Does FinTech adoption improve bank performance?

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Abstract: In this paper, we estimate the effect of FinTech activities on bank performance by using data on 355 American banks from 2010 to 2020. Our results show that FinTech plays a significant role in promoting bank performance. Bank performance can be improved by 0.30% when the FinTech level is improved by one unit. We also find that the impact of FinTech on bank performance is heterogeneous in terms of bank size and chartered membership. In particular, the influence of FinTech on the leading banks and the state-chartered nonmember banks is more significant than on small and medium banks. Thirdly, the development of bank financial technology in every region of the United States is uneven. In addition, we put forward policy suggestions on how FinTech can promote bank performance in four aspects.

Keywords: FinTech; bank performance; commercial banks; heterogeneous impact; bank size; chartered membership; American banks; SysGMM; fixed effects; ordinary least squares.

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1 Introduction

The use of financial technology (FinTech) has transformed the banking industry and impacted bank performance. FinTech is not only changing how banks operate by making traditional business comprehensively digitised, but also playing an important role in promoting cost reduction and the development of new products and services with higher quality to meet consumers' (especially the millennials') demand for convenient, customised, and low-cost financial services (Federal Reserve Board, 2022). However, there still exists a debate whether FinTech is beneficial or not to commercial banks.

Some researchers have pointed that the rising of new communication channels with the combination of emerging technologies, such as equity crowdfunding, peer-to-peer (P2P) lending and Third-Party Payment, are seizing the credit market of traditional banks and leading to the vertical and horizontal disintegration of the traditional bank business model (Buchak et al., 2018; Boot, 2021; Calomiris, 2021). Few empirical studies show FinTech not only has a significant negative influence on the profitability of commercial banks, but also increases the fragility of financial institutions in the developed financial markets (Chen et al., 2020; Fung et al., 2020). The account-level data growth of Lending Club, the biggest online peer-to-peer loan platform in US, indicates that FinTech leaders are penetrating areas that are underserved by traditional banks (Jagtiani and Lemieux, 2018). It has also been shown that the FinTech growth in the Indonesian market has a negative influence on local bank performance (Phan et al., 2020). So, does FinTech indeed lead to financial disintermediation and has a negative effect on banks' performance? This doubt is inconsistent with the fact that banks are not only the earliest form of financial industry but also the main area to develop financial technology (Schindler, 2017). The Pulse of FinTech H2' 21 report reveals that strengthening partnerships as financial services extend into a broader range of daily transactions through the use of embedded banking was one of the key FinTech trends in 2021 and shows most of the FinTech investment of US$105 billion flowed into Payments and digital banking (KPMG, 2022).

The aforementioned debate and little empirical evidence regarding the effect of FinTech on bank performance provide the main motivations for this research. This paper mainly aims to study the impact of FinTech on bank performance, and contributes to the literature in the following three ways.

First, this paper expands and supplements the scope of existing bank FinTech literature by using the latest 11 years data of American banks to empirically test whether or not FinTech has influenced banks' performance. After the global financial crisis of 2008, FinTech has developed rapidly with banks pulling back from some lending activities (Schindler, 2017). As far as we know, there are only a few studies focusing on the relationship between FinTech and bank performance (Phan et al., 2020; Zhao et al., 2022). This is due to the fact that the established literature mainly focuses on the non-commercial banking fields such as the third-party payment, P2P online loan and digital currency, and also due to the lack of data on bank FinTech.

Second, this paper designs and builds a new bank FinTech index system which can be used to measure the FinTech level of every bank. As can be seen in the existing literature, researchers can use technologies to quantify some items which are not directly reported in any document, such as to measure investor sentiment and investors' preferences by using AI, machine learning or data mining (Kašelan et al., 2014; Ruan et al., 2020). Therefore, based on the definition of FinTech presented by the Financial Stability Board (FSB) in 2017, we build a novel FinTech index system from three dimensions, which include 45 keywords representing the degree of FinTech application in the respective banks, and which is also shown to be consistent with the trend of bank FinTech development in America (see discussion in Section 3.2.2). To our knowledge, this is the first study to measure the level of Bank FinTech in US using such detailed information.

Finally, this paper investigates the effects of FinTech on banks' performance. This paper builds a comprehensive indicator representing bank performance by considering seven aspects of banks' operation, rather than a single traditional financial profitability measure such as Tobin's Q, the return on assets (ROA) or the return on equity (ROE) (Adams and Mehran, 2012; Ryu and Yu, 2021), which makes our analysis more comprehensive. We also look into the potentially heterogeneous effect of FinTech in terms of bank size, headquarters location and chartered membership status.

Our empirical results confirm that FinTech plays a significant role in promoting bank performance. That is, bank performance can be improved by 0.30% as FinTech initiative increases by 1 unit. There is an obvious heterogeneity in the impact of FinTech on bank performance given that the significance and intensity of the FinTech's effect on bank performance vary with bank size and chartered membership. In particular, the influence of FinTech on the leading banks and the state-chartered nonmember banks are more significant than that on other banks. Moreover, our empirical results show that the development of bank financial technology in different regions of the United States is uneven. Our results are robust to alternative proxies of our main variables, alternative sampling, and heterogeneity issues. We tackle the endogenous nature of the relationship between FinTech initiatives and bank performance by using the lag of our main independent variable as an instrument for FinTech in generalised method of moments (GMM) regressions.

The reminder of this paper is organised as follows. Section 2 reviews the pertinent literature and puts forward our hypotheses. Section 3 presents the sample, variables, and model used. Section 4 shows our baseline results, while Sections 5 and 6 report our robustness and heterogeneity tests respectively. Section 7 concludes and presents some practical suggestions for the development of bank FinTech.

2 Literature review

The dynamism of modern finance comes from applications of science and technology (Arner et al., 2015). Financial technology (FinTech) has introduced new technologies into the financial sector (Goldstein et al., 2019; National Economic Council, 2017) and attracted the attention of researchers all over the world while becoming the focus of the market since 2016. It is officially defined by the Financial Stability Board (2017) as a technology-enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on the provision of financial services. However, Amalia (2016) defines it as a new type of company that changes the way people pay, remit, borrow and invest. The Financial Conduct Authority and Puschmann (2017) see FinTech as a process of financial innovation. In this paper, we follow the concept presented by the Financial Stability Board, considering that the impact of FinTech on banking has been substantial, which covers both the digital transformation for banks' front-end services and the upgrading for back-end technology. As this paper is focused on whether bank FinTech can help improve bank performance, we carry out our literature review in line with the following aspects.

First, FinTech makes the traditional 'bricks-and-mortar' banking model go digital and thus yield considerable value to banks (Chen et al., 2019). For a long time, traditional bank institutions have been the earliest adopters of key information technologies, which can be testified by the first automated teller machine (ATM) or cash machine produced in 1960's (Schindler, 2017). This trend is then further developed at the end of 20th century. Nevertheless, the rapid development of emerging technologies such as Artificial Intelligence (AI), blockchain, cloud computing, big data, Internet of things, have put banks under great pressure from different stakeholders (Rodrigues et al., 2022; Schulte et al., 2017). To deal with this disruption, banks have moved from a traditional intermediary role to mobile internet activities (Chen et al., 2017). On the one hand, banks have built online and mobile tools by introducing the emerging technologies to connect their back-end operations with the front-end of customer communication (Bons et al., 2012). On the other hand, banks maintain their core competitiveness for the technology power in the whole financial industry by merging and acquiring other FinTech companies (Chen et al., 2017). There is evidence showing that these bank FinTech activities have yielded significant value to banks. Ciciretti et al. (2009), for instance, find there is a significant link between offerings of Internet banking products and bank performance. Akhtar and Nosheen (2022) claim that mergers and acquisitions (M&As) between banks and FinTech companies have a significant positive impact on banks' operating performance.

