Banking sector earnings management using loan loss provisions in the Fintech era

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Abstract

This paper analyse banking sector earnings management using loan loss provisions in the Fintech era. The findings show evidence for bank income smoothing using loan loss provisions. There is greater income smoothing in the second-wave Fintech era compared to the first-wave Fintech era, and the presence of strong institutions did not lower income smoothing in the second wave era. Bank income smoothing is also greater in (i) BIS and EU countries than in non-EU countries and G7 countries, (ii) well-capitalised banking sectors, and (iii) during economic booms, in the second wave Fintech era. The implication is that the competition for loans and deposits by banks and Fintech lenders in the second-wave Fintech era created additional incentives for banks to engage in income smoothing to report competitive and stable earnings.

Keywords: banking sector, income smoothing, regulatory quality, legal quality, market power, Fintech, nonperforming loans, earnings smoothing, loan loss provisions, earnings management, digital finance.

JEL classification: G21, G28.

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1. Introduction

Financial technology, or Fintech, is the process of combining financial services with digital innovation. Fintech has risen significantly in developed countries for four reasons: (i) increase in bank regulation, (ii) greater use of technology by banks to reduce cost, (iii) the bad perception of banks after the 2008 global financial crisis, and (iv) the growing distrust of financial institutions from the public after the global financial crisis (Arner, 2016). A growing literature examines the implications of Fintech for the banking sector (see Dapp and Slomka (2015), Arner et al (2016), Philippon (2016), Alt et al (2018) and Ozili (2018)). This paper extends the literature by examining whether the Fintech era is associated with greater earnings management in the banking sector.

Recent research documents that the activities of Fintech players have depressive effects on the banking sector, such as loss of income (Thakor, 2019), loss of market share (Zalan and Toufaily, 2017), and loss of loyal bank customers and employees (Alt et al, 2018; EY, 2018). These effects are likely to affect banks' interest income and profit margins. The nature of banks' financial reporting is that banks can alter the level of specific accruals to report a desired level of profit given their prevailing circumstance. Banks can engage in earnings management to reveal private information and properly manage investors' expectations regarding earnings in the fintech era, or they can opportunistically manage earnings for economic reasons. To the extent that the activities of Fintech lenders generate more difficult business conditions for banks (e.g., less demand for retail bank loans, low profit margins, greater regulation of banks while Fintech lenders enjoy less regulation through regulatory sandbox), banks are likely to face more survival and competition concerns. These adverse conditions typically create incentives for banks to hide the effect of these conditions on their performance by managing reported earnings over time. Specifically, in the context of banks, one might expect a bank to opportunistically reduce loan loss provisions to persistently report higher earnings possibly to avoid perceptions that the bank has a competitive disadvantage, losing borrowers, and losing customers to Fintech businesses.

The literature document evidence for earnings management using loan loss provisions (LLPs) in banks (e.g., Bushman and Williams, 2012; Beatty and Liao, 2014; Kilic et al, 2013). LLPs are an attractive tool for earnings management in banks because LLPs are the most significant accrual in banks (Ozili and Outa, 2017). Bank managers use their judgement and discretion to determine the size of reported loan loss provisions (Beatty and Liao, 2014). This discretion creates an opportunity for bank managers to overstate or understate provisions estimates to influence the level of reported earnings.

Understanding how the Fintech era affects bank earnings management is important because Fintech lenders can disrupt the business model of traditional banks by modifying the payment system, transforming how bank customers access credit using innovative non-bank channels, and by targeting the customers that are already being served by dominant banks (Alt et al, 2018; Lu, 2017), which creates competition, and can compel bank managers to manage earnings in order to report competitive earnings in the Fintech era. However, as discussed in Section 2.3, there is ex-ante tension in the hypothesis on whether banks may engage in income smoothing or income-increasing earnings management in the Fintech era.

To study the link between banking sector earnings management and the Fintech era, we rely on country-level financial information for developed countries. To measure earnings management at the country level, we use available country earnings data, specifically, net interest margin, and then add back provisions to the net interest margin variable in order to derive the pre-managed earnings variable at the country level. To measure the Fintech era, we divide the Fintech era into the first-wave Fintech era and the second-wave Fintech era. The results show evidence for bank income smoothing using loan loss provisions. There is greater income smoothing in the second-wave Fintech era compared to the first-wave Fintech era, and the presence of strong institutions did not lower income smoothing in the second wave era. Bank income smoothing is also greater in (i) BIS and EU countries than in non-EU countries and G7 countries, (ii) well-capitalised banking sectors, and (iii) during economic boom in the second wave Fintech era.

This paper contributes to the literature along several dimensions. First, the recent literature has viewed the Fintech era as an important game changer in the finance industry, with important implications for the banking sector (Arner, 2016). This paper complements the recent literature by showing that the banking sector responded to the threat posed by Fintech businesses in the Fintech era by engaging in income smoothing using loan loss provisions. This paper is the first to examine how the Fintech era influence banking sector earnings management. The study uses a unique approach to detect country-level earnings management in the banking sector. To capture country-level earnings management, we construct a new model. In the model, loan loss provisions were added-back to the country earnings variable to derive the pre-managed earnings variable and to test its relation with loan loss provisions. Secondly, this paper contributes to the banking literature by linking credit risk provisioning to bank accounting and the Fintech era. The literature shows that adequate provisioning is important for managing credit risk in the banking system (Olszak et al, 2017; Bouvatier and Lepetit, 2012). Our study complements this literature by showing that the banking sector had fewer provisions in the second-wave Fintech era compared to the first-wave Fintech era, which indicates under-provisioning and poor credit risk management in the second wave Fintech era. Thirdly, this study is the first to identify the Fintech era as a determinant of banking sector earnings management. It extends prior studies on income smoothing by identifying another determinant of income smoothing which is the changes brought about by the Fintech era. Consistent with the main hypothesis, the findings show that there is greater income smoothing in the second wave Fintech era. Four, this study contributes to the current debate on how the Fintech evolution would disrupt the banking sector. Fintech promoters argue that Fintech will disrupt banks by attracting bank customers, causing banks to lose market share which would lead to depressed earnings for banks and cause banks to manage earnings. We build our hypothesis around this idea, and the results confirm that the disruption brought about by the second wave Fintech era created incentives for banking sector earnings smoothing using loan loss provisions.

The rest of the paper is organized as follows. Section 2 presents the literature review and develops the hypotheses. Section 3 describes the data, sample selection, and research design. Section 4 presents the empirical results. Section 5 provides the conclusions.

