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Differential Impact of Fintech and GDP on Bank Performance: Global Evidence

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Abstract: Using the World Bank Global Findex Database for 91 countries in 2014, 2017, and 2021, we examine whether fintech levels influence bank performance and whether fintech's interaction with GDP per capita causes differential effects on bank performance globally. Since fintech levels were already very high for rich countries when the World Bank started providing fintech development statistics in 2014, we estimate *AbFintech* by regressing fintech levels on GDP per capita by year. *AbFintech* is the difference between the fintech level and its fitted values. Then, using multiple regression analyses, we investigate the impact of *AbFintech* on bank performance worldwide, focusing on the differential effects of *AbFintech* and GDP levels on bank performance**. We find** *AbFintech* significantly increases bank performance, primarily in less developed countries. Specifically, *AbFintech* increases banks' ROA in the least developed countries and net interest margin in the 75th percentile countries. Also, *AbFintech* decreases the cost-to-income ratio in the 75th percentile countries, while it increases the ratio in the most developed countries. *AbFintech* does not affect the ratio of noninterest income to total income, regardless of the level of economic development.

Keywords: fintech; abnormal fintech; bank performance; ROA; net interest margin; income mix; cost structure

JEL classification: G10; G15; G 20; G 21; O0; O3

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1. Introduction

We examine the impact of fintech development on bank performance using the global data extracted from the World Bank Database. The Financial Stability Board defines fintech as "technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions and the provision of financial services (https://www.fsb.org/work-of-the-fsb/ financial-innovation-and-structural-change/fintech/)." Fintech activities cover virtually all the spectrum of financial services at both the retail (i.e., households and small and medium enterprises) and wholesale (corporations, non-bank financial institutions and inter-bank) levels, including (i) payments, clearing and settlement; (ii) deposits, lending and capital raising; (iii) insurance; (iv) investment management; and (v) market support (Financial Stability Board, 2017). "The big promise of fintech is to build on the potential cost-cutting allowed by digital technologies to dramatically reduce financial frictions (p. 111, Bofondi and Gobbi 2017)."

Stulz (2022) provides a shorter definition of fintech as "financial innovation that is based on the use of digital technologies and big data." He expects fintech firms to be able to compete with incumbent banks by offering cheaper and better products more conveniently. Constraints and costs associated with (large) incumbent banks, such as regulatory costs, legacy IT systems, and organizational frictions inherent in diversified firms, operate as advantages for fintech firms. At the same time, he argues that incumbent banks have their competitive advantages, such as large established customer bases, experience in dealing with regulators, and a broader set of product offerings.

Fintech service providers enhance competition in financial markets by delivering services provided by incumbent financial institutions more efficiently or introducing new services, but they will not replace traditional financial institutions (Navaretti, Calzolari, and Pozzolo 2017). Incumbent banks are actively responding to the competition from fintech firms by replicating fintech models such as online lending platforms or partnering with fintech firms. Therefore, traditional financial institutions and fintech firms will likely coexist and compete (Bofondi and Gobbi 2017).

Numerous studies examine the effect of fintech development on bank performance. The results are mixed. Among others, Phan, Narayan, Rahman, and Hutabarat (2020) report that the growth of fintech firms in Indonesia negatively affects bank performance measured by net income to total assets (ROA), net income to equity (ROE), net interest margin (NIM), and yield on earning assets (YEA). Katsiampa, McGuinness, Serbera, and Zhao (2022) also report fintech firms' entry into the credit market erodes traditional Chinese banks' profitability measured by ROA and ROE.

Several studies report fintech development is positively associated with the performance of financial institutions. For example, Haddad and Hornuf (2021) examine 87 countries for 2006-2018 and report that the number of fintech startup formations is significantly positively associated with ROA, ROE, NIM, and stock returns of traditional financial institutions. Nguyen, Tran, and Ho (2022) find fintech credit significantly positively affects the risk-adjusted ROA and ROE by examining 73 countries for 2013-2018. Li, Spigt, and Swinkels (2017) report the stock returns of incumbent retail banks in the United States are significantly positively related to the growth of fintech funding volume and the growth of the number of fintech deals. Ky, Rugemintwari, and Sauviat (2019) examine the effect of mobile money services by banks on their performance in the East African Community (Burundi, Kenya, Rwanda, Tanzania, and Uganda) from 2009 to 2015. They report mobile money services significantly enhance banks' profitability measured by ROA, ROE, and Z-score.

Those studies examine individual countries or multiple countries in aggregate. Unlike the existing literature, we segment our sample of 91 countries into quartiles based on GDP per capita. As our primary contribution to the literature, we investigate the effect of the interaction between fintech and country income levels on bank performance. We predict the marginal contribution from fintech innovations during our sample period is greater in underdeveloped countries than in rich countries since fintech adoption has already been widespread in rich countries by the time the World Bank started providing fintech development indices, and developing economies can benefit from backwardness advantage (Barsby 1969; Andersson and Axelsson 2016). To properly execute the regression analyses without being tampered with by the multicollinearity issue, we invented a new fintech development measure, abnormal fintech (*AbFintech*).