Secondly, FinTech allows banks to improve customer satisfaction and thus gain the base of profitability. As emphasised by Schindler (2017), the demand for innovative products and services that the younger generation wants is the key factor for FinTech's development. By developing FinTech, large parts of banks' business are now based on information technologies, and many products and services of online banking and mobile banking have been developed to better meet the demands of households and companies (Jünger and Mietzner, 2020). With the ability to segment, select, and attract customers by using all kinds of financial technologies (Berg et al., 2020; Keramati et al., 2016; Königstorfer and Thalmann, 2020; Saxena et al., 2017), the digital ecosystem with banks are formed, which enables banks to improve profitability. Smeureanu et al. (2013) find banks can reduce costs by using machine learning. Sheng (2021) points out that FinTech effectively enhances the ability of banks to broaden credit to small and medium enterprises while Marinč (2013) finds that FinTech better allows banks to exploit economies of scale and scope, which are most evident in transaction banking. There is also evidence indicating that open FinTech innovation by banks has effects on their future profits (Cappa et al., 2022).

Thirdly, FinTech innovates the forms of banks' operation and management, which improves their efficiency in many aspects. The adoption of new technologies and the innovation of financial products have a significant relationship with bank performance. Blockchain has enhanced the efficiency of banks as it has revolutionised the underlying technology of their payment clearing and credit information systems (Guo and Liang, 2016). The use of AI in chatbots, virtual assistants, and ATMs have improved banks' technical efficiency (Mor and Gupta, 2021). It has been found that cloud computing may help banks to reduce costs (Chen et al., 2022). Innovations in lending and payment brought by FinTech provide opportunities for banks to improve technical efficiency and reduce costs, which has a significant relationship with banks' performance (Ciciretti et al., 2009). Using data on Chinese commercial banks, Lee et al. (2021) conduct an empirical analysis on the effect of FinTech on banks' efficiency, and a positive relationship between them. In particular, FinTech have changed banks' management structure. Banks with no branches relying on Internet banking have achieved relatively higher levels of profits, deposits and loans (Onay and Ozsoz, 2013).

Fourthly, there are empirical studies showing that FinTech has an influence on banks' operations. Yao and Song (2021) find that FinTech cannot only reduce the economic capital of commercial banks regarding market risk but also have the cost of transaction information lowered. Cheng and Qu (2020) show that FinTech can significantly reduce Chinese banks' credit risk. Also, Wang et al. (2021) find that commercial banks adopting FinTech can strengthen risk control capabilities. By analysing 65 commercial banks between 2008 and 2020, Li et al. (2022) find that improvements in banks' FinTech innovation can significantly reduce their risk-taking. Evidence in Europe also shows that FinTech has a significant influence on bank performance. Kou et al. (2021) argue that payment and money transferring systems is the most important FinTech -based investment for European banks as it is considered to have a positive impact on the ease of banks' receivable collection. By focusing on the experience of Italian commercial banks, Ciciretti et al. (2009) conclude that there is a strongly positive relationship between FinTech products offered and bank performance. By using data on 18 Turkish retail banks for 18 years, Onay and Ozsoz (2013) find that the development of Internet banking can significantly improve banks' profits per branch, deposits and loans. Forcadell et al. (2020) provide international evidence showing that mutual reinforcement of banks corporate sustainability and digitalisation strategies can more effectively enhance their market performance.

Given the discussion above, our main hypothesis is:

Banks' performance is positively affected by FinTech initiatives.

3 Methodology

3.1 Data

We start by considering over 800 listed US banks but, due to data availability, our sample consists of 355 US banks listed on two stock exchanges, the New York Stock Exchange and the NASDAQ, and headquartered in eight regions[1] of the country. Our sample period starts in 2010 given that FinTech sprouted after the 2008 financial crisis, especially with some emerging financial technologies, such as AI, Big Data, Blockchain, which became popular in 2010 onward.

The FinTech and financial data at the micro bank level are manually gathered in Form 10-K or annual report of the banks, which are downloaded from the official websites of the New York Stock Exchange, the NASDAQ and the banks analysed. Our macroeconomic data are retrieved from the official websites of the Federal Reserve, the Bureau of Economic Analysis, and the World Bank. Other relevant accounting data comes from the Standard & Poor's Capital IQ database and Compustat Bank. We winsorise the continuous variables at the upper and lower 1% levels to avoid the influence of extreme values.

3.2 Variables

3.2.1 Dependent variable and measure

Unlike previous research, which only uses a sole indicator, such as ROA (return on average assets), ROE (return on average equity) or NIM (net interest margin) to represent bank performance (Havrylchyk et al., 2011; Jiang et al., 2013; Liang et al., 2013; Pathan, 2013), we shift the emphasis from this traditional measure by proposing a novel, comprehensive indicator (as shown in Table 1).

Table 1 The performance index evaluation system for American banks

	One-level indicator	*Two-level indicator*	*Indicator design*
The index evaluation system for bank performance (PERF)	Result of business	ROA	Return on asset
		ROE	Return on stockholders' equity
		NIM	Net interest margin
	Financial condition	LDR	loan-to-deposit ratio
		CAR	Total capital ratio
		Tier1	Tier 1 capital ratio
		Tier1L	Tier 1 leverage ratio

First, we select three indicators to represent the results of business, four indicators to represent the financial condition, which are consistent with the management's discussion and analysis in every bank's annual report. Then we obtain the common factor by dimension reduction. Furthermore, we calculate the composite index for bank performance by using the Principal Component Analysis and Factor Analysis methods. Finally, we obtain the data for each sample bank performance by using the normalisation method.

We have measured the comprehensive performance of 355 sample banks since 2010. In Table 2, we can note that the first three principal components can well reflect the information of each indicator for bank performance, as its cumulative value totals 72.0 over 60%, and each unit root is greater than 1. It also can be noted from Table 3 that the principal component of Factor 2 with the landing value over 80% can reflect the information about one bank's results of business while Factor1 can appropriately reflect the information regarding one bank's financial condition. In addition, the value of the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy in our data is 0.641, the value of the Bartlett test of sphericity is less than 0.001. All these values strongly suggest that our results are reliable and can explain the performance of the banks in our sample.