2. Literature review and hypothesis development

2.1. Fintech evolution

Fintech, or financial technology, is the process of combining financial services with digital innovation (Ozili, 2018). Fintech has a long history and has evolved over two distinct evolutionary phases – the first wave era and the second wave era (see table 1a). The first wave Fintech evolutionary phase was a period described as the Fintech 1.0 and Fintech 2.0 era. The first wave Fintech evolution witnessed the transition from analogue technology to digital technology which was led mostly by traditional financial institutions (Arner, 2016). The second wave Fintech evolutionary phase was a period described as the Fintech 3.0 and Fintech 3.5 era. The second wave

Fintech evolution witnessed the emergence of new players, such as banking apps and Fintech start-ups, alongside existing large companies that acted as banking vendors (Arner, 2016; Arner et al, 2016), as shown in table 1b.

Table 1a: Fintech evolution

Evolution	First wave evolutionary phase		Second wave evolutionary phase	
Date	1866 – 1967	1967 – 2007	2008 to present	
Era	Fintech 1.0	Fintech 2.0	Fintech 3.0	Fintech 3.5
Geography	Global / Developed countries	Global / Developed countries	Developed countries	Emerging / Developing countries
Key elements	Infrastructure / computerisation	Traditional / internet	Mobile / Start-ups / New entrants	
Shift Origin	Linkages	Digitalization	2008 financial crisis / smartphone	Last mover advantage

Source: Arner (2016), p.8.

The 2008 global financial crisis led to a major change in the Fintech evolutionary phase. The increase in bank regulation, greater use of technology by banks to reduce cost, the bad perception of banks after the global financial crisis, and the growing distrust of financial institutions from the public after the global financial crisis were the catalysts that encouraged and allowed new entrants to emerge in the financial sector (Arner, 2016). Startups and technology companies led the post-2008 Fintech era, which is also called the second wave Fintech era, as shown in table 1b. Many customers patronized the products and services offered by Fintech startups and technology companies such as automated teller machines (ATMs), point-of-sale machines, card readers, and many of these customers were already being served by banks. Fintech lenders gained entry into credit markets and began competing with banks for market share, which had the consequence of depressing the interest income margin of banks.

Table 1b: Fintech players

First-wave Fintech (1967 – 2007)	1967	First ATM (Barclays)
	1968-1970	BACS, CHIPS
	1971	NASDAQ
	1973	SWIFT
	1981	Bloomberg
	1983	Mobile phone
	1987	Program trading
	1983-1985	Online banking (NBS, WF)
	1986	Big Bang, Single European Act
	1990s	Quantitative risk management / VaR models
	1999	Internet / Dot.Com Bubble

	2007	iPhone launched
Second-wave Fintech (2008 to present)	2008	Global Financial Crisis; 'Blockchain' is founded
	2009	BitCoin is launched; 'Square' mobile payments solutions is founded
	2009	'Kickstarter' introduced a reward-based crowdfunding platform
	2011	P2P money transfer service 'Transferwise' is created
	2011 to 2016	'Blockchain' applications are launched
Source: Arner (2016) and updated by author		

A growing body of literature examine how the development of Fintech affects bank behavior and performance. Alt et al (2018) argue that the Fintech revolution will cause banks to lose their market share, possibly because (i) customers' loyalty to a main bank will decrease and customers will favor relationships with multiple financial service providers, and (ii) non-banks and new start-up businesses will emerge that offer focused financial services. Dapp and Slomka (2015) analyse banks' response to Fintech development, and argue that the fallout from the global financial crisis, the changing consumption behaviour of customers and the stringent regulatory requirements that banks face, have led to the emergence of Fintech players in the financial sector. They also argue that the increasing patronage of Fintech players by banks' loyal customers will lead to a decline in the net interest margin of traditional banks. Phan et al (2019) examine whether the growth of financial technology (Fintech) negatively affects bank performance. Using a sample of 41 banks, they show that the growth of Fintech firms negatively affects bank performance. Lu (2017) analyse the effect of rising Fintech on banks in the UK. They argue that Fintech disruptors have no historical legacy and adopt a simplified and low-cost business model based on the internet and smartphones, which gives them a clear competitive advantage over banks. Many of the Fintech disruptors target British customers such as small businesses and personal consumers who have been overlooked by incumbent banks, which helped them to win significant market shares, despite their short history. Lu show that it remains difficult for Fintech to shake up the banking industry dominated by UK banks, and it could take several years, if not decades, for new Fintech lenders to build up sufficient scale to rival dominant banks in the UK. Philippon (2016) assess the potential impact of Fintech on the finance industry, focusing on financial stability and access to financial services. The study finds that financial services remain surprisingly expensive, which explains the emergence of new entrants such as Fintech players. Philippon (2016) then argue that the current regulatory approach is subject to significant political economy and coordination costs, and therefore unlikely to deliver much structural change while, on the other hand, Fintech can bring deep changes but is likely to create significant regulatory challenges.

2.2. LLP and earnings management in banks

A large body of banking literature provides substantial evidence on the opportunistic use of loan loss provisions to manipulate reported earnings (e.g., Beatty and Liao, 2014; Bushman and Williams, 2012; Balla and Rose, 2015; Ozili and Arun, 2018; Kilic et al, 2013). The literature show that bank managers use their discretion in loan loss provisioning to manage reported earnings, which often take the form of income smoothing or income-increasing earnings management. Bushman and Williams (2012) examine how managerial discretion in loan loss provisioning leads to greater risk-taking among banks, and find that banks use discretionary LLPs for income smoothing purposes. Aristei and Gallo (2019) show that banks facing increasing levels of risk had higher LLPs and also engaged in earnings management practices to stabilise their earnings over time. Tran et al (2019) find evidence of greater earnings management in public banks than private banks.

Balla and Rose (2015) investigate whether the tightening of accounting constraints associated with the Securities and Exchange Commission (SEC)'s 1998 SunTrust decision affected the relationship between earnings and loan loss provisioning for US banks. They find that shortly after the SEC action, the relationship between earnings and provisions weakened for public banks but not for private banks, which implies that private banks engaged in earnings management using loan loss provisions to a greater extent than public banks. Ozili and Arun (2018) examine whether European systemic banks use loan loss provisions to smooth earnings to a greater degree than non-systemic banks. They find that income smoothing is pronounced among global systemically important banks (G-SIBs) in the post-financial crisis period and pronounced among non-global systemically important banks (non-G-SIBs) in the pre-crisis period. Kilic et al (2013) find that US banks use loan loss provisions for earnings smoothing purposes when SFAS 133 prevented banks from using derivatives to smooth income. SFAS 133 is the US Financial Accounting Standard Board (FASB)'s accounting standard for the 'accounting for derivative instruments and hedging activities'.