Consistent with our prediction, we find that *AbFintech* significantly increases bank performance, primarily in less developed countries. Specifically, *AbFintech* increases ROA in the least developed countries and NIM in the 75th percentile countries. Interestingly, the positive effect of *AbFintech* on NIM declines in magnitude and significance as the fintech application setting moves from the less developed to the richer countries. *In addition, AbFintech* decreases the cost-to-income ratio (i.e., improves bank efficiency) in the 75th percentile countries, while it increases the cost-to-income ratio (i.e., worsens bank efficiency) in the richest countries. However, there is no significant association between *AbFintech* and the income mix ratio, measured as noninterest income to total income.

We make two significant contributions to the extant literature on the effect of fintech on financial industry performance. First, we devised a new measure of fintech development, *AbFintech*, generated by regressing fintech levels on GDP per capita. *AbFintech* represents regression residuals for individual countries by year. By controlling GDP per capita in measuring fintech levels, we can measure the fintech effects on bank performance more accurately as we avoid the multicollinearity issue in the regression analysis that arises from the high correlation between GDP per capita and fintech development. Second, we investigate the interaction effects of *AbFintech* with the country's income category by segmenting the sample into quartiles of income levels. To our knowledge, no previous studies have examined the interaction effects of fintech and the country's income level.

This article reviews extant literature and develops hypotheses in the next section. Section 3 presents data and descriptive statistics. The research design is detailed in Section 4, and the results are provided in Section 5. Section 6 provides the implications and limitations of the study. Finally, Section 7 summarizes and concludes.

2. Literature Review and Hypotheses Development

2.1. Prior Literature

Numerous studies examine the effect of fintech on bank performance or behavior, covering individual countries (Li, Spigt, and Swinkels 2017; Misati, Kamau, Kipyegon, and Wandaka 2020; Phan, Narayan, Rahman, and Hutabarat 2020; Wang, Xiuping, and Zhang 2021; Katsiampa, McGuinness, Serbera, and Zhao 2022; Li, Zhu, and Qin 2022; Zhao, Li, Yu, Chen, and Lee 2022), particular regions on the globe (Vives 2017; Ky, Rugemintwari, and Sauviat 2019), and many countries across the world (Haddad and Hornuf 2021; Nguyen, Tran, and Ho 2022). In addition, some studies examine the impact of disruptive technologies and P2P platforms on banks (Chen, Wu, and Yang 2019; Tang 2019). The results are mixed.

Phan, Narayan, Rahman, and Hutabarat (2020) examine the growth in the number of fintech firms and its impact on bank performance in the Indonesian market from 1998 to 2017. They report that the growth of fintech firms negatively affects bank performance measured by ROA, ROE, NIM, and YEA (yield on earning assets). Katsiampa, McGuinness, Serbera, and Zhao (2022) study how the growth of exchange-listed fintech lenders in China for 2013-2019 affects the banks' financial performance. They find that fintech firms' entry into the credit market erodes traditional banks' profitability measured by ROA and ROE.

Zhao, Li, Yu, Chen, and Lee (2022) study fintech development in China and its impact on bank performance from 2003 to 2018. Based on the fintech development index constructed by the total number of fintech companies established, registered capital, number of financing events and amount of financing, they report that fintech development improves banks' capital adequacy and management efficiency but worsens asset quality and earning power. They argue that competition from the fintech industry (e.g., P2P lending) causes Chinese banks' asset quality and earning power to deteriorate.

Li, Zhu, and Qin (2022) construct a fintech index by textual analysis of the annual reports of 36 commercial banks in China for 2003-2019 and assess the impact of fintech on the revenue margin of commercial banks. They examine the four dimensions of fintech, including technology basis (represented by the keywords of big data, cloud computing, AI, blockchain, and biometrics), electronic communication (E-bank and online bank), electronic financing (Internet lending and network financing), and electronic payment (mobile payment). Their findings are mixed in the sense that technological basis has a significantly negative effect on the performance of commercial banks, whereas electronic payment has a positive impact.

Li, Spigt, and Swinkels (2017) investigate the impact of digital banking startups on the stock returns of traditional banks using the data of the US digital banking startups (funding volume and the number of deals) and the US retail banks from 2010 to 2016. They find that the stock returns of incumbent retail banks are significantly positively associated with the fintech funding growth and the number of fintech deals. They argue that the results present no evidence of incumbents' value destruction by the growth of the fintech industry but rather that the fintech industry has a positive spillover to the traditional retail banking industry.

Misati, Kamau, Kipyegon, and Wandaka (2020) examine the effect of fintech services on bank performance in Kenya from 2009 to 2018. They use the value of mobile transactions and the number of mobile accounts to measure the level of fintech services. When all banks are examined, the value of mobile transactions is positively related to the banks' ROE, whereas the effect of the number of mobile accounts is insignificant. However, when the sample is segmented into groups of large, medium, and small banks, the positive effect of the value of mobile transactions on bank profitability is most pronounced for large banks. For small banks, the impact of the mobile transaction value is insignificant. In contrast, the number of mobile accounts negatively affects the banks' ROE during the interest-rate capping period in the later sample period, September 2016 to June 2018.

Wang, Xiuping, and Zhang (2021) assess the impact of fintech on the Chinese banking industry from 2008 to 2017. Their fintech development indicators include big data, artificial intelligence, distributed technology, the interconnectedness of technology, and technology security. They report that fintech development improves the total factor productivity[1] of Chinese commercial banks. They argue fintech helps reduce bank operating costs, improve service efficiency, strengthen risk control capabilities, and create enhanced customer-oriented business models.