Table 2 Results of principal components/correlation for bank's performance

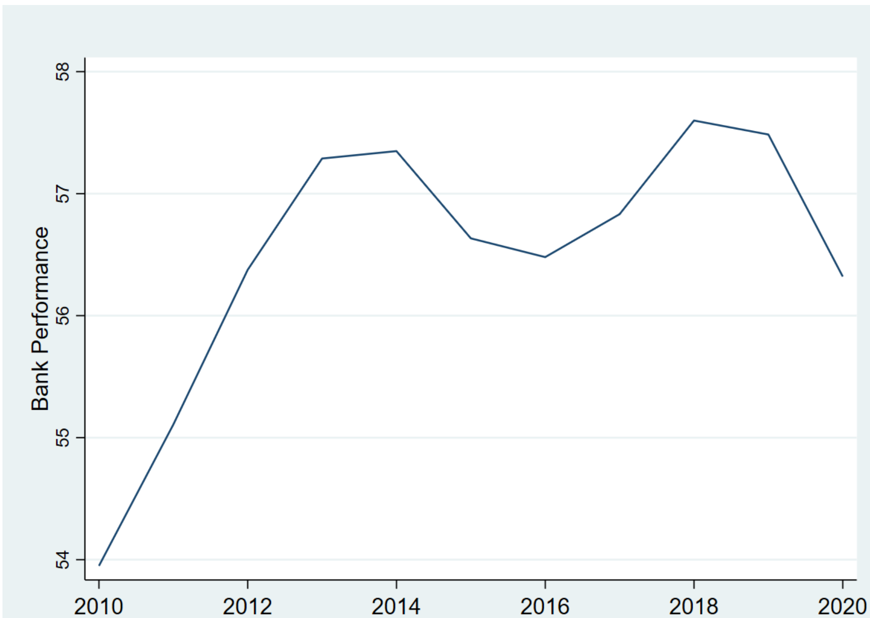
Factor	*Eigenvalue*	*Difference*	*Proportion*	*Cumulative*
Factor1	2.578	1.196	0.368	0.368
Factor2	1.382	0.300	0.198	0.566
Factor3	1.082	0.105	0.155	0.720
Factor4	0.977	0.357	0.140	0.860
Factor5	0.620	0.288	0.088	0.948
Factor6	0.332	0.303	0.047	0.996
Factor7	0.029	0	0.004	1.000
Bartlett test of sphericity	Kaiser-Meyer-Olkin Measure of Sampling Adequacy KMO = 0.641 p-value = 0.000			

Table 3 Results of rotated factor loadings and unique variance for bank's performance

Variable	*Factor1*	*Factor2*	*Factor3*	*Uniqueness*
roa	0.007	0.825	–0.039	0.318
roe	0.013	0.831	0.010	0.310
nim	0.007	0.091	0.498	0.744
ldr	–0.043	–0.042	0.868	0.243
tc	0.967	–0.011	–0.088	0.058
cr1	0.966	–0.006	–0.095	0.058
Lr	0.841	0.060	0.251	0.227

We use the annual mean of the performance of our sample banks to represent the yearly performance for US banking industry and show the yearly change trend in Figure 1. In general, the performance of the American banking industry shows an upward trend, which is consistent with the actual upward development of US banking along with the gradual recovery of the economy after the financial crisis in 2008. We can also use economic facts to explain the two inflection points in Figure 1. In 2015 and 2016, bank performance was affected mainly due to the high growth of FinTech as some traditional markets of banks were seized by new non-bank FinTech companies such as the third-party payment. Later, with the introduction of government's FinTech framework, bank performance returned to the upward trend. Nevertheless, with the outbreak of the global COVID-19 in 2020, bank performance was inevitably affected by this serious impact.

Figure 1 Bank performance of US from 2010 to 2020 (see online version for colours)



3.2.2 Independent variables and measure

The level of bank FinTech is our core explanatory variable. However, as far as we know, there is no existing data or resource for us to accurately measure bank FinTech. In view of methods to quantify investors' preferences or investor sentiment (Kašćelan, 2014; Kinyua, 2021), we use data mining to measure the level of FinTech activities in American banks.

First, we set each bank's FinTech word-frequency library in line with FinTech keywords. Our principles for designing FinTech keywords are as follows:

1 it should be consistent with the FinTech definition put forward by the Financial Stability Board in 2017

2 it should cover both traditional information technologies and emerging financial technologies that result in new business models, applications, processes, products, or services to both the front-end and back-end of the bank

3 it can represent FinTech initiatives by the respective listed bank.

Finally, as shown in Table 4, we consider 45 keywords extracted from two dimensions: technology and innovation in terms of products and services.

Table 4 Bank FinTech index thesaurus

Dimension	*Classification*	*Keywords*
Technology	Traditional techniques	1. Technology (2. technologies) 3. internet 4. web 5. database (6. databases)
	Communication technology	7. telephone 8. mobile
	Emerging technologies	9. cyber 10. FinTech (11. data 12. AI 13. cloud 14. blockchain 15. chain)
Product and service	Transformation to back-end	16. Website (17. Websites) 18. system (19. Systems) 20. platform (21. platforms) 22. model (23. models) 24. cybersecurity (25. cyberattack) 26. risk monitoring (27. risk identification)
	Transformation to front-end	28. credit card 29. ATM (30. ATMs) 31.APP 32. online (33. digital 34. digitally 35. self-service) 36. automatic 37. Smart 38. immediate (39. real-time) 40. remote (41. network)
	Transformation to the whole	42. telephone banking 43. online banking (44.digital bank 45. digitisation)

Secondly, we capture and calculate the frequency of every keyword in banks' form-10K by using data mining. It should be noted that because some keywords are not found in some banks' annual report, especially in those of small and medium-sized banks, we further merge and sum up the frequency of some keywords, so that the number of FinTech becomes the sum of the frequency of eight keywords: FinTech, AI, Cloud, Blockchain, Chain, machine learning, biometric, and encryption. Finally, we get 24 indicators to show banks' adoption of FinTech initiatives, as shown in Tables 5 and 6.

Table 5 Results of principal components/correlation for bank FinTech

Factor	*Eigenvalue*	*Difference*	*Proportion*	*Cumulative*
Factor1	5.973	4.166	0.249	0.249
Factor2	1.806	0.301	0.075	0.324
Factor3	1.505	0.235	0.063	0.387
Factor4	1.271	0.165	0.053	0.440
Factor5	1.106	0.013	0.046	0.486
Factor6	1.093	0.067	0.045	0.531
Factor7	1.026	0.026	0.043	0.574
Factor8	1.000	0.017	0.042	0.616
Factor9	0.983	0.022	0.041	0.657
Factor10	0.961	0.121	0.040	0.697

Table 5 Results of principal components/correlation for bank FinTech (continued)

Factor	*Eigenvalue*	*Difference*	*Proportion*	*Cumulative*
Factor11	0.840	0.102	0.035	0.732
Factor12	0.737	0.013	0.031	0.763
Factor13	0.724	0.024	0.030	0.793
Factor14	0.700	0.062	0.029	0.822
Factor15	0.638	0.063	0.027	0.849
Factor16	0.574	0.041	0.024	0.872
Factor17	0.534	0.031	0.022	0.895
Factor18	0.503	0.024	0.021	0.916
Factor19	0.479	0.094	0.020	0.935
Factor20	0.385	0.043	0.016	0.952
Factor21	0.342	0.043	0.014	0.966
Factor22	0.299	0.009	0.012	0.978
Factor23	0.290	0.058	0.012	0.990
Factor24	0.232	0	0.010	1.000
Bartlett test of sphericity	Kaiser-Meyer-Olkin Measure of Sampling Adequacy KMO = 0.873 p-value = 0.000			