Other studies identify several factors that influence the extent of earnings management by banks. Osma et al (2019) investigate the influence of prudential supervisors' independence in constraining income smoothing behavior in European banks, and find that political and industry independence of the supervisor constrains income smoothing. Ozili (2019a) investigates bank earnings smoothing, focusing on the effect of corruption on the extent of income smoothing by African banks. The study finds that African banks use loan loss provisions to smooth positive earnings particularly in the post-2008 financial crisis period but this behaviour is reduced by strong investor protection; also, African banks in highly corrupt environments smooth their positive earnings as opposed to smoothing the entire profit distribution. Ozili (2017) examine whether the way African banks use loan loss provisions to smooth earnings is influenced by capital market motivations and the type of auditor. The study finds that African banks use loan loss provisions to smooth reported earnings, and this behavior is not reduced among African banks audited by a Big 4 auditor.

Pinto et al (2019) investigate the role of corporate governance mechanisms and foreign direct investment (FDI) in restraining earnings smoothing among African banks. They examine banks from 20 African countries from 2011 to 2017, and find that African banks use LLPs to reduce earnings volatility, and this behaviour is reduced in countries with greater foreign direct investment inflows. Hong et al (2019) investigate the role of loan loss provisions in analysts' decision to follow banks, and find that abnormal loan loss provisions, regardless of whether it is income-increasing or income-decreasing, reduce analyst coverage. Vishnani et al (2019) analyse whether earnings are managed in the banking industry in India. They analyse 84 banks in India, and find that Indian banks engage in income smoothing practices.

Overall, these studies document that banks use LLPs for earnings management in the banking sector when they have the opportunity to do so. However, the literature has not examined whether bank earnings management using LLPs increased or decreased during the Fintech era. This study fills this gap in the literature.

2.3. Hypothesis development

The emerging Fintech literature argue that the activities of Fintech startups and lenders can disrupt the financial system (Lu, 2017; Ozili, 2018). In the banking sector, the presence of Fintech lenders in the market for loans and deposits can lead to greater competition between Fintech lenders and banks (Lynn et al, 2019). Fintech Lenders will compete for market share by targeting banks' loyal customers and distant customers in the same market for loans and deposits (Navaretti et al, 2018). This will reduce the market share of dominant banks and reduce the net interest margin of banks, which will ultimately depress the earnings of banks. To mitigate this risk, banks will have incentives to engage in earnings management using loan loss provisions which is the most important accrual for banks.

Therefore, we make two predictions. The first prediction is that banks, faced with increased competition from Fintech lenders, will smooth reported earnings over time so that reported earnings is never too high or too low, and we expect this behavior to be more pronounced in the second wave Fintech era than in the first wave Fintech era because the second wave era witnessed the entry of many Fintech lenders whose presence in the credit market can depress banks' net interest margin compared to the first wave era.

The second prediction is that banks may prefer to engage in income-increasing earnings management as opposed to income smoothing. Banks can achieve this by keeping fewer loan loss provisions in order to opportunistically increase reported earnings at all times, possibly to avoid perceptions that the bank is unable to compete with Fintech lenders and rival banks, and this behavior may be more pronounced in the second wave Fintech era than in the first wave Fintech era.

H1: there is greater bank income smoothing using loan loss provisions in the second wave Fintech era.

H2: banks engage in income-increasing earnings management in the second wave Fintech era

3. Data and Methodology

3.1. Data

Country data was collected for 35 countries. All countries in the sample are developed countries. The study focus on developed countries because developed countries have a well-developed Fintech industry that can potentially disrupt the banking sector compared to developing countries whose Fintech markets are still too small to disrupt banking systems. Financial statement information for each country was collected from the World Bank's global financial development (FINDEX) database. The sample period covers the 1998 to 2016 period, which captures a significant part of the first wave and second wave Fintech era. Arner (2016)'s Fintech era classification was used as the basis to determine which period falls into the first wave and second wave Fintech era.

Data was available for some variables and unavailable for other variables. Some unavailable data were generated as a derivative of two existing data, particularly, the LLP and LG variables. Macroeconomic information such as real gross domestic product growth rate was collected from the World Economic Forum archived in the World Bank database. Country institutional information was collected from the World Governance Indicators (WGI) database of the World Bank. Some variables have missing observations which gives an unbalanced panel sample. See Appendix 1 for source of data and variable description.

3.2. Methodology

The model specification is a modified version of the models used in prior literature (see Bushman and Williams, 2012; Ozili, 2019a&b; Wheeler, 2019).

The baseline model to estimate bank earnings management using loan loss provisions, is given below:

$$LLPi,t \;=\; c + \beta 1EBTPi,t + \beta 2NPLi,t + \beta 3CARi,t + \beta 4LGi,t + \beta 5LAWi,t + \beta 6CNi,t + \beta 7RQi,t + \beta 8\Delta GDPi,t + e \ldots\ldots\ldots\ldots. equation\ (1)$$

After taking into account the fintech era, the model is re-specified below:

$$LLPi,t \;=\; c + \beta 1EBTPi,t + \beta 2EBTP * FTi,t + \beta 3FTt + \beta 4NPLi,t + \beta 5CARi,t + \beta 6LGi,t + \beta 7LAWi,t + \beta 8CNi,t + \beta 9RQi,t + \beta 10\Delta GDPi,t + e \ldots\ldots\ldots\ldots. equation\ (2)$$

Where, LLP = ratio of loan loss provisions to gross loans of the banking sector of each country; NPL = ratio of nonperforming loans to gross loans of the banking sector of each country; EBTP = the pre-managed earnings variable; CAR = ratio of tier 1 capital to total risk-weight assets; FT = binary variable that equal one for the 2008 to 2016 period which represents the second-wave Fintech era, and equal zero from 1998 to 2007 which represents the first-wave of the Fintech era; LG = the supply of private credit to the economy; LAW = rule of law index representing the quality of the legal system; CN = Lerner index, representing market power; RQ = regulatory quality index; ΔGDP = real gross domestic product growth rate; t = year; i = country; c = β0 or the constant term.

The model above expressed the loan loss provisions ratio as a function of its non-discretionary[1] determinants (NPL, LG and ΔGDP), discretionary determinants (CAR and EBTP), and other external influence (LG, LAW, CN, RQ and FT).