Ky, Rugemintwari, and Sauviat (2019) study the effect of mobile money services by banks on their performance in the East African Community (Burundi, Kenya, Rwanda, Tanzania, and Uganda) from 2009 to 2015. They report significantly positive relationships between mobile money services and banks' profitability measured by ROA, ROE, and Z-score. Also, they document a significantly negative association between mobile money services and banks' efficiency, measured by the cost-to-income ratio. Vives (2017) notes that mobile-based payment services significantly impact countries where a small percentage of people own a current account at a bank. In African countries, people have greater access to a mobile phone than a traditional bank account, and thus, these countries are becoming testing grounds for new payment systems.

Haddad and Hornuf (2021) examine the effect of the number of fintech startups on the performance of financial institutions from 87 countries from 2006 to 2018. They report that an increase in fintech startups positively affects incumbent financial institutions' performance while its impact has declined recently. Specifically, the number of fintech startups is positively associated with ROA, ROE, NIM, and stock returns of traditional financial institutions. However, the fintech startups' positive impact has been weakened during 2012-2018 compared to 2005-2011. They also report that large financial institutions most benefited from fintech startup formations, while there is no evidence of benefits for small financial institutions.

Nguyen, Tran, and Ho (2022) examine the relationship between fintech credit and bank performance in 73 countries from 2013 to 2018. They measure fintech credit by the ratio of credit provided by fintech to GDP and bank performance by ROA, ROE, risk-adjusted ROA and risk-adjusted ROE. Risk adjustment is made by dividing the performance by its standard deviation. They find that fintech credit is negatively related to the banks' ROE but positively related to the risk-adjusted ROA and ROE. They argue that fintech lenders chip away some profits from incumbent banks but also benefit banks in terms of improved stability.

Chen, Wu, and Yang (2019) study the value of fintech innovation by constructing a data set of fintech patent applications over the 2003-2017 period based on the Bulk Data Storage System (BDSS) of the United States Patent and Trademark Office (USPTO). They report that fintech innovations are valuable to the financial sector as a whole, while certain fintech innovations negatively impact some financial industries. For example, mobile transaction innovations negatively affect the banking industry in terms of stock market responses but positively affect the payments industry. When innovations involve disruptive technologies from young nonfinancial startups, they affect financial industries more negatively. They also find that market leaders suffer less from disruptive innovation due to their enormous financial resources and technical economies of scale, enabling them to invest heavily in their own innovation. Chen, Wu, and Yang (2019) shed light on empirical tests of theories on how innovation from outside of an industry can harm or benefit incumbent firms (Lieberman and Montgomery 1988; Henderson and Cockburn 1996; Christensen 1997; Adner 2012) and on how incumbents can protect themselves from outside threats by using their own innovation (Dasgupta and Stiglitz 1980; Gilbert and Newbery 1982; Aghion, Harris, Howitt, and Vickers 2001; Aghion and Griffith 2005).

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[1] They use total factor productivity (TFP) as a proxy for commercial banks' competitiveness. To assess TFP, they use banks' labor costs and registered capital as inputs and loans, profits, and deposits as outputs.

Tang (2019) examines whether P2P platforms and banks are substitutes or complements in the consumer credit market using data from LendingClub's website for P2P loans from 2009 to 2012 and Call Reports for bank data. Tang finds deterioration in P2P borrower quality as borrowers migrating from banks to P2P platforms due to reduced credit supply by banks are of worse quality than existing P2P borrowers, indicating P2P platforms act as substitutes for banks. However, tang also finds that bank borrowers migrating to P2P platforms applied for larger loans than existing P2P borrowers, suggesting P2P platforms operate as complements to banks in the small loan market.

2.2. *Testable Hypotheses*

Our test period covers relatively recent years of 2014, 2017, and 2021 when the World Bank's global fintech development indicators are publicly available. Since fintech innovations had already widely permeated in advanced countries by the time the World Bank started announcing global fintech indices and developing countries have an advantage of backwardness (Barsby 1969; Andersson and Axelsson 2016), the marginal contribution from fintech innovations is expected to be greater in underdeveloped countries than in rich countries for our sample period. Also, when it comes to the financial performance of banks impacted by fintech development worldwide, the interaction effects between fintech levels and countries' income levels need to be considered. Hence, we hypothesize abnormal fintech levels' interaction effects with the country's income category differ in affecting bank performance globally. Specifically, we test the following three hypotheses for bank performance indicators.

H1: Interaction effects between per capita GDP and fintech have differential impacts on bank profitability across the globe.

H2: Interaction effects between per capita GDP and fintech have differential impacts on bank income mix across the world.

H3: Interaction effects between per capita GDP and fintech have differential impacts on cost structure worldwide.

By testing these hypotheses, we contribute to the literature where existing studies do not consider the interaction effects and the backwardness issue of fintech innovation.

3. Data

3.1. *Data Source and Bank Performance Metrics*

We collected the data from the World Bank Global Findex Database at https://www.worldbank.org/en/publication/globalfindex/Data#sec1. The World Bank started providing global fintech development indicators in 2014 and updated them twice in 2017 and 2021. Fintech metrics include, among others, 'Made or received a digital payment,' 'Made a digital payment,' 'Paid utility bills: using a mobile phone,' 'Sent domestic remittances: through a mobile phone,' 'Made a digital in-store merchant payment: using a mobile phone, mobile money account,' and 'Individuals using the Internet' for various age categories, gender groups, and income levels for 126 countries, though some countries have missing values. Considering data availability and representativeness, we use 'Made or received a digital payment (% age 15+) (Series code: g20.t.d)' as a proxy for fintech to examine the impact of fintech on bank performances across the world.