Table 6 Results of rotated factor loadings and unique variance for bank FinTech

Variable	*Factor1*	*Factor2*	*Factor3*	*Factor4*	*Factor5*	*Factor6*	*Factor7*	*Factor8*	*Uniqueness*
Technology	0.804	0.029	–0.273	–0.144	–0.021	0.017	0.023	0.009	0.257
Internet	0.232	0.119	–0.037	0.439	0.529	–0.113	0.244	–0.250	0.323
Web	0.071	–0.062	–0.046	–0.075	0.169	0.259	0.382	0.797	0.105
Cyber	0.661	–0.061	–0.345	0.243	–0.238	–0.064	0.189	0.040	0.282
Database	0.255	–0.144	–0.191	–0.187	0.388	0.210	–0.676	0.197	0.152
Telephone	0.069	0.053	0.186	0.093	0.211	–0.206	0.288	0.052	0.777
Mobile	0.439	0.400	0.230	0.158	–0.099	–0.089	–0.119	0.257	0.471
FinTech	0.684	–0.114	–0.211	0.043	–0.041	0.099	0.050	–0.105	0.447
Website	0.483	–0.192	0.042	–0.040	0.431	0.120	0.086	–0.230	0.466
System	0.782	–0.255	–0.159	0.071	0.027	0.029	–0.042	0.042	0.287
Platform	0.615	0.168	–0.041	–0.194	0.182	–0.223	–0.150	–0.051	0.447
Model	0.803	–0.194	0.028	–0.225	–0.060	0.136	–0.004	–0.041	0.243
Credit card	0.494	0.139	0.235	–0.379	–0.170	0.046	0.061	–0.107	0.491
ATM	0.223	0.259	0.268	0.393	0.070	0.495	–0.030	–0.026	0.405
APP	0.321	0.430	0.353	–0.217	–0.151	0.005	0.026	0.054	0.514
Digital-service	0.482	0.325	0.044	–0.102	–0.121	–0.259	–0.010	–0.002	0.568
Automatic	0.325	–0.595	0.526	0.168	–0.100	–0.197	–0.101	0.075	0.172
Smart	0.283	0.368	0.402	0.110	0.155	0.184	–0.038	–0.001	0.552

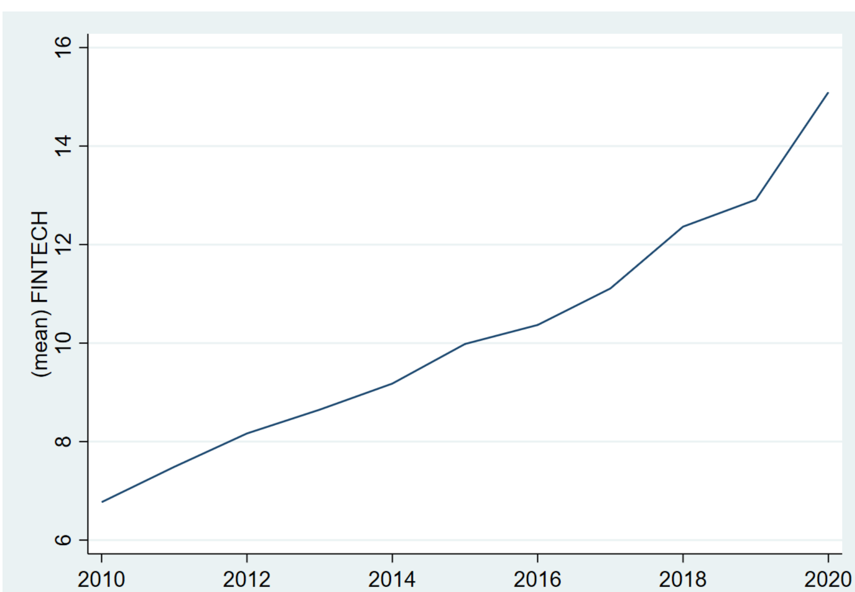
Table 6 Results of rotated factor loadings and unique variance for bank FinTech (continued)

Variable	*Factor1*	*Factor2*	*Factor3*	*Factor4*	*Factor5*	*Factor6*	*Factor7*	*Factor8*	*Uniqueness*
Real-time	0.410	–0.600	0.513	0.145	–0.073	–0.140	–0.056	0.059	0.156
Remote	0.720	0.113	–0.012	0.203	0.014	0.040	–0.077	0.082	0.413
Cybersecurity	0.541	–0.031	–0.383	0.334	–0.261	–0.101	0.005	0.074	0.364
Risk-monitoring	0.448	–0.154	0.072	–0.457	0.047	0.241	0.390	–0.201	0.309
Telephone-banking	0.009	0.007	0.036	0.220	-0.359	0.542	-0.077	-0.214	0.477
Digital-banking	0.486	0.395	0.049	0.029	0.023	-0.227	-0.107	0.005	0.541

Thirdly, we extract eight common factors and calculate the level of FinTech for every sample bank in different sample periods by using Principal Component Analysis and Factor Analysis. As seen in Table 5, the cumulative value of the top eight principal components is 61.6% with a unit root greater than 1, the value of the Kaiser-Meyer-Olkin measure of sampling adequacy is 0.873, and the value of the Bartlett test of sphericity is less than 0.001. These results confirm the credibility of our results. Additionally, Table 6 shows what degree of the keywords is reflected by each factor.

Furthermore, we estimate the development trend of bank FinTech in US by using the data measured above. As shown in Figure 2, the level of bank FinTech in US has been consistently presenting an upward trend since 2010, which reaches its highest point in 2020 as the demand for non-contact services has promoted the rapid development of bank FinTech.

Figure 2 The development of Bank Fintech in US since 2010 (see online version for colours)



Also, following Carbó-Valverde et al. (2020), we take the information and technology expense ratio (ITR) as an auxiliary proxy variable to further examine the impact of FinTech.

3.2.3 Control variables

Based on the existing literature, we choose eight indicators as control variables at the macro and micro levels (see Table 7).

Table 7 Variables – description and data source

Type of variable	*Variable*	*Definition*
Dependent variables	PERF	Bank performance index
	ROA	Return on asset
Independent variables	FinTech	Bank FinTech index
	ITR	The information and technology expense to noninterest expense ratio
Control variables	MP	Market power, calculated as $\text{Asset}_{it}/\sum\text{Asset}_{it}$
	SER	shareholders' Equity to asset ratio
	OPR	Expense of salaries and employee benefits to noninterest expense ratio
	IDR	Income diversification ratio
	ALLR	Allowance for loan losses to Total non-performing loans ratio
	LNSIZE	Logarithm of total assets
	CPI	Consumer price index
	LIBOR3M	Average of three-month dollar Libor

As for the micro bank level, we control for market share, financing ability, internal management ability, diversified development ability, and risk-resisting ability.