The LLP ratio, which is the dependent variable, was derived by multiplying the nonperforming loan (NPL) ratio data with the loan loss coverage (LLC) ratio data which, arithmetically, eliminates the NPL numerator from the former ratio and eliminates the NPL denominator from the latter ratio, which gives the ratio of loan loss provisions to gross loan using the formula below:

$$LLP \,/\, GL = (NPL \,/\, GL) * (LLP \,/\, NPL)$$

Where NPL ratio = nonperforming loans divided by gross loan; the LLC ratio = actual amount of loan loss provisions divided by nonperforming loans.

For the explanatory variables, the EBTP and FT are the main variables of interest because the interaction of these two variables show whether income smoothing using loan loss provisions is present to a greater degree in the second wave Fintech era compared to the first wave Fintech era.

EBTP is the income smoothing variable (EBTP). In the literature, the EBTP variable is a bank-level variable measured as 'earnings before profit and tax divided by total assets' which is often referred to as the 'pre-managed earnings variable' (see Bushman and William, 2012; Kilic et al, 2013; Ozili, 2018), but this variable is unobservable at the country level (Ozili, 2019b), and therefore, cannot be used directly in the country-level analyses in this study. A proxy variable was constructed using available country-level earnings data such as net interest margin (NIM), return on asset (ROA) and return on equity (ROE). The net interest margin ratio was introduced into the model rather than ROA or ROE, because ROA and ROE take into account many operational expenses that are unrelated to loan loss provisions, thus, ROA and ROE cannot be used. Net interest margin is more appropriate to measure EBTP because net interest margin is the only earnings variable that is closest to loan loss provisions in bank financial reporting.

To derive the pre-managed earnings variable (EBTP), the net income margin ratio was adjusted by adding back loan loss provisions to the NIM ratio using the formulae: EBTP = NIM *

[1] Other non-discretionary LLP determinants in the literature include: loan to asset ratio, loan charge-offs, loan growth etc. These variables are only observable at bank-level but not at the country-level. This is the reason why only the NPL and ΔGDP variables were used in this study as the main non-discretionary determinants of LLP in the LLP modeling in equation 1.

[(1+LLP)/100)]. The purpose of this adjustment is to create a replica of the 'earnings before tax and provisions' variable traditionally used in the existing literature. The literature shows that a significant and positive sign on the EBTP coefficient indicates the presence of income smoothing using loan loss provisions while a significant and negative sign on the EBTP coefficient indicates the absence of income smoothing using loan loss provisions (see Bushman and William, 2012, Kilic, 2013, Ozili, 2019b).

FT is a binary variable that equal one for the 2008 to 2016 period which represents the second-wave Fintech era, and equal zero from 1998 to 2007 which represents the first-wave of the Fintech era. A positive relationship between FT and LLP is expected because the second wave era was a period characterized by strict regulation and supervision in the banking sector of developed economies.

For the control variables, the nonperforming loan (NPL) variable controls for bank provisioning in response to bad loans. Prior literature shows that banking sectors that have high nonperforming loans will keep higher provisions (see Ozili, 2019a); therefore, a positive sign for NPL coefficient is predicted.

The CAR variable captures the use of loan loss provisions to manage regulatory capital ratio by banks. This is consistent with the capital management hypothesis which argues that banks with low capital use LLPs to boost their capital levels to avoid violating the minimum capital requirements (see. Kilic et al, 2013; Ozili and Arun, 2018); therefore, a negative sign for the CAR coefficient is expected.

The real gross domestic product growth rate (ΔGDP) variable is introduced into the model to control for bank provisioning during fluctuating business cycles. Generally, banks will keep fewer provisions in good times and higher provisions in bad times because they expect fewer loan defaults in good times, and higher loan defaults in bad times (Ozili, 2018; Wang et al, 2019), implying a negative relationship between ΔGDP and LLP.

The total loan to GDP (LG) ratio is introduced into the model to capture the size of private credit provided to the economy by banks. It measures the extent to which the economy is driven by private bank credit, and captures the dominant role played by banks in financial intermediation. The LG ratio measures the amount of credit provided to the private sector by banks as a share of

GDP. Banks in credit-driven developed economies would normally keep higher general provisions to mitigate contemporaneous credit risk in their loan portfolio (Ozili, 2019b), therefore, a positive relationship between LLP and LG is predicted. The LG ratio for the country level is derived arithmetically by multiplying the 'credit to deposit ratio' data with the 'bank deposit to GDP' data in the World bank database, using the formula below.

$$LOAN \;/\; GDP \;=\; (LOAN \;/\; BANK\ DEPOSIT) \;*\; (BANK\ DEPOSIT \;/\; GDP)$$

Next, it is important to control for the impact of the prevailing legal, regulatory quality and competitive environment on banking sector earnings management using loan loss provisions. To do this, three institutional variables were introduced into the model: the regulatory quality index (RQ) variable, rule of law (LAW) variable, and the Lerner index (CN).

The regulatory quality index (RQ) variable captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. Higher values of RQ indicate greater regulatory quality. A negative relationship between LLP and RQ is expected because banks in high regulatory quality environments will perform better - they have high profitability and fewer nonperforming loans; and in such environments, banks would keep fewer loan loss provisions due to lower NPLs (Ozili, 2019a).

For the Lerner index (CN) variable, higher values of CN indicate greater market power. A negative relationship between LLP and CN is expected because banks with high market power usually have weak incentives to minimise credit risk – they are more likely to lend to high-risk borrowers (Delis et al, 2017), and such banks tend to keep fewer provisions, rather than more provisions, in order to increase their profit levels which will reinforce their market power in the industry.

For the LAW variable, higher values of LAW indicate greater legal system quality. A negative relationship between LLP and LAW is expected because banks in strong legal environments are able to use the power of the courts to compel debtors to repay their debt which reduces the level of nonperforming loans (Cristini et al, 2001; Ozili, 2019b), thereby leading to fewer provisions. Finally, the models are estimated using fixed effect regression model. Table 2 presents a summary of the expected signs of the variables.