We use conventional bank performance metrics as dependent variables, measured by return on assets after tax (ROA) (series code: GFDD.EI.05) and net interest margin (NIM) (series code: GFDD.EI.01). We also investigate how fintech development affects banks' income mix and cost structure. Income mix is defined as noninterest income to total income (series code: GFDD.EI.03). Banks' cost structure is proxied by the cost-to-income ratio (series code: GFDD.EI.07). We also collect country statistics from the World Bank Database to control country characteristics.

3.2. *Sample*

We start with 115 countries, subject to data availability on fintech, bank performance, and control variables in all three years of 2014, 2017, and 2021. We delete countries if key fintech, bank performance, and control variables are unavailable in the three years. The filtering process left us with a final sample of 91 countries. Therefore, we have 273 country-year observations for analyses from 91 countries in the three years.

3.3. Descriptive Statistics and Correlation Matrix

Table 1 shows descriptive statistics for the variables of interest, including bank performance, fintech, and macroeconomic variables. The mean bank performance measured by ROA and NIM was 1.1 percent and 3.8 percent during our sample period, respectively. As expected, interest is a dominant source of income for banks, indicated by the ratio of noninterest income to total income. Noninterest income is less than 40 percent of the total income on average. The cost-to-income ratio, denoted as cost structure and commonly used to measure bank efficiency, is 56 percent on average. Bank performance measures show much less variation worldwide than income mix or cost structure. The global fintech levels average 62 percent. The fintech levels (untabulated) rapidly rose globally at 54 percent, 62 percent, and 70 percent in 2014, 2017, and 2021, respectively.

Table 1. Descriptive statistics (n = 273).

Measure	Mean	Median	S.D.	Min.	Max.
Return on assets (ROA, %)	1.09	0.99	1.14	-5.84	6.74
Net interest margin (NIM, %)	3.80	3.17	2.63	0.17	14.11
Income mix (%)	37.66	34.37	13.02	10.71	79.01
Cost structure (%)	55.97	55.61	11.76	26.15	94.50
Fintech (%)	61.66	63.66	28.87	4.17	100.00
AbFintech (%)	0.00	1.91	14.29	-43.17	51.45
Population (Natural log of millions)	2.85	2.80	1.53	-0.83	7.25
Inflation (%)	5.60	3.32	9.70	-2.84	113.29
GDP Growth (%)	4.16	3.96	3.56	-20.74	15.34

Notes: Return on assets = After-tax net income / Total assets; Net interest margin = Net interest income / Interest-bearing assets; Income mix = Noninterest income / Total income = Noninterest income / (Net interest income + Noninterest income); Cost structure = Operating expenses / (Net interest income + Other operating income); We do not use the Fintech in the analyses. It is shown here for information purposes only.

The correlation matrix (Table 2) shows negative correlations between bank performance (ROA and NIM) and fintech. In contrast, the correlation between income mix and fintech is positive. Fintech correlates positively with cost structure, indicating fintech increases cost. The correlation coefficients for the entire sample indicate that fintech negatively affects bank performance. Suppose we use fintech as a key explanatory variable to investigate fintech's effect on bank performance. In that case, we have an omitted variable issue, not adequately controlling the high correlation between fintech levels and GDP levels. Also, if we include both fintech and GDP levels as explanatory variables, we have a serious multicollinearity issue. Thus, we use abnormal fintech (*AbFintech*, elaborated in Section 4.2) to address multicollinearity issues and correctly detect fintech's impact on bank performance. By construction, *AbFintech* has a zero average since it represents the average of the regression residuals (Table 1).

Table 2. Correlation matrix (n = 273).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(2)	0.59							
(3)	-0.13	-0.30						
(4)	-0.29	-0.05	0.43					

(5)	-0.29	-0.56	0.27	0.09				
(6)	0.05	0.04	0.12	0.04	0.49			
(7)	0.02	0.02	-0.04	-0.05	-0.19	-0.01		
(8)	0.30	0.45	0.06	-0.08	-0.19	0.02	0.10	
(9)	0.20	0.13	-0.15	-0.08	-0.04	-0.06	-0.07	0.08

(1) ROA, (2) NIM, (3) Income mix, (4) Cost structure, (5) Fintech, (6) AbFintech, (7) Population, (8) Inflation, (9) GDP growth.

3.4. Differences in Bank Performance by Quartile Groups

Table 3 reports differences in bank profitability, income mix, and cost structure across four quartile groups based on GDP per capita before considering the abnormal fintech levels. Panel A shows bank performance and variation decline as we move from the least developed to the most developed country group. ROA for the first quartile countries (the least developed) is more than two times that of the fourth quartile countries (the most developed), while NIM for Q1 countries is more than four times that of Q4 countries. On the other hand, less developed countries show greater variation in ROA and NIM compared with advanced economies. Interestingly, the richest countries earn the largest noninterest income as a percentage of total income. Compared to Q1 (Q2) countries, Q4 countries' income mix is 8 (10) percentage points higher. The income mix indicates that banks in less developed countries rely more heavily on interest income than in advanced economies. There is minimal variation in cost structure across the quartile groups.