Following the research by Sudrajad and Hübner (2019), we use market power (MP) to represent market share of banks because it can be translated into non-traditional income and thus improve banks' revenues, which is calculated as follows:

$$\text{MP}_{it} = \text{Asset}_{it}/\sum\text{Asset}_{it}, \tag{1}$$

where $i = 1,2, ..., N$, indicates the ith bank in our sample. $t = 1,2, ..., T$ indexes the time period.

As the equity capital financing from capital market is the base for bank carrying on business as well as covering the requirement of capital, we choose the shareholders' equity to total asset ratio (SER) to represent the financing ability of the bank.

Following Kamukama et al. (2017), we use the expense of salaries and employee benefits to total non-interest expense ratio as a control variable indicating the operating capability of the bank (OPR), which not only improves its own competitive advantage but also has indirect influence on its performance.

Furthermore, the diversification in loans, deposits, assets, and geography has a strong relationship with cost added and profit reduced (Berger, 2010). We then take the income diversification ratio (IDR) as a control variable representing the potential development capacity of banks, which is calculated as follows:

$$IDR = 1 - \left[\frac{II}{II + NIT}\right]^2 + \left[\frac{NII}{II + NIT}\right]^2 \tag{2}$$

where II and NIR stand for interest income and non-interest income respectively. Moreover, following Chen et al. (2021) and Lartey et al. (2021), we control for the ratio of allowance for loan losses (ALLR) to represent the risk resilience of banks given that risk affects banks' performance.

In addition, Hughes et al. (2019) show that bank size matters for bank performance. Hence, we include the logarithm of total assets (LNSIZE) in our regressions as a control variable.

Considering that both the banks' business and financial products are inevitably affected by macroeconomic conditions and market interest rates, we control for consumer price index (CPI) and the three-month London Interbank Offered Rate (LIBOR3M) in our model.

3.3 Model specification

The operation of banks usually has two characteristics. On the one hand, it has an inertia characteristic, that is, the bank performance in a particular period may be affected by past performance. On the other hand, there may be a causal relationship between bank performance and its individual characteristic variables. Therefore, following existing studies (Xu, 2011; Pathan, 2013), we introduce the first lag of the explained variable as an independent variable, and write our econometric model as follows:

$$\begin{aligned} \text{PERF}_{i,t} = {} & \beta_0 + \beta_1 {*} \text{PERF}_{i,t-1} + \beta_2 {*} \text{FinTech}_{i,t} + \beta_3 * \text{BANK}_{i,t} + \beta_4 * \text{MACRO}_{i,t} \\ & + \lambda_{\text{i}} + \delta_t + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where i = 1,2, ..., N, indicates the ith bank in our sample. t = 1,2, ..., T indexes the time period. λ and δ are the dummy variables for bank and year effects, respectively. $\varepsilon_{i,t}$ represents a random error term. β are the parameters to be estimated. $\text{PERF}_{i,t}$ indicates the performance of bank i in year t, which is a composite index measured by seven variables. $\text{PERF}_{i,t-1}$ is the first lag of $\text{PERF}_{i,t}$ as bank performance has the characteristics of time continuity. $\text{FinTech}_{i,t}$ reflects the level of FinTech of bank i in year t, as explained before. $\text{BANK}_{i,t}$ comprises a set of micro bank level control variables, containing the ratio of shareholders' equity, compensation and benefits, diversified revenue, allowance for loan losses to total loans, and size, which are related to bank i in year t. $\text{MACRO}_{i,t}$ refers to macro level control variables, CPI and the Libor rate.

Since we introduce the one-period lag of the explained variable, we use the Generalised Method of Moment for systems (sysGMM) to estimate our model. In line with Blundell and Bond (1998), Bond (2002), and Roodman (2009), four criteria support this use. First, the Hansen test cannot reject the original assumption that our instrumental variables are valid. Secondly, the AR (2) test does not reject the original assumption that there is no second-order sequence correlation in the random error term of the first-order difference equation. Thirdly, our analyses meet "the rule of thumb", according to which the number of instruments should not exceed the number of observations. Finally, the estimated value of the lag term is between the values estimated by the ordinary least square (OLS) and the fixed effects (FE) models, which we present ahead for comparison.

4 Empirical results

4.1 Descriptive statistics

The summary statistics of all variables are presented in Table 8. The minimum and maximum values of these two main variables (performance and FinTech) in our study are respectively 0.01 and 100, which shows a relatively broad range and hints that we should take into account the heterogeneity involved in the context of our study.

Table 8 Summary statistics of all variables

Variable	*Obs*	*Mean*	*Std. Dev*	*Min*	*Max*
PERF	3284	56.576	5.619	0.01	100
ROA	3284	0.926	0.675	–1.99	4.18
FinTech	3284	10.483	7.172	0.01	100
ITR	3284	4.019	2.444	0.01	24.08
MP	3284	0.335	1.76	0.01	32.26
SER	3284	10.959	2.781	–0.17	32.46
OPR	3284	30.658	7.127	13.42	51.97
IDR	3284	43.244	26.856	4.52	151.14
ALLR	3283	1.301	0.696	0.25	4.47
LNSIZE	3284	15.162	1.723	8.83	21.71
CPI	3284	1.705	0.73	0.1	3.2
LIBOR3M	3284	0.905	0.782	0.234	2.327

4.2 Multicollinearity test and fisher type stationary test

Before conducting our regression analyses, we have run the following two tests. Firstly, we perform the multicollinearity test to all bank-specific variables. As shown in Table 9, all variance inflation factors (VIFs) are less than 5, suggesting that there is no multicollinearity between the variables. Second, we run the Fisher Type stationary test to the panel data. Given that the p-values of all explanatory variables are equal to zero, we can conclude that the seven explanatory variables are stable, which allows us to move on to our main regressions.

4.3 Results

We estimate Equation (3) by using three methods: ordinary least square (OLS), fixed effects (FE), and system GMM (sysGMM). Our results are reported in Table 10. The validity of the instruments used in column (3) is supported by the following four results.

First, the p-value (0.115) of the Hansen test indicating that it cannot reject the null hypothesis according to which all instrumental variables are valid.

Table 9 Multicollinearity test and Fisher Type stationary test

Variable	*VIF*	*Fisher Type Test*
PERF		2296.2847***
		(0.0000)
FinTech	2.040	1371.3728 ***
		(0.0000)
MP	1.570	1305.0449***
		(0.0000)
SER	1.500	1791.5493***
		(0.0000)
IDR	1.570	1589.2019***
		(0.0000)
ALLR	1.440	1896.4888***
		(0.0000)
LNSIZE	2.330	1344.8511***
		(0.0000)

The p-value in the Fisher Type is showed in parentheses based on Phillips-Perron tests.
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10 Effects of bank FinTech on performance from 2010 to 2020