Table 2: Information about the variables and the predicted sign		
Variable	Expected/Predicted Sign	Description
LLP	Dependent Variable	Ratio of loan loss provisions to gross loan ratio
EBTP	(+)	Pre-managed earnings variable
FT	(+)	Binary variable for the second-wave fintech era relative to the first-wave Fintech era
NPL	(+)	Ratio of non-performing loan to gross loan
CAR	(-)	Ratio of tier 1 capital to total risk-weight assets
LG	(+)	Supply of private credit to the economy
LAW	(-)	Rule of law index, measuring legal system quality
CN	(-)	Lerner index, a measure of market power.
RQ	(-)	Regulatory quality index
ΔGDP	(-)	Real gross domestic product growth rate

3.3. Descriptive statistics and correlation

Table 3 reports the summary of the descriptive statistics. LLP, on average, is 2.87% of gross loan. LLP is higher in Greece, Cyprus and Romania, and much lower in Canada and Australia. EBTP is 2.29, on average, and is much higher in Iceland, Hungary and Bulgaria, indicating that these countries have a profitable banking sector. EBTP is lower in Ireland, Luxembourg and Switzerland. CAR is higher in Bulgaria, Iceland and Luxembourg and much lower in Portugal and Australia. NPL is 5.18% on average, and is higher in Croatia, Italy and Cyprus. ΔGDP, on average, is about 2.42% and lower in Greece and Italy while Lithuania and Latvia have higher ΔGDP. Overall, the result from the descriptive statistics suggest that there are wide variations across the countries in the sample. See Appendix A2 and A3 for the descriptive statistic in the first and second wave Fintech era, respectively.

Table 3: Country descriptive statistics (mean values)										
S/N	Countries	LLP	NPL	EBTP	ΔGDP	LAW	CN	RQ	LG	CAR
1	Canada	0.32	0.88	2.07	2.35	11.3	0.27	7	105.55	13.7
2	United States	1.06	1.95	3.60	2.28	10.9	0.27	7	51.19	13.4
3	Japan	1.33	3.38	1.19	0.71	10.5	0.33	7	116.22	12.7
4	France	2.59	4.21	0.96	1.56	10.5	0.13	7	86.88	12.9
5	Germany	1.73	3.66	1.02	1.42	10.4	0.04	7	96.48	14.4
6	Italy	4.99	10.24	1.91	0.44	10.9	0.11	7	76.84	11.8
7	United Kingdom	1.24	2.33	1.61	2.032	10.3	0.27	7	-	14.9
8	Norway	0.65	1.212	1.72	1.76	10.2	0.33	7	88.56	13.6
9	Iceland	3.19	4.66	4.15	3.41	8.6	0.18	5.9	136.36	16.8
10	Switzerland	0.60	1.52	0.82	1.94	9.8	0.12	6.5	153.37	14.4
11	Sweden	0.52	1.11	1.37	2.54	10.3	0.24	7	110.81	12.7
12	Spain	2.64	3.47	1.74	2.05	10.5	0.27	7	127.55	12.4
13	Portugal	3.66	5.51	1.52	0.92	10.2	0.18	6.9	128.28	11.1
14	Netherland	0.73	2.52	1.29	1.77	10.1	0.15	6.8	114.77	13.8
15	Luxembourg	0.21	0.45	0.81	3.51	7.6	0.15	5.6	83.93	16.9
16	Ireland	3.70	7.88	0.78	5.37	9.8	0.21	6.6	104.95	15.3
17	Greece	7.64	14.83	2.78	0.51	10.5	0.22	6.9	79.34	12.6
18	Finland	0.37	0.54	1.07	1.90	10.1	-0.05	6.7	72.87	15.6
19	Denmark	1.27	2.36	1.22	1.35	10.1	0.24	6.7	152.57	15.2
20	Belgium	1.42	2.86	1.32	1.69	10.2	0.12	6.8	61.51	14.9
21	Austria	1.90	2.65	2.01	1.76	10.2	0.23	6.8	90.91	14.5
22	Australia	0.34	0.97	1.96	3.19	10.1	0.11	6.9	105.79	11.1
23	New Zealand	0.39	1.15	2.04	2.81	10.2	0.15	7	122.00	12.4
24	Slovenia	4.13	7.22	2.90	2.37	13.1	0.19	9.7	54.62	13.2
25	Romania	11.43	14.76	4.52	3.32	14.5	0.23	10.7	22.80	16.7
26	Poland	5.09	8.89	3.63	3.75	14.4	0.22	10.7	37.27	13.8
27	Malta	1.91	7.32	2.33	3.72	6.8	0.23	4.9	101.74	15.3
28	Lithuania	3.72	9.21	2.82	4.07	12.9	0.22	9.4	34.13	15.6
29	Latvia	3.35	5.27	3.15	3.96	12.5	0.24	9.1	49.82	14.7
30	Hungary	3.69	6.98	4.03	2.34	13.9	0.19	10.2	43.94	14.1
31	Estonia	0.84	1.66	2.78	3.76	13.3	0.15	10.1	61.34	18.7
32	Cyprus	9.14	24.69	3.45	2.48	8.4	0.23	5.4	174.58	13.1
33	Czech Republic	4.47	8.23	3.06	2.55	13.7	0.27	9.7	42.94	14.3
34	Croatia	5.85	10.05	3.81	1.74	13.4	0.27	10.2	53.48	18.2
35	Bulgaria	6.05	9.74	4.86	3.19	14.1	0.29	10.4	41.68	22.1
	Total (mean)	**2.87**	**5.18**	**2.29**	**2.42**	**11**	**0.21**	**7.6**	**87.14**	**14.52**

Table 4 reports the Pearson correlation coefficients and the associated p-values. LLP is positively correlated with the FT variable (0.19***). The correlation between LLP and FT is significant, which indicates that banking sector provisions were higher in the second wave era compared to the first wave era. LLP is negative and significantly correlated with ΔGDP (-0.16***), indicating that banking sector provisioning is procyclical with fluctuating business cycles. LG is also significant and negatively correlated with LLP, and indicates that loan loss provision is higher in credit-driven countries. The LAW and RQ coefficients are positive and significantly correlated with LLP. This indicates that loan loss provision is higher in countries that have a strong legal system and in countries that have high regulatory quality. Also, NPL and CAR are positively correlated with LLP which indicate that loan loss provision is higher in banking sectors that have higher nonperforming loans and higher regulatory capital ratios. Overall, the correlations are sufficiently low to be concerned about multi-collinearity.