Panel B reports the mean differences in profitability, income mix, and cost structure between the Q1 and Q4 country groups. The results show differences between the Q1 and Q4 groups are highly significant, except for the cost structure. The difference in the cost structure between Q1 and Q4 is marginally significant.

Table 3. Bank performance by quartile groups and mean difference tests.

Panel A. Bank performance comparison among quartile groups (unit: %).

Measure	Classification of countries into quartile groups based on GDP per capita								Total	
	Q1 (Poor)		Q2		Q3		Q4 (Rich)			
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
ROA	1.64	1.37	1.25	1.23	0.80	1.05	0.67	0.38	1.09	1.14
NIM	5.97	3.05	4.72	1.98	3.02	1.51	1.46	0.66	3.80	2.63
Income mix	35.37	12.57	33.90	11.15	37.78	12.84	43.86	13.50	37.66	13.03
Cost structure	55.38	10.41	53.54	11.41	56.66	11.32	58.79	13.43	55.97	11.76

Panel B. Mean difference tests for performance between Q1 (poor) and Q4 (rich) country groups.

Measure	Group	n	Mean	S.D.	t-stat	p(T<=t) one-tail
ROA	Q1	69	1.64	1.37	5.70	0.000
	Q4	66	0.67	0.38		
NIM	Q1	69	5.97	3.05	12.00	0.000
	Q4	66	1.46	0.66		
Income mix	Q1	69	35.37	12.57	-3.78	0.000

	Q4	66	43.86	13.50		
Cost structure	Q1	69	55.38	10.41	-1.64	0.052
	Q4	66	58.79	13.43		

Notes: ROA = After-tax net income / Total assets; NIM = Net interest income / Interest-bearing assets; Income mix = Noninterest income / Total income; Cost structure = Operating expenses / (Net interest income + Other operating income).

4. Research Design

4.1. Control Variables

The control variables are: population (modified by taking the natural logarithm of one million people; code: SP.POP.TOTL), inflation (GDP deflator %; code: NY.GDP.DEFL.KD.ZG), GDP growth % (code: NY.GDP.MKTP.KD.ZG), GDP per capita (modified by taking natural logarithm; code: NY.GDP.PCAP.CD), and year dummies (YD1 for 2017, YD2 for 2021). We select those variables to control distinct country characteristics while avoiding multicollinearity issues. In addition, we examined many alternative control variables, including political, cultural, and legal variables and industry structure. Specifically, we considered control of corruption, government effectiveness, political stability and absence of violence/terrorism, regulatory quality, rule of law, voice and accountability, and primary industry's (agriculture, forestry, and fishing) share in the GDP. However, they are highly related to each other and to GDP per capita and fintech levels as well. Therefore, we decided not to include them as control variables.

4.2. Multicollinearity Issues and Abnormal Fintech

We use "Made or received a digital payment (% Age 15+)" as a proxy for original fintech. Then, we regress fintech levels on GDP per capita by year and use the regression residuals to estimate abnormal fintech levels (*AbFintech*) as follows:

$$AbFintech_{ct} = Fintech_{ct} - (\alpha_0 + \alpha_1 GDP\ per\ capita_{ct}) \qquad (1)$$

where *c* stands for individual countries, and *t* stands for 2014, 2017 and 2021, respectively.

The reason for using regression residuals as estimated abnormal fintech is because fintech levels correlate highly with GDP per capita (correlation coefficient = 0.87). A high positive correlation coefficient is expected since fintech levels would be high (low) for countries with high (low) GDP per capita.

4.3. Contemporaneous Regression Model

We assume that the abnormal fintech levels in the current year affect bank performance in the same year. In other words, we ignore the lagged effect of fintech levels on bank performance. The contemporaneous model enables us to use all the data provided in the World Bank Database for 2014, 2017, and 2021. The contemporaneous regression model is as follows:

$$Y = \beta_0 + \beta_1 AbFintech + \beta_2(Q1 * AbFintech) + \beta_3(Q2 * AbFintech) + \beta_4(Q3 * AbFintech) + \beta_5 Population + \beta_6 Inflation + \beta_7 GDP\ growth + \beta_8 YD1 + \beta_9 YD2 + \varepsilon \qquad (2)$$

In this model, the Q4 quartile (the richest) group is a default group to which the three other groups' differential impact on bank performance is tested.

5. Results

5.1. Analyses of Bank Performance

The regression results with ROA after tax as a dependent variable (Panel A of Table 4) show that $AbFintech$ does not affect banks' ROA. However, when interactions of *AbFintech* with income levels are considered, the results become significant for one income category. More specifically, *AbFintech* significantly increases ROA for banks in the first-quartile countries (the least developed countries) compared to banks in the fourth-quartile countries (the richest countries). On the other hand, the impact of $AbFintech$ on ROA in second- and third-quartile countries is insignificant and indistinguishable from that of the fourth-quartile countries. Also, inflation and GDP growth positively affect ROA.