	(1)	*(2)*	*(3)*
Dependent variable		*PERF*	
Estimation approaches	*OLS*	*FE*	*sysGMM*
$PERF_{t-1}$	0.556^{***}	0.296^{***}	0.423^{***}
	(0.000)	(0.000)	(0.000)
FinTech	0.0129	–0.0263	0.0235^{*}
	(0.243)	(0.137)	(0.059)
MP	0.0163	0.189	0.0417
	(0.691)	(0.543)	(0.429)
SER	0.568^{***}	1.037^{***}	0.773^{***}
	(0.000)	(0.000)	(0.000)
PMR	-0.0716^{***}	-0.0514^{***}	-0.104^{***}
	(0.000)	(0.002)	(0.000)
IDR	0.0189^{***}	0.0315^{***}	0.0209^{***}
	(0.000)	(0.000)	(0.000)
ALLR	0.0874	-0.506^{***}	0.0378
	(0.414)	(0.001)	(0.867)
SIZE	-0.499^{***}	-3.328^{***}	-0.670^{***}
	(0.000)	(0.000)	(0.000)

Table 10 Effects of bank FinTech on performance from 2010 to 2020 (continued)

	(1)	*(2)*	*(3)*
Dependent variable		*PERF*	
Estimation approaches	*OLS*	*FE*	*sysGMM*
CPI	0.301^{**}	-1.149^{***}	–0.191
	(0.034)	(0.000)	(0.124)
LIBOR3M	0.212^{*}	0.127	0.13751
	(0.091)	(0.300)	(0.167)
Constant	26.46^{***}	82.49^{***}	36.29^{***}
	(0.000)	(0.000)	(0.000)
Bank fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
AR(1)(p-value)	–	–	0.007
AR(2)(p-value)	–	–	0.192
Hansen Test(p-value)	–	–	0.115
Number of instruments	–	–	134
Number of obs	2919	2919	2919
Number of groups	355	355	355

The values in parentheses are p-values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The time effect is controlled but not reported for brevity. We assume that all explanatory variables except the lag of $PERF_{t-1}$ and FinTech are exogenous variables.

Second, the fact that the p-value of AR(1) is less than 0.01 and the p-value of AR(2) is larger than 0.1, which means that the Abond test does not reject the null hypothesis, according to which the error term has no autocorrelation.

Third, the coefficient of the lagged term (0.423), which is between 0.296 (estimated by using FE) and 0.556 (estimated by using OLS).

Fourth, the number of instruments (134), which is less than the number of banks in our sample (355).

Therefore, we analyse the regression results according to column (3) in Table 6 estimated by means of system-GMM.

The coefficient of bank FinTech index (FinTech) shows that FinTech has a positive effect on bank performance, which is significant at the 10% level and relatively close to the 5% level given that its p-value is 0.059. Also, on average, the performance of banks increases by 0.30% with the standard deviation of the whole performance level of the bank increased by 1 unit.[2] This conclusion supports our hypothesis and suggests that commercial banks should make full use of all the opportunities brought by FinTech to enhance the innovation in both the traditional business and the Off-Balance-Sheet activities.

Secondly, the coefficient of the first-order lag of bank performance being significantly positive shows that bank performance has a cumulative effect in itself as the good bank performance in the last period not only can boost market confidence to some extent but it can also make bank managers set higher operating goals, which may have a positive effect on the current performance. The positive and significant coefficients of the equity to asset ratio and the income diversification ratio indicate that the stronger the market-oriented financing ability and the higher the diversified development ability of commercial banks are at a certain level of bank FinTech, the more conducive it is to improve the operating performance of commercial banks. OPR, derived from the expenditure for employees' salary and pension ratio, represents the management level of the bank. The result estimated by sysGMM illustrates that it has a negative effect on bank performance and suggests that commercial banks should accelerate digital transformation in the field of organisation structure and business operations. Establishing fewer or no branches, using robot services, building mobile banking or online banking, all of these can contribute to reduce management costs and improve bank performance with the help of FinTech. The coefficient of bank size is negative, which is consistent with the conclusions in some previous studies (e.g., Gupta and Mahakud, 2020). We interpret these results as a signal that FinTech may make the size effect no longer significant because whoever masters technology can take advantage of financial technology.

Also, the results for our two macro variables, CPI and London Interbank Offered Rate (LIBOR), can be explained from an economic angle. Usually, excessive CPI will make the Federal Reserve implement a tighter monetary policy. This has a big influence on the liquidity of banks and impact their decisions. Therefore, the coefficient of CPI estimated in the regression is consistent with the forecasting of economic development. LIBOR is not only the cost for banks being financed by the financial market but also the base for bank pricing all financial products. Highly developed financial markets and abundant financial products in US allow banks to gain higher profit than their financing cost, which is reflected by the positive coefficient of LIBOR.

5 Endogeneity and robustness tests

In this section, we use two methods, alternative variables and a sub-sample to check whether our results are robust or not. Given that the instruments are valid in the sysGMM regressions, we conduct all the following tests based on that approach.

5.1 Endogeneity control

Although we have weakened the endogenous problem in our model by using instrumental variables in the sysGMM regressions, we still cannot completely rule out this issue because the FinTech measure we use in our initial analyses is mainly based on the perceptions of bank leaders, which may lead to a measurement error with respect to the variable's true value. Moreover, reverse causality between bank performance and bank FinTech is possible. That is, bank performance may influence banks' willingness and ability to adopt financial technologies. Therefore, we take two measures to deal with this problem.

We replace the main explanatory variable (FinTech) with its two-period lag given that the current bank performance cannot have any influence on the past level of bank FinTech. Having included the one-period lag of the dependent variable in the model, we turn to the two-period lag of the core explanatory variable without using its first order lag. As is shown in column (3) of Table 11, the re-estimated results of the coefficient of the lag of bank performance, the p-value of AR(2) and Hansen Test, and the number of instruments meet the requirements of the sysGMM approach, and show that our baseline results are robust and reliable.

Table 11 Results of the endogenous test for the regression

	(1)	*(2)*	*(3)*
Dependent variable		*PERF*	
Estimation approaches	*OLS*	*FE*	*sysGMM*
$PERF_{t-1}$	0.563^{***}	0.295^{***}	0.434^{***}
	(0.000)	(0.000)	(0.000)
$FinTech_{t-2}$	0.00935	–0.0300	0.0200^{*}
	(0.431)	(0.120)	(0.068)
Bank fixed effects	yes	yes	yes
Year fixed effects	yes	yes	yes
AR(1)(p-value)	–	–	0.008
AR(2)(p-value)	–	–	0.209
Hansen Test(p-value)	–	–	0.151
Number of instruments	–	–	69
Number of obs	2919	2919	2562
Number of groups	355	355	337

The values in parentheses are p-values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The time effect is controlled but not reported for brevity.

5.2 Robustness tests

We replace the measures of independent variables and use sub-samples to conduct a series of robustness tests.

5.2.1 Altering the measure of bank FinTech

As the development of bank FinTech cannot take place without proper investment, we use the investment on information technology (which is mainly referred to the expenditure of information technology, software, data processing, etc. and can be collected from the annual report of form-10K) as an alternative proxy of bank FinTech. As can be seen from the column (2) in Table 12, both the positive and negative direction and significance of the regression coefficients are consistent with the results found in Section 4. The estimated result of the key independent variable shows that FinTech has a positive effect on bank performance with significance at the 10% level.

