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In the Context of the SSM-EUI Partnership on SSM Banking Supervision Learning Services

WORKING PAPER

Fintech and bank credit risk: Does financial structure matter? Evidence from spatial analysis

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Abstract

This study examines the impact of FinTech on bank credit risk across 63 countries from 2013 to 2021. We employ a novel measure based on FinTech investment activities to directly capture FinTech development. The analysis distinguishes between bank-based and market-based financial systems to assess whether FinTech's influence on bank credit risk varies in different financial structures. We account for spatial dependence in bank risk across countries by utilising various spatial models. Our findings first reveal the existence of positive spatial dependence in bank credit risk across countries. It implies that risk in the banking sector has a positive spillover effect to neighbouring countries, thereby validating the necessity of spatial analysis. Second, utilising the Spatial Durbin Model, which best describes our data, we find that FinTech reduces bank credit risk both domestically and across borders. Third, this risk-reducing effect of FinTech is predominantly driven by economies with bank-based financial systems, whereas it is absent in those with market-based financial structures. Finally, within bank-based countries, the credit risk-mitigating impact of FinTech is more pronounced in financially underdeveloped economies compared to those with well-developed financial markets.

Keywords

FinTech, Financial Structure, Bank-based Financial System, Market-based Financial System, Spatial models

JEL classification

C21, E44, G21, G29

1. Introduction

Over the past fifteen years, Financial Technology (FinTech) has been etching indelible changes in the infrastructure, provision and delivery of financial services (Bussmann, 2017; Gomber et al., 2018). This has raised academic interest in how FinTech is shaping the financial sector, the possibilities they offer for efficiency, productivity, profitability and disintermediation on the one hand and the associated risk implications on the other (Safari and Yu, 2014; Peters and Panayi