Panel B of Table 4 reports the factors that affect banks' NIM (net interest margin) globally. While $AbFintech$ significantly decreases NIM ($\beta_1 = -0.126$ and t = -3.172) in the fourth-quartile countries, it significantly positively affects NIM at the conventional level in the first and second quartile countries. The effect of *AbFintech* in the third quartile countries is marginally significant. The declining coefficient and significance of the *AbFintech* effect in the first (0.225 at the 1% level), second (0.097 at the 5% level), and third quartile countries (0.078 at the 10% level) indicate that the marginal benefit from adopting fintech innovation wears out as the fintech application setting moves to the richer countries. Inflation and GDP growth positively affect NIM. Also, consistent with the law of diminishing marginal returns, $AbFintech$'s impact on NIM has decreased over time, as evidenced by the significant negative coefficient of YD2 (-1.248), indicating a significantly lower NIM in 2021 than in 2014.

Table 4. Bank profitability.

Panel A. ROA after tax as a dependent variable.					
	Coefficients	S.E.	t-stat	p-value	Adj. R^2
Intercept	0.644	0.176	3.655	0.000	0.166
AbFintech	-0.028	0.020	-1.394	0.165	
Q1*AbFintech	0.057	0.021	2.671	0.008	
Q2*AbFintech	0.028	0.022	1.301	0.194	
Q3*AbFintech	0.010	0.022	0.472	0.637	
Population	0.007	0.042	0.156	0.876	
Inflation	0.028	0.007	4.092	0.000	
GDP growth	0.062	0.019	3.343	0.001	
YD1	0.150	0.155	0.964	0.336	
YD2	-0.119	0.166	-0.718	0.473	
Panel B. NIM as a dependent variable.					
	Coefficients	S.E.	t-stat	p-value	Adj. R^2
Intercept	3.117	0.347	8.979	0.000	0.389
AbFintech	-0.126	0.040	-3.172	0.002	
Q1*AbFintech	0.225	0.042	5.347	0.000	
Q2*AbFintech	0.097	0.043	2.262	0.025	
Q3*AbFintech	0.078	0.044	1.795	0.074	
Population	0.012	0.083	0.150	0.881	
Inflation	0.105	0.013	7.771	0.000	
GDP growth	0.111	0.037	3.009	0.003	

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YD1	-0.083	0.306	-0.270	0.787
YD2	-1.248	0.327	-3.821	0.000

Table 5 reports how the income mix (Noninterest income / Total income) is affected by various factors globally. We find that *AbFintech* does not affect income mix no matter what the country's wealth level is. There is no differential interaction effect of per capita income levels with the fintech development on the income mix ratio. GDP growth negatively affects the ratio, while 2021 marginally positively affects the ratio.

Table 5. Income mix as a dependent variable.

	Coefficients	S.E.	t-stat	p-value	Adj. R^2
Intercept	39.130	2.173	18.008	0.000	0.027
AbFintech	0.089	0.248	0.359	0.720	
Q1*AbFintech	0.002	0.264	0.007	0.994	
Q2*AbFintech	-0.030	0.269	-0.110	0.912	
Q3*AbFintech	0.060	0.272	0.222	0.825	
Population	-0.481	0.516	-0.931	0.353	
Inflation	0.089	0.084	1.058	0.291	
GDP growth	-0.690	0.230	-3.002	0.003	
YD1	2.760	1.917	1.439	0.151	
YD2	3.891	2.044	1.904	0.058	

Table 6 reports the factors associated with the banks' cost structure (cost / income) globally. The results reveal that *AbFintech* increases the cost-to-income ratio (i.e., worsens bank efficiency) in the richest countries, while significantly decreasing the ratio (i.e., improving bank efficiency) in less wealthy countries. Interestingly, the *AbFintech*'s effect of improving the cost structure gets stronger and more significant as the fintech application setting moves from the first quartile countries (-0.510 at the 5% level), the second quartile countries (-0.649 at the 1% level), to the third quartile countries (-0.677 at the 1% level).

Table 6. Cost structure as a dependent variable.

	Coefficients	S.E.	t-stat	p-value	Adj. R^2
Intercept	58.383	1.973	29.587	0.000	0.016
AbFintech	0.600	0.225	2.666	0.008	
Q1*AbFintech	-0.510	0.239	-2.131	0.034	
Q2*AbFintech	-0.649	0.244	-2.657	0.008	
Q3*AbFintech	-0.677	0.247	-2.738	0.007	
Population	-0.519	0.469	-1.107	0.269	
Inflation	-0.089	0.076	-1.167	0.244	
GDP growth	-0.223	0.209	-1.066	0.287	
YD1	-0.677	1.741	-0.389	0.698	
YD2	0.755	1.856	0.407	0.684	

In sum, we find that *AbFintech* favorably affects banks' performance, primarily in less developed countries, as predicted. Specifically, *AbFintech* increases ROA in the least developed

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countries and net interest margin in the 75th percentile countries. *In addition, AbFintech* decreases the cost structure of banks (improves efficiency) in the 75th percentile countries, while it increases the cost structure of banks (worsens efficiency) in the richest countries. However, there is no significant association between *AbFintech* and the income mix ratio, measured as noninterest income to total income.

5.2. Robustness Checks: Analyses by Quartile Group

Table 7 reports regression results by quartile group. Panel A shows *AbFintech significantly* increases banks' ROA in the least developed countries while *AbFintech* marginally decreases ROA in the most developed countries. Panel B shows *AbFintech* increases NIM only in the least developed countries. In the third and fourth quartile countries, *AbFintech* decreases NIM. In Panel C, we find no significant association between *AbFintech* and income mix in any quartile group countries. We also find that the cost structure is insensitive to *AbFintech* in all the quartile groups (Panel D). Overall, the results are qualitatively compatible with the previous analyses except for the cost structure.