Table 4: Pearson correlation matrix for the variables

Correlation	LLP	EBTP	FT	NPL	CAR	ΔGDP	LG	LAW	RQ	CN
LLP	1.00 -----									
EBTP	0.48*** (10.71)	1.00 -----								
FT	0.19*** (3.79)	-0.14*** (-2.82)	1.00 -----							
NPL	0.89*** (39.38)	0.37*** (7.79)	0.27*** (5.60)	1.00 -----						
CAR	0.26*** (5.39)	0.19*** (3.79)	0.39*** (8.21)	0.26*** (5.21)	1.00 -----					
ΔGDP	-0.16*** (-3.13)	0.14*** (2.83)	-0.54*** (-12.63)	-0.24*** (-4.91)	-0.14*** (-2.77)	1.00 -----				
LG	-0.14*** (-2.91)	-0.44*** (-9.59)	0.26*** (5.30)	-0.03 (-0.73)	-0.16*** (-3.15)	-0.38*** (-8.13)	1.00 -----			
LAW	0.36*** (7.46)	0.31*** (6.52)	0.46*** (10.07)	0.31*** (6.48)	0.30*** (6.21)	-0.09* (-1.82)	-0.34*** (-7.16)	1.00 -----		
RQ	0.42*** (9.16)	0.41*** (8.73)	0.31*** (6.27)	0.36*** (7.46)	0.35*** (7.27)	0.04 (0.83)	-0.47*** (-10.56)	0.93*** (49.71)	1.00 -----	
CN	0.01 (0.30)	0.13*** (2.67)	0.12** (2.36)	0.01 (0.36)	0.04 (0.86)	0.04 (0.91)	0.01 (0.19)	0.21*** (4.31)	0.21*** (4.33)	1.00 -----

4. Empirical results

4.1. Testing the income smoothing hypothesis

The result is reported in column 1 of table 5. The EBTP coefficient is positive and significant, which indicates evidence of income smoothing in the banking sector. This result supports the income smoothing hypothesis, and confirms the findings of Ozili and Arun (2018) and Bushman and Williams (2012).

For the control variables, NPL coefficient is positive and significant in column 1, which confirms that banking sectors that have high nonperforming loans keep more provisions, and this is consistent with Ozili (2019a). The CAR coefficient is positive and insignificant, and does not support the capital management hypothesis which proposed a negative relationship between LLP and CAR. The ΔGDP coefficient is positive and insignificant. LG coefficient is also positive and insignificant. The LAW coefficient is negative and significantly related to LLP in column 1. This result confirms the expectation that banks in strong legal environments use the power of the courts to compel debtors to repay their debt which reduces the size of nonperforming loans and leads to fewer loan loss provisions. This result supports the findings of Cristini et al (2001) and Ozili (2019b). The RQ coefficient is positive and insignificant. in column 1. The CN coefficient is negative and insignificant.

4.2. Income smoothing in the Fintech era

Next, the FT binary variable is interacted with the EBTP variable to determine whether income smoothing is present in the second wave era to a greater extent than in the first wave era.

$$
\begin{aligned}
LLPi,t \;=\; & c + \beta 1EBTPi,t + \beta 2\boldsymbol{EBTP} * \boldsymbol{FTi,t} + \beta 3FTt + \beta 4NPLi,t + \beta 5CARi,t + \beta 6LGi,t \\
& + \beta 7LAWi,t + \beta 8CNi,t + \beta 9RQi,t + \beta 10 \Delta GDPi,t \\
& + e \ldots\ldots\ldots\ldots.\, equation\ (2)
\end{aligned}
$$

The result is reported in column 2 of table 5. The EBTP*FT coefficient is positive and significant at the 5% level in column 2, which indicates evidence of greater income smoothing using loan loss provisions in the second-wave Fintech era compared to the first-wave Fintech era. One explanation for this result is that the Fintech firms in the second-wave Fintech era introduced intense competition to banks combined with the strict banking regulation and supervision in the second-wave era, which motivated banks to smooth earnings to mitigate the depressive effect of Fintech competition on bank earnings.

4.3. Additional analyses

4.3.1. Effect on regional and political blocs

Some regional blocs require members to adopt a uniform set of regulatory and supervisory rules to regulate and supervise the activities of Fintech players and banks in the bloc. The ultimate aim of such rules is to ensure a sustainable co-existence of banks and Fintech lenders operating in the same market for loans and deposits. Some regional blocs introduce a strict supervisory regime that moderate the competition for loans and deposit by banks in order to create some opportunities for Fintech lenders.

The prediction is that banks in a regional or political bloc will smooth income when they are faced with regulatory constraints that limit their ability to compete with Fintech lenders for loans and deposit in the market place. Four regional blocs were analysed: the European Union (EU) countries, non-EU countries (NEU), the G7 countries also referred to as the ‘most developed economies’ (MDE), and the Bank of International Settlement[2] (BIS) member-countries. Binary variables were used to divide the sample into four groups. The ‘EU’ binary variable was assigned a value of one if the country is a member of the European union and zero otherwise. The ‘NEU’ binary variable was assigned a value of one if the country is not a member of the European union and zero otherwise. The ‘BIS’ binary variable was assigned a value of one if the country is a member of the Bank of International Settlement and zero otherwise. The ‘MDE’ binary variable was assigned a value of one if the country is a member of the G7 countries and zero otherwise. The estimated model is shown below:

$$LLPi,t = c + \beta 1EBTPi,t + \beta 2NPLi,t + \beta 3CARi,t + \beta 4\Delta GDPi,t + \beta 5LGi,t + \beta 1LAWi,t + \beta 6RQi,t + \beta 7CNi,t + \beta 8FTt + \beta 9MDEi + \beta 10BISi + \beta 11EUi + \beta 12NEUi + \beta 13\boldsymbol{MDE * EBTP * FTi,t} + \beta 14\boldsymbol{BIS * EBTP * FTi,t} + \beta 15\boldsymbol{EU * EBTP * FTi,t} + \beta 16\boldsymbol{NEU * EBTP * FTi,t} + e \ldots\ldots \text{equation 3}$$

[2] The mission of the BIS is to promote monetary and financial stability in the financial system of member countries. The BIS believes that sufficient provisioning can act as a cushion to absorb some portion of unexpected losses in abnormal periods, thereby contributing to financial stability in member countries.

The estimation results are reported in column 3 to 6 of table 5. The EU*EBTP*FT and BIS*EBTP*FT coefficients are positive and statistically significant at the 1% level. This indicates greater bank income smoothing using loan loss provisions in the second wave fintech era compared to the first-wave Fintech era for EU and BIS countries. Arguably, the EU and BIS countries have the most stringent banking regulation, therefore, the result implies that banking sector income smoothing was more persistent in regional blocs that have the strongest banking regulation such as the EU and BIS member countries. This conclusion supports the argument in the literature that stringent regulation can encourage banks to smooth out abnormal fluctuation in their income in order to avoid regulatory scrutiny of bank earnings (Ozili, 2017; Kilic et al, 2013).