5.2.2 Sub-sampling the data into two periods

In 2017, the framework for FinTech published by Obama government formulated a program of action for the development of financial technology in the United States. Also in the same year, the definition of financial technology issued by The Financial Stability Board had a far-reaching impact on the world. Because of this, we divide our sample into two sub-samples: from 2010 to 2016 and from 2017 to 2020. Then we run new regressions by using sysGMM and present the respective results in columns (3) and (4) of Table 12. Besides all the results showing that our conclusions obtained above have no substantial changes and remain stable, we can see that FinTech has a more significant influence on bank performance since 2017, as the estimated p-value of FinTech is significant at the level of 5% for the period starting in 2017, and the other is only significant at the level of 10%.

Table 12 Results of three alternative measures for robustness tests

	(1)	*(2)*	*(3)*
Dependent variable		*PERF*	
Alternative criteria	*FinTech = ITR*	*Year < 2017*	*Year>=2017*
$PERF_{t-1}$	0.481^{***}	0.434^{***}	0.365^{***}
	(0.000)	(0.000)	(0.003)
FinTech	0.2056^{*}	0.0546^{*}	0.0424^{**}
	(0.087)	(0.090)	(0.027)
Bank fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
AR(1)(p-value)	0.006	0.036	0.054
AR(2)(p-value)	0.180	0.271	0.685
Hansen Test(p-value)	0.126	0.422	0.105
Number of instruments	107	25	32
Number of obs	2919	1615	1304
Number of groups	355	293	354

These results are obtained by means of the sysGMM approach. ITR refers to the information and technology expense ratio. The values in parentheses are p-values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The time effect is controlled but not reported for brevity.

6 Further discussions

Facing the all-round impact brought by the rapid development of financial technology, different banks may have different response and actions. The leading banks, those who have advantages of large-scale asset and trans-regional operations, may take the lead in recognising the importance of FinTech, conduct an all-round FinTech strategy, and accelerate the digital transformation. On the contrary, small size banks usually adapt themselves to the scenario set by leading institutions. Meanwhile, the level of economic development and the support policies in different states also affect the level of FinTech development of the bank headquartered in this state. In addition, the differences in financial supervision policies to nationally chartered, state-chartered member bank and state-chartered non-member bank is also an important factor to the development of FinTech. Given that the heterogeneity among different banks may have an unpredictable impact on the relationship between FinTech and bank performance, it is necessary for us to perform a heterogeneity test to better understand the FinTech's influence on bank performance. That is, in this section, we take into consideration of some banks' characteristics, bank size, bank headquarters location and membership status, to further investigate how these factors moderate the influence of FinTech on bank performance. At the same time, as processing the dynamic panel requires that the time span is smaller than the number of banks, we do not sub-sample our data in terms of different aspects to estimate the model separately. Also, we firstly assure the results meet the requirements of estimating the dynamic panel prior for analysing the estimated results.

6.1 The role of bank size

In September 2019, the Federal Reserve and other federal banking agencies adopted a rule according to which financial institutions with total assets less than $10 billion should comply with a community bank leverage ratio while the other banks should meet other qualifying criteria. Hence, it seems that 'assets of $10 billion' would be a good standard to distinguish the size of banks, but this is not appropriate because the value of banks' total assets changes with time. We then choose the stock exchange where a bank is listed as a criterion to classify it in terms of size, given that banks listed on the New York Stock Exchange are leading banks while those listed on the NASDAQ Stock Exchange are small or medium. This is justified by the fact that companies listed on New York Stock Exchange are usually mature enterprises with large scale and good financial condition while the others are mainly growing firms. After introducing two dummy variables, ISNYSE (representing whether the bank is listed on New York Stock Exchange), ISNASDAQ (representing whether the bank is listed on NASDAQ stock exchange), and adding their interaction with FinTech to our model, named as FINTNYSE and FINTNASDAQ respectively, we find the results shown in Table 13.

The results shown in column (3) of Table 13, which are based on sysGMM, support our baseline analyses. Firstly, the directions of the estimated coefficient of two interaction terms are the same, but their significance are different. The same direction shows that FinTech has the same influence on the bank's performance both in the leading banks and the small and medium banks. The interaction term of FinTech and the leading banks is significant at the 10% level while the other is not significant, which indicates that the application of FinTech in the leading banks has a more significant effect on bank performance. This can be explained by the fact that the leading banks drive the innovation of FinTech in the banking industry and such information is reflected in the Form-10K. Secondly, FinTech has the same positive effect on bank performance in both groups of banks as both coefficients are positive. Finally, the signs of coefficients of other control variables are also consistent with our expectations but, for brevity, they are not reported in Table 13.

6.2 The role of headquarters location

Normally, banks do business primarily in the region or state in which they are headquartered. Previous studies have also confirmed that corporate headquarters location can not only affect its capital structure, ownership structure, and stock return (Gao et al., 2011; Li et al., 2014) but is also related to bank performance (Tonts and Taylor, 2010). Hence, cultural, economic, scientific and environmental factors of the region or state where a bank is headquartered could affect the development of its activities. We therefore check whether the influence of FinTech on bank performance is also affected by their location.

Table 13 Effects of bank FinTech on performance from 2010 to 2020

	(1)	*(2)*	*(3)*
Dependent variable		*PERF*	
Estimation approaches	*OLS*	*FE*	*sysGMM*
$PERF_{t-1}$	0.556^{***}	0.296^{***}	0.374^{***}
	(0.000)	(0.000)	(0.000)
FINTNYSE	0.0148	–0.0091	0.0196^{*}
	(0.199)	(0.654)	(0.073)
FINTNASDAQ	0.008	-0.0626^{**}	0.0370
	(0.563)	(0.023)	(0.203)
Bank fixed effects	yes	yes	yes
Year fixed effects	yes	yes	yes
AR(1)(p-value)	–	–	0.009
AR(2)(p-value)	–	–	0.206
Hansen Test(p-value)	–	–	0.173
Number of instruments	–	–	48
Number of obs	2919	2919	2919
Number of groups	355	355	355

The values in parentheses represent p-values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The time effect is controlled but not reported for brevity.

As the headquarters of our sample bank are distributed in eight US regions, we introduce eight dummy variables, GreatLakes, Mideast, NewEngland, Plains, RockyMountain, Southeast, FarWest, Southwest, to represent whether the bank is headquartered in this region. Furthermore, we also add these eight dummy variables' interactions with FinTech to our model, which are named FINTGreatLakes, FINTMideast, FINTNewEngland, FINTPlains, FINTRockyMountain, FINTSoutheast, FINTFarWest, and FINTSouthwest. The results are shown in Table 14.

Comparing the results in columns (1) and (2) of Table 14 by using the approaches of OLS and FE, we see that the results shown in column (3) estimated by using the sysGMM method are robust. On the one hand, the estimated coefficients of the eight interaction terms are all positive, which indicates that FinTech is helpful for all banks in every region to improve their performance. On the other hand, only three estimated coefficients of the interaction items are significant over the level of 5%, which indicates that the development of FinTech is unbalance throughout the United States, and some regions may not have built a good environment for developing bank FinTech. To be more specific, the effect of FinTech on bank performance in the region of Plains is the most significant, the regions of New England and Far West come second, but the effect in Far West is greater than that in the other two regions.