Table 7. Robustness checks: Regressions by quartile group.

Panel A. ROA as a dependent variable.												
	Q1 (Low income)			Q2			Q3			Q4 (High income)		
	Coeff	t-stat	p-val	Coeff	t-stat	p-val	Coeff	t-stat	p-val	Coeff	t-stat	p-val
Intercept	2.28	4.37	0.00	0.77	1.82	0.07	0.10	0.33	0.74	0.48	3.32	0.00
AbFintech	0.03	2.77	0.01	0.00	0.26	0.79	-0.01	-0.93	0.36	-0.01	-1.96	0.06
Population	-0.26	-2.13	0.04	-0.01	-0.10	0.92	-0.01	-0.09	0.93	-0.05	-1.49	0.14
Inflation	0.01	1.35	0.18	0.00	0.19	0.85	0.09	4.10	0.00	0.04	2.46	0.02
GDP growth	0.08	2.59	0.01	0.08	1.41	0.16	0.06	1.34	0.18	0.10	3.52	0.00
YD1	-0.38	-1.02	0.31	0.44	1.12	0.27	0.31	1.06	0.29	0.12	1.22	0.23
YD2	-0.38	-0.98	0.33	0.07	0.13	0.89	-0.18	-0.47	0.64	-0.27	-1.91	0.06
Adj R^2		0.217			-0.032			0.226			0.328	
Panel B. NIM as a dependent variable.												
	Q1 (Low income)			Q2			Q3			Q4 (High income)		
	Coeff	t-stat	p-val	Coeff	t-stat	p-val	Coeff	t-stat	p-val	Coeff	t-stat	p-val
Intercept	8.91	10.01	0.00	4.21	6.62	0.00	2.79	8.46	0.00	0.57	2.17	0.03
AbFintech	0.08	5.19	0.00	-0.01	-0.51	0.61	-0.05	-4.84	0.00	-0.03	-2.57	0.01
Population	-0.91	-4.42	0.00	-0.11	-0.79	0.43	-0.10	-1.15	0.25	0.17	2.80	0.01
Inflation	0.06	3.65	0.00	0.06	1.85	0.07	0.11	4.92	0.00	0.07	2.39	0.02
GDP growth	0.09	1.87	0.07	0.20	2.44	0.02	-0.04	-0.70	0.48	0.17	3.15	0.00
YD1	-0.69	-1.09	0.28	0.15	0.26	0.80	0.39	1.24	0.22	-0.01	-0.05	0.96
YD2	-1.96	-3.00	0.00	-1.50	-2.02	0.05	-0.24	-0.56	0.57	-0.70	-2.72	0.01
Adj R^2		0.543			0.101			0.558			0.263	
Panel C. Income mix as a dependent variable.												
	Q1 (Low income)			Q2			Q3			Q4 (High income)		
	Coeff	t-stat	p-val	Coeff	t-stat	p-val	Coeff	t-stat	p-val	Coeff	t-stat	p-val
Intercept	39.53	7.38	0.00	37.00	10.21	0.00	35.93	8.59	0.00	45.79	7.36	0.00
AbFintech	0.10	1.06	0.29	-0.02	-0.21	0.83	0.19	1.61	0.11	-0.40	-1.31	0.19
Population	-0.41	-0.33	0.74	-0.48	-0.60	0.55	-0.60	-0.57	0.57	-0.66	-0.46	0.65

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											-	
Inflation	0.12	1.19	0.24	0.46	2.54	0.01	0.51	1.72	0.09	-1.32	1.90	0.06
								-			-	
GDP growth	-0.60	-1.98	0.05	-1.16	-2.52	0.01	-0.22	0.34	0.74	-1.04	0.83	0.41
YD1	-0.61	-0.16	0.87	-0.56	-0.17	0.87	2.77	0.69	0.49	8.12	1.90	0.06
YD2	-3.79	-0.96	0.34	1.69	0.40	0.69	2.39	0.44	0.66	13.06	2.13	0.04
Adj R²		0.026			0.084			0.015			0.013	

Panel D. Cost structure as a dependent variable.

	Q1 (Low income)			Q2			Q3			Q4 (High income)		
	Coeff	t-stat	p-val	Coeff	t-stat	p-val	Coeff	t-stat	p-val	Coeff	t-stat	p-val
Intercept	68.34	15.97	0.00	55.93	14.34	0.00	60.46	15.93	0.00	54.71	10.00	0.00
AbFintech	0.05	0.68	0.50	-0.10	-1.08	0.28	-0.10	-0.92	0.36	0.12	0.44	0.66
Population	-2.70	-2.73	0.01	-1.48	-1.72	0.09	-1.38	-1.44	0.16	3.62	2.86	0.01
Inflation	-0.11	-1.33	0.19	0.18	0.94	0.35	-0.07	-0.26	0.80	-1.60	-2.62	0.01
GDP growth	-0.26	-1.07	0.29	-0.04	-0.09	0.93	-0.55	-0.95	0.35	-1.65	-1.51	0.14
YD1	0.62	0.20	0.84	-0.89	-0.24	0.81	0.96	0.26	0.79	-1.53	-0.41	0.69
YD2	-3.63	-1.16	0.25	0.96	0.21	0.83	4.07	0.83	0.41	7.43	1.38	0.17
Adj R²		0.097			-0.013			-0.045			0.229	

We also implemented regression analyses using lagged $AbFintech$ (results not tabulated for the sake of space). We found qualitatively similar results to the contemporaneous regression analyses except for the effect of lagged $AbFintech$ on the cost structure. The cost structure regression fails to produce any significant coefficients.