The MDE*EBTP*FT and NEU*EBTP*FT coefficients are negative and significant at the 1% level, which indicates reduced bank income smoothing using loan loss provisions in the second wave era compared to the first-wave era for non-EU countries and for G7 countries. One explanation for the reduced bank income smoothing in these two regional blocs may be attributed to weak regulation and supervision of banks in these two blocs, which possibly removed the incentive for banks to use loan loss provisions to smooth income.

Table 5: Income smoothing during Fintech era in the EU, non-EU, BIS and G7 countries						
	Income smoothing	Interaction effect	Effect on regional and political blocs			
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
C	0.671 (1.19)	0.577 (0.87)	-0.148 (-0.25)	-0.798 (-1.38)	-1.606** (-2.33)	-0.763 (-1.35)
EBTP	0.207*** (3.37)	0.142** (2.08)	0.123** (2.01)	0.292*** (5.24)	0.157** (2.49)	0.305*** (5.53)
EBTP*FT		0.156** (2.11)				
EU*EBTP*FT			0.394*** (5.16)			
MDE*EBTP*FT				-0.447*** (-3.04)		
BIS*EBTP*FT					0.425*** (5.29)	
NEU*EBTP*FT						-0.423*** (-3.01)
FT		-0.438* (-1.95)	-0.836*** (-3.68)	-0.033 (-0.16)	-0.864*** (-3.48)	-0.017 (-0.08)
EU			-0.024 (-0.14)			
MDE				0.238 (1.22)		
BIS					1.358*** (3.28)	
NEU						0.078 (0.39)
NPL	0.412*** (33.94)	0.407*** (32.89)	0.401*** (30.75)	0.416*** (31.75)	0.431*** (34.19)	0.411*** (31.19)
CAR	0.019 (0.87)	0.035 (1.39)	0.014 (0.58)	0.007 (0.27)	0.001 (0.03)	0.006 (0.23)
ΔGDP	0.019 (1.07)	0.022 (1.11)	0.014 (0.58)	-0.001 (-0.05)	0.031 (1.34)	0.001 (0.03)
LG	0.005 (1.47)	0.005 (1.59)	-0.001 (-0.82)	-0.001 (-0.67)	0.004** (1.97)	-0.001 (0.03)
LAW	-0.124* (-1.89)	-0.131* (-1.83)	-0.076 (-0.92)	-0.009 (-0.09)	-0.209*** (-2.62)	-0.025 (-0.29)
RQ	0.033 (0.29)	0.055 (0.47)	0.190* (1.74)	0.124 (0.99)	0.324*** (3.14)	0.138 (1.20)
CN	-0.745 (-1.55)	-0.859* (-1.78)	-0.738* (-1.66)	-0.678 (-1.49)	-0.601 (-1.41)	-0.643 (-1.42)
Country Fixed effect	Yes	Yes	No	No	No	No
Year Fixed effect	No	No	No	No	No	No
R^2	92.34	92.48	85.15	84.38	86.33	84.45
Adjusted R^2	91.43	91.50	84.69	83.90	85.92	83.97
F-statistic	98.27	94.67	189.16	178.21	208.47	179.17
Prob (F-statistic)	0.000	0.000	0.000	0.000	0.000	000
No of Observations	375	375	375	375	375	375

4.3.2. Effect of institutional quality

The literature shows that strong institutions can impose additional monitoring on banks, to discourage bank managers from engaging in activities that increase earnings opacity particularly income smoothing which increase the opacity of reported earnings (see, Kanagaetnam et al, 2014; Bouvatier et al, 2014; Ozili, 2019a). Next, I test whether institutional quality influences the extent of bank income smoothing using loan loss provisions in the first and second wave Fintech era using the model below.

$$LLPi,t = c + \beta 1EBTPi,t + \beta 2NPLi,t + \beta 3CARi,t + \beta 4\Delta GDPi,t + \beta 5LGi,t + \beta 6LAWi,t + \beta 7RQi,t + \beta 8CNi,t + \beta 9FTt + \beta 10\boldsymbol{RQ * EBTP * FTi,t} + \beta 11\boldsymbol{LAW * EBTP * FTi,t} + \beta 12\boldsymbol{CN * EBTP * FTi,t} + e \ldots\ldots\ldots..equation\ 4$$

The estimation results are reported in column 1 to 3 of table 6. The RQ*EBTP*FT and LAW*EBTP*FT coefficients are positive and significant. This indicates that strong regulatory quality and strong legal systems are significantly associated with greater income smoothing in the second-wave era than in the first-wave era. This implies a positive relationship between income smoothing and institutional quality in the second-wave era. One explanation for this result is that the presence of strong legal institutions and regulatory quality did not discourage the use of loan loss provisions for banking sector income smoothing in the second-wave era. The CN*EBTP*FT coefficient is not significant.

4.3.3. Effect of capitalization and fluctuating business cycles

Early studies, such as Laeven and Majnoni (2003), show that the need to meet the minimum regulatory capital requirement and the prevailing state of the business cycle may create additional incentives for banks to smooth income using loan loss provisions. To test this hypothesis, the high-capital variable (WC), the recession variable (REC) and the economic boom (BOOM) variables were introduced into the model. The three binary variables are interacted with the EBTP variable, as shown in the model below.

$$LLPi,t = c + \beta 1BTPi,t + \beta 2NPLi,t + \beta 3CARi,t + \beta 4\Delta GDPi,t + \beta 5LGi,t + \beta 6LAWi,t + \beta 7RQi,t + \beta 8CNi,t + \beta 9FTt + \beta 10WCi,t + \beta 11RECi,t + \beta 12BOOMi,t + \beta 13\boldsymbol{WC * EBTP * FTi,t} + \beta 14\boldsymbol{BOOM * EBTP * FTi,t} + \beta 15\boldsymbol{REC * EBTP * FTi,t} + e \ldots..equation\ 5$$

The estimation results are reported in Table 6. The WC*EBTP*FT and BOOM*EBTP*FT coefficients are positive and statistically significant. This indicates greater income smoothing in banking sectors that are well-capitalised and during economic booms in the second wave era relative to the first-wave era. The REC*EBTP*FT coefficient is insignificant.