Table 14 Effects of bank FinTech on performance from 2010 to 2020

	(1)	*(2)*	*(3)*
Dependent variable		*PERF*	
Estimation approaches	*OLS*	*FE*	*sysGMM*
$PERF_{t-1}$	0.554***	0.301***	0.380***
	(0.000)	(0.000)	(0.000)
FINTGreatLakes	0.0194	–0.0144	0.0187
	(0.201)	(0.758)	(0.431)
FINTMideast	0.00417	–0.0169	0.00406
	(0.718)	(0.523)	(0.780)
FINTNewEngland	–0.000250	–0.0368	0.0458*
	(0.989)	(0.542)	(0.060)
FINTPlains	0.0349**	–0.0503	0.0395***
	(0.025)	(0.139)	(0.004)
FINTRockyMountain	–0.00717	–0.366***	0.0493
	(0.824)	(0.003)	(0.540)
FINTSoutheast	0.0115	0.0413	0.0132
	(0.389)	(0.274)	(0.584)
FINTFarWest	0.0326	–0.131	0.0824*
	(0.252)	(0.215)	(0.066)
FINTSouthwest	–0.000188	0.00112	–0.00138
	(0.878)	(0.715)	(0.388)
Bank fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
AR(1)(p-value)	–	–	0.009
AR(2)(p-value)	–	–	0.206
Hansen Test(p-value)	–	–	0.252
Number of instruments	–	–	114
Number of obs	2919	2919	2919
Number of groups	355	355	355

The values in parentheses are p-values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The time effect is controlled but not reported for brevity.

6.3 *The role of membership status*

We also conduct a heterogeneity test focused on different membership status. US banks have three chartered memberships, Nationally chartered member, State-chartered member bank and State-chartered nonmember, which are usually called national banks, state-chartered member banks, and state-chartered non-member banks, respectively. These different membership statuses correspond to different US regulators. The first two are regulated by the Federal Reserve, and the last one is regulated by the Federal Deposit

Insurance Corporation. Broadly speaking, we assume that the Federal Reserve is relatively stricter in terms of supervision than other US regulators. Previous studies have shown that more 'tolerant' regulatory environment is one of the key drivers for FinTech development (Hua and Huang, 2021), and strong supervision cannot only reduce the operational risks of banks but also have an impact on bank performance (Hirtle et al., 2020). Hence, we introduce three dummy variables, NAT, SMB and SUM, to respectively represent the three membership statuses mentioned above, and to investigate whether FinTech has a different influence on bank performance according to their chartered status. In the same way, we add their interaction with FinTech in our regressions and call them FINTNAT, FINTSMB, FINTESUM respectively. The results are shown in Table 15.

Table 15 Effects of bank FinTech on performance from 2010 to 2020

	(1)	*(2)*	*(3)*
Dependent variable		*PERF*	
Estimation approaches	*OLS*	*FE*	*sysGMM*
$PERF_{t-1}$	0.555^{***}	0.295^{***}	0.376^{***}
	(0.000)	(0.000)	(0.000)
FINTNAT	0.0146	-0.0661^{*}	0.0115
	(0.261)	(0.066)	(0.694)
FINTSMB	0.0030	0.0063	0.0029
	(0.821)	(0.813)	(0.884)
FINTSUM	0.0194	-0.0372^{*}	0.0354^{*}
	(0.119)	(0.100)	(0.082)
Bank fixed effects	yes	yes	yes
Year fixed effects	yes	yes	yes
AR(1)(p-value)	–	–	0.010
AR(2)(p-value)	–	–	0.204
Hansen Test(p-value)	–	–	0.108
Number of instruments	–	–	59
Number of obs	2919	2919	2919
Number of groups	355	355	355

The value in parentheses are p-values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The time effect is controlled but not reported for brevity.

The results in column (3) are still robust and reliable. As can be seen from the estimated coefficients of the three interaction terms, FinTech has a positive effect on bank performance for all kinds of chartered member banks, but only the coefficient of the interaction term between FinTech and State-chartered non-member banks is significant at the 10% level. This indicates that State-chartered non-member banks may have the most relaxed financial regulatory environment, which provides impetus for the development of financial technology.

7 Conclusions

The integration between big data and emerging technologies, including cloud computing, AI, block chain, the Internet of things, is reshaping the financial sector, financial products and services (Agarwal and Zhang, 2020; Hasnat, 2018; Zhao, 2021). In view of the latest empirical research literature, we have estimated the effect of FinTech on bank performance by using the system GMM method and a dynamic unbalanced panel data, which is formed by 355 US banks from 2010 to 2020. Our major conclusions are as follows. First, FinTech has a significant effect on bank performance in US, where bank performance would increase 0.30% for each unit of FinTech improvement. Secondly, the significance and intensity of the FinTech's effect on bank performance vary with the characteristics of size and membership. In particular, the influence of FinTech on the leading banks and the State-chartered nonmember banks are more significant. Thirdly, the development of bank financial technology in different regions of the United States is uneven, which is noticed in two aspects. On the one hand, it is found that the development of FinTech in three regions, New England, Plains and Far West, has a significant effect on bank performance, but is not significant in most regions. On the other hand, the significance of the FinTech's impact in the Plains region is the highest, but its strength is the least, which is just the opposite in the region of Far West. Finally, management ability, diversified development ability, risk-resisting ability at the level of the bank, and economic and financial environment are all affecting the role of bank FinTech.

Our research also has the following insights. First, our empirical results show that FinTech has effectively improved bank performance in US, which strongly suggests that commercial banks should actively embrace financial technology and accelerate digital transformation. This indicates that commercial banks should amplify the input of technology in the development of intelligent devices and systems, especially the development of core banking systems as the legacy infrastructure is holding the banks back (KPMG, 2021). Commercial banks should further accelerate the digital transformation for its front-end business, as the automatic, digital and smart application scenarios are the base for improving customer experience. Second, this could also encourage commercial banks to continually broaden the scope of their FinTech's applications. We agree with the view that the surface FinTech innovations can meet the demands from the public, but only the genuine, foundational FinTech innovation can help commercial banks better improve their ability for digital transformation (Schindler, 2017). Third, different types of banks should formulate reasonable financial technology strategies only suitable for their own development. For those leading banks, by virtue of their strong financial strength and rich management experience, they could carry out abundant FinTech innovations to enhance the potential ability for their diversified development, and thus lead the development of FinTech in the whole banking industry. Small and medium banks, besides actively integrating into the tide of the development of FinTech, should rationally utilise financial technologies such as AI, cloud computing, Big Data, etc. to obtain greater performance by improving the management ability and the quality and efficiency of financial services. Also, we suggest commercial banks should focus on the risk of FinTech to prevent excessive risk-taking. Our empirical results show that given a certain level of FinTech, the higher the ability to control risk, the higher the bank performance. Therefore, commercial banks should closely monitor their FinTech actions and opportunities by establishing an efficient data collection system, and building an early warning mechanism that could be based on the use of Big Data, for instance.

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Notes

[1]According to the "Contributions to Percent Change in Real Gross Domestic Product, by State and Region" annual report published on the official website of US Bureau of Economic Analysis, US are divided into the following regions: New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountain, and Far West.

[2]This value can be approximately obtained by multiplying the FinTech's regression coefficient by that variable's standard deviation and then dividing the resulting product by the mean of performance (PERF).