6. Implications and Limitations

Fintech significantly affects traditional banks in terms of competition, customer service, banking costs, and security of financial transactions. First, fintech increases competition as fintech startups enter the financial services market, offering new and innovative services that challenge traditional banking models. Incumbent banks have to adapt and develop their technological solutions to remain competitive. Second, fintech makes it easier for customers to access financial services and complete transactions online, leading to greater convenience and satisfaction. Incumbent banks must improve their digital offerings to keep pace with customer expectations. Third, fintech improves the speed and accuracy of financial transactions, reducing banks' costs and improving overall performance. Lastly, fintech brings new security measures, such as authentication and blockchain technology, which are used to safeguard transactions. In sum, fintech potentially contributes to banks' performance by enabling banks to broaden services and improve efficiency.

Our study makes methodological contributions to the literature by introducing the abnormal fintech metric. As shown in Table 2, the simple correlation coefficients potentially falsely indicate that fintech negatively affects bank performance since GDP per capita is not considered. Therefore, we may reach invalid conclusions if we do not use the abnormal fintech measures. *AbFintech* can be applied in future research to assess fintech's differential effect on bank performance worldwide. We elaborate on the need for using *AbFintech* by noting multicollinearity issues of using many interrelated variables, such as GDP per capita and legal and cultural variables, as control variables in a global setting. For example, GDP per capita highly correlates with variables such as rule of law, regulatory quality, control of corruption, transparency, government effectiveness, industry composition, and, most importantly, fintech levels. So, the use of *AbFintech* is not just to measure the information content of fintech but also to overcome multicollinearity issues in comparative studies involving many countries.

In addressing fintech's impact on global bank performance, we used the World Bank data, which has been publicly available since 2014. We show that the World Bank's financial development variables can be a valuable data source for analyzing differences in global banking industries and possible policy implications for individual countries. We are unaware of other studies using the World Bank data for global bank performance analyses.

Our study has some limitations. First, fintech must have affected the bank performance in developed countries earlier. However, we did not investigate fintech's impact on bank performance before the World Bank started providing fintech development indices. Second, we did not address the security issues brought by fintech developments since we only focused on fintech's impact on bank performance. Hence, fintech's impact on banking security measures is left for future studies. Lastly, the proxy for fintech in our study (Made or received a digital payment, %, age 15+) is one of many possible proxies. However, we believe it is a reasonable proxy for fintech because the largest number of fintech firms is in the payments category (Stultz 2022).

7. Summary and Conclusions

We examine how fintech development affects bank performance using the data of 91 countries collected from the World Bank Database for 2014, 2017, and 2021. Unlike the existing literature, we segment our sample into quartiles based on GDP per capita and investigate the effect of interaction between fintech and country income levels on bank performance. We devise a new measure of fintech development, i.e., abnormal fintech ($AbFintech$) generated by regressing fintech levels on GDP per capita. We predict the marginal contribution from fintech innovations is greater in underdeveloped countries than in developed countries. Consistent with our prediction, we find that $AbFintech$ significantly positively affects bank performance, primarily in underdeveloped countries. Specifically, $AbFintech$ significantly increases ROA in the least developed countries and significantly increases net interest margin in the 75th percentile countries. We significantly contribute to the existing literature by (1) inventing a new measure of fintech development, i.e., abnormal Fintech ($AbFintech$), and (2) investigating abnormal fintech's interaction effects with the country's income category by segmenting the sample into quartiles of income levels.

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Appendix. Variables and definitions

Series name	Series code	Definition
Bank return on assets (%, after tax)	GFDD.EI.05	Commercial banks' after-tax net income to yearly averaged total assets.
Bank net interest margin (%)	GFDD.EI.01	Accounting value of bank's net interest revenue as a share of its average interest-bearing (total earning) assets.

Bank noninterest income to total income (%)	GFDD.EI.03	Bank's income that has been generated by noninterest related activities as a percentage of total income (net-interest income plus noninterest income). Noninterest related income includes net gains on trading and derivatives, net gains on other securities, net fees and commissions and other operating income.
Bank cost-to-income ratio (%)	GFDD.EI.07	Operating expenses of a bank as a share of the sum of net-interest revenue and other operating income.
Bank overhead costs to total assets (%)	GFDD.EI.04	Operating expenses of a bank as a share of the value of all assets held. Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax assets, discontinued operations and other assets.
Made or received a digital payment (% age 15+)	g20.t.d	The percentage of respondents who report using mobile money, a debit or credit card, or a mobile phone to make a payment from an account--or report using the internet to pay bills or to buy something online or in a store--in the past year.
Population, total	SP.POP.TOTL	We transformed the variable by taking the natural logarithm of millions of people.
Inflation, GDP deflator (annual %)	NY.GDP.DEFL.KD.ZG	We use the variable provided by the World Bank.
GDP growth (annual %)	NY.GDP.MKTP.KD.ZG	We use the variable provided by the World Bank.
GDP per capita (current US$)	NY.GDP.PCAP.CD	We transformed the series by taking a natural logarithm.

Source: The World Bank Databank.

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