Table 6: Income smoothing, institutional quality, capitalization and fluctuating business cycles

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
C	-0.048 (-0.08)	-0.692 (-1.18)	-0.115 (-0.20)	1.025 (1.51)	0.427 (0.62)	0.379 (0.57)
EBTP	0.146** (2.51)	0.234*** (3.74)	0.127** (2.09)	0.119* (1.82)	0.211*** (2.98)	0.208*** (3.29)
RQ*EBTP*FT	0.043*** (5.30)					
CN*EBTP*FT		0.356 (1.38)				
LAW*EBTP*FT			0.029*** (5.04)			
WC*EBTP*FT				0.013*** (3.55)		
REC*EBTP*FT					-0.019 (-0.25)	
BOOM*EBTP*FT						0.174** (2.22)
FT	-0.901*** (-3.87)	-0.382 (-1.62)	-0.918*** (-3.84)	-0.373** (-2.05)	-0.120 (-0.69)	-0.350* (-1.81)
WC				-0.012 (-0.31)		
REC					-0.154 (-0.66)	
BOOM						-0.313** (-1.97)
NPL	0.405*** (31.54)	0.413*** (31.14)	0.406*** (31.59)	0.405*** (33.39)	0.413*** (33.61)	0.412*** (33.87)
CAR	0.016 (0.66)	0.001 (0.34)	0.018 (0.74)	0.029 (0.71)	0.024 (0.95)	0.035 (1.37)
ΔGDP	0.011 (0.45)	-0.006 (-0.25)	0.010 (0.43)	0.028 (1.47)	-0.003 (-0.12)	0.026 (1.14)
LG	0.0004 (0.21)	0.0001 (0.04)	0.0004 (0.25)	0.004 (1.17)	0.005 (1.62)	0.005 (1.61)
LAW	-0.127 (-1.54)	-0.109 (-1.28)	-0.167** (-2.01)	-0.101 (-1.43)	-0.103 (-1.44)	-0.097 (-1.38)
RQ	0.217** (2.01)	0.273** (2.46)	0.285*** (2.66)	-0.004 (-0.04)	0.036** (0.32)	0.034 (0.29)
CN	-0.779* (-1.76)	-0.915* (-1.89)	-0.784* (-1.77)	-0.891* (-1.87)	-0.765 (-1.58)	-0.774 (-1.61)
Country Fixed Effect	No	No	No	Yes	Yes	Yes
Year Fixed Effect	No	No	No	No	No	No
R^2	85.12	84.06	85.02	92.66	92.46	92.52
Adjusted R^2	84.71	83.62	84.61	91.68	91.39	91.51
F-statistic	208.23	191.88	206.57	94.72	91.26	92.71
Prob (F-statistic)	0.000	0.000	000	0.000	0.000	0.000
No of Observations	375	375	375	375	375	375

5. Conclusion

The paper analysed banking sector income smoothing in the Fintech era.

The findings report evidence for bank income smoothing using loan loss provisions. There is greater income smoothing in the second-wave Fintech era compared to the first-wave Fintech era. The presence of strong institutions did not lower income smoothing in the second wave era. Bank income smoothing is also greater in (i) well-capitalised banking sectors, (ii) during economic booms, and in (iii) BIS and EU countries than in non-EU countries and G7 countries, in the second wave Fintech era.

The main message from the findings is that the competition for loans and deposits by banks and Fintech lenders in the second-wave Fintech era created additional incentives for banks to smooth income in order to report competitive earnings and to make banks' reported earnings appear stable in the second-wave Fintech era.

The implication of the findings is that banking sector income smoothing is likely to increase in the coming years as more Fintech lenders enter the market for loans and deposits, and their presence will further reduce the net interest margin of banks. Recent regulations and policies seek to create a more favourable marketplace for Fintech lenders to reduce the dominance of banks in the loan and deposit markets. Banks may respond by partnering with Fintech lenders rather than seeing them as rivals, but this may not necessarily mitigate income smoothing behavior in the banking sector. Finally, bank supervisors should understand how the entry of many Fintech lenders in the market for loans and deposits affect banks' financial reporting quality. They should pay attention to how banks, in response to competition from Fintech lenders, manipulate reported earnings in order to report competitive earnings. This behavior, if present, will increase the opacity of banks' reported earnings and can mislead investors in their assessment of the true economic reality of banks in the banking sector.

This study has some limitations. One, every country is at different stages of Fintech development. This study did not consider country-specific Fintech developments due to lack of available data. Another limitation of the study is related to the specification of the linear model. Linear functions may not capture potential non-linearity or idiosyncrasies that might influence the extent of banking sector income smoothing in the Fintech era.

Future research can investigate other cross-country events that affect banking sector income smoothing using loan loss provisions. Future research can also investigate how political events in developing and transition countries affect bank earnings management in the Fintech era. Such studies should take into account the fact that most developing and transition countries have a small Fintech market which are underdeveloped.

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Appendix

Appendix 1: Variable description		
Indicator	Short definition	Source
LLP	Ratio of loan loss provisions to gross loans (%)	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF)
ΔGDP	Gross domestic product growth rate	World Bank national accounts data, and OECD National Accounts data files.
LG	Credit to private sector by banks as a share of GDP.	Bankscope, Bureau van Dijk (BvD)
CAR	Ratio of bank regulatory capital to total risk-weighted assets (%)	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF)
CN	Lerner index	Global financial development indicator in the World bank database
NPL	Bank nonperforming loans to gross loans (%)	Financial Soundness Indicators Database (fsi.imf.org), International Monetary Fund (IMF)
RQ	Regulatory quality index	World Governance Indicator in the world bank database
LAW	Rule of law / quality of legal system	World Governance Indicator in the World bank database
FT	Fintech era variable	Constructed by author
NIM	Net interest margin	Global financial development indicator in the World bank database
EBTP	Earnings before tax and provisions, derived by adding back provisions to the net interest margin ratio.	Constructed by author

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A2: Descriptive statistics - First wave Fintech era									
	LLP	EBTP	CAR	ΔGDP	LAW	CN	LG	NPL	RQ
Mean	2.21	2.55	13.02	3.70	9.85	0.19	76.76	3.57	6.89
Median	1.54	2.19	12.40	3.59	9.00	0.19	73.48	2.20	6.00
Std. Dev.	2.45	1.46	3.54	2.421	2.34	0.13	43.08	4.30	1.81
Observations	245	244	311	350	280	343	327	303	280

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A3: Descriptive statistics – second wave Fintech era									
	LLP	EBTP	CAR	ΔGDP	LAW	CN	LG	NPL	RQ
Mean	3.41	2.15	16.03	0.99	12.03	0.23	98.86	6.79	8.28
Median	2.1	1.89	15.42	1.64	12.00	0.25	93.26	4.04	8.00
Std. Dev.	4.11	1.24	3.94	3.57	2.09	0.11	45.61	7.81	1.72
Observations	292	292	310	315	315	213	289	303	315