhibits a significant positive effect on the efficiency of urban commercial banks in the eastern provinces. Conversely, it significantly negatively impacts their efficiency in the central and western regions.

5. Discussion

Financial technology fundamentally streamlines and digitises various banking operations, thus diminishing the reliance on labour-intensive manual processes and by extension enhancing operational efficiency. For instance, the introduction of online banking and mobile applications empowers customers to execute many banking services autonomously obviating the need to visit bank branches and conserve valuable time and resources physically. Additionally, fintech endeavours to reduce the entry barriers to financial services rendering them accessible to a broader spectrum of individuals. This fosters heightened financial inclusion enabling a more extensive populace to partake in economic activities, thereby creating additional business opportunities for urban commercial banks.

Upon scrutinising the regression findings, it becomes evident that each control variable exerts a discernible impact on Chinese urban commercial banks although with varying degrees of significance. The capital adequacy variable yields noteworthy results displaying a positive influence at the 1% significance level indicated by a coefficient of 0.7006. This signifies that for every incremental unit rise in the capital adequacy ratio of urban commercial banks, there is a substantial corresponding enhancement of 0.7005 in their efficiency. High capital adequacy levels give banks a more robust capability to navigate diverse risks, encompassing credit, market and operational risks. Ample capital reserves serve as a bulwark mitigating the reverberations of financial market volatility and economic perturbations on banks, thereby elevating their stability and capacity to sustain operations.

Conversely, both the cost-return ratio and bank asset size variables register statistically significant adverse effects on the efficiency of urban commercial banks. These findings suggest that higher operational costs may be attributable to amplified expenditure in operations, management and human resources, potentially alluding to some resource inefficiencies that impede overall bank efficiency. Additionally, as a bank's assets expand, the scope and magnitude of its operations correspondingly increase resulting in heightened managerial intricacies. The proliferation of branches, staff and business units necessitates intensified coordination, supervision and resource allocation. This may lead to protracted decision-making processes and less efficient communication ultimately impairing the bank's overall efficiency.

Furthermore, the level of economic development positively influences the efficiency of urban commercial banks. In an environment marked by economic growth, businesses and individuals typically exhibit improved financial health diminishing the likelihood of default. Consequently, the default rate on bank loans is prone to decrease curbing the formation of non-performing assets and augmenting the efficiency and profitability of the bank.

The salutary effects of fintech on urban commercial bank efficiency in China's coastal eastern provinces can be attributed to multifaceted factors. Firstly, these regions often boast well-developed financial ecosystems encompassing financial institutions, technology companies and burgeoning startups. Such ecosystems foster collaboration and innovation enabling banks to seamlessly integrate into the broader financial landscape, tap into their resources and expertise and thereby augment their operational efficiency. Furthermore, the eastern provinces are known for their vibrant innovation milieu and the domain of fintech is no exception. This fosters a conducive environment for banks to embrace novel technologies and explore innovative business paradigms enhancing their operational efficiency and competitive edge. Fintech can significantly enhance banks' market coverage and cater to the diverse financial needs of various demographic segments, thus galvanising business growth and efficiency given these regions' relatively dense population and expansive market size.

These areas boast advanced infrastructure development and substantial technological investments providing robust support for the flourishing fintech landscape. This support facilitates banks' adoption of cutting-edge technologies, streamlining business processes and enhancing customer experiences. In a nutshell, the proliferation of fintech in the eastern provinces exerts a multifaceted influence on the efficiency of urban commercial banks invigorating and catalysing the entire financial ecosystem.

In contrast, in the central and western provinces of China, the developmental impact of fintech on the efficiency of urban commercial banks appears to be negative. This divergence stems from the pronounced disparity between these central and western regions and their eastern counterparts regarding digital infrastructure and Internet penetration. The ascent of fintech may exacerbate the digital divide within these provinces as residents in certain areas may face impediments to full-scale adoption of digital financial services. This could marginalise specific demographic segments in financial activities, augmenting the operational intricacies banks operating in these regions face.

At the same time, the development of fintech may also lead to increased competition in the market, attracting internet financial companies and technology companies to participate in the financial sector creating a competitive situation with traditional urban commercial banks. This may force banks to invest more resources in marketing and innovation, thus increasing their operational pressure. The introduction and application of fintech require a significant investment in technology to bring benefits. In the central and western provinces given the relative lag in economic development, banks may be constrained by limited capital and need to invest significant resources especially in technology upgrades and training which may pressure their financial position. In addition, traditional financial concepts and habits still exist in central and western provinces making some residents more inclined to use traditional banking services and wary of emerging digital financial services. This may constrain the promotion and application of fintech and affect its effectiveness in the region. In a nutshell, although fintech development can help urban commercial banks improve their efficiency in many ways; its negative impacts must be considered in the central and western provinces of China.

The cost-return ratio exerts a deleterious influence on the efficiency of urban commercial banks across different regions, namely the East, Central and West. These findings hold robust statistical significance with all regions demonstrating adverse effects at the 1% significance level. Moreover, the magnitude of this negative impact varies with the central region exhibiting the most pronounced influence nearly double that observed in the eastern and western regions, thus underscoring its heightened significance.

Conversely, the level of economic development manifests divergent effects on the efficiency of urban commercial banks depending on the region under consideration. Economic development yields a positive impact in both the eastern and central regions that attains significance at the 5% level. In contrast, the western region experiences a negative influence on efficiency similarly reaching the 5% significance level. A noteworthy observation is the considerable influence of economic development within the central region, which exerts the most substantial impact on urban commercial bank efficiency.

This regional divergence in the influence of economic development can be elucidated by the potentially constrained economic diversity and scale of activities within the western provinces relative to their eastern and central counterparts. Due to a comparatively smaller economic scope, commercial banks in these regions may encounter fewer financial needs and investment prospects constraining their potential for business expansion and efficiency enhancement.

The regression analysis underscores the consistent and statistically significant positive impact of the capital adequacy ratio on the efficiency of urban commercial banks across all regions. Specifically, the coefficients are 0.4517, 2.7594, and 0.4091 for the East, Central and West regions. This finding implies that regions with more balanced economic development such as the central provinces tend to prioritise risk management and financial stability. A robust capital adequacy ratio enhances a bank's capacity to mitigate risks and reduce the likelihood of non-performing assets ensuring stable and resilient banking operations. This heightened emphasis on risk management potentially contributes to the more substantial positive effect of the capital adequacy ratio on bank efficiency in the central region.

Conversely, the size of banks' assets exerts a significant and negative influence on the efficiency of urban commercial banks in both the eastern and western regions with coefficients of -0.1654 and -0.2244, respectively. This suggests that for each unit increase in asset size, the efficiency of urban commercial banks in these regions diminishes by 0.1654 and 0.2244, respectively. This inhibitory effect of asset size is more pronounced in the central region characterised by more significant variability and a more significant coefficient indicating that larger banks in this region face complexities associated with managing a larger scale of operations. The expanded size necessitates increased coordination, supervision and resource allocation leading to slower decision-making and less efficient communication, ultimately impacting overall bank efficiency.

The level of non-interest income that harms the efficiency of urban commercial banks in the central and western regions passes a 1% significant level test and has a significant positive effect on the efficiency of urban commercial banks in the eastern region because the eastern provinces are economically developed and have a more mature financial market so commercial banks tend to be able to provide more diversified financial products and services in these regions. Non-interest income usually covers a variety of sources such as fees, commissions, investment income, etc. This diversified business model helps banks reduce their dependence on traditional interest income and improve the resilience and profitability of their businesses.

6. Conclusion

This paper empirically analyses the impact of fintech development on the efficiency of Chinese urban commercial banks by taking Chinese regions as the research object and selecting panel data from 31 Chinese provinces from 2011 to 2021. The study's conclusions are as follows: Nationally, fintech development has positively contributed to the efficiency of Chinese urban commercial banks and the introduction of fintech has triggered changes in automated and digitized processes which have brought about significant efficiency improvements in banks' operations. Taking a regional outlook into account, it becomes apparent that the influence of fintech on the efficiency of urban commercial banks varies across different regions of China. The findings reveal that in the eastern region, fintech exerts a significantly positive effect on the efficiency of urban commercial banks. Conversely, in the central and western regions, fintech appears to have a detrimental impact on these banks with the central region exhibiting the most pronounced negative coefficient. This observation underscores the heightened influence of fintech development on the efficiency of urban commercial banks within the central region.

The document delves into the significant impact fintech has on the operational efficiency of China's urban commercial banks using the Super Slacks-Based Measure (Super-SBM) model and System GMM for thorough analysis. It uncovers how fintech facilitates digital transformation within banks and enhances operational efficiency, customer experience and risk management capabilities. This research provides valuable insights for policymakers on leveraging fintech for banking service optimization, emphasizing its varied effects across different Chinese regions, thereby contributing to the banking sector's sustainable development and competitive edge.

The exploration into the efficacious integration of fintech within China's urban commercial banks delineates the transformative potential inherent in digitizing banking operations. However, this study acknowledges certain constraints that may impede the universal applicability of its findings. Primarily, the heterogeneity of regional economic development within China presents a notable challenge. The disparate levels of technological infrastructure and digital literacy across various provinces could significantly influence the efficacy of FinTech solutions. Moreover, the dynamic nature of fintech itself characterized by rapid technological advancements and regulatory shifts may render some of the study's insights temporal or context-specific. Additionally, the reliance on secondary data sources and the specific methodologies employed such as the Super-SBMs and System GMM models may encapsulate inherent biases or limitations in capturing the multifaceted impact of fintech on banking efficiency.

Future research on the relationship between fintech and banking efficiency could take a multidimensional approach covering a wider range of financial institutions beyond urban commercial banks. Investigating the impact of fintech on rural banking or non-bank financial institutions could provide a comprehensive picture of the generalized impact of fintech. Second, longitudinal studies tracking the evolution of fintech impact over time can shed light on trends and changes in fintech efficacy in the context of a changing technological and regulatory environment. Third, qualitative research on the perceptual and experiential dimensions of fintech adoption by banking professionals and customers can enrich quantitative findings and provide a holistic understanding of its impact. Finally, a comparative analysis of China's fintech ecosystem with those of other major economies can provide valuable lessons and strategies for optimizing global fintech integration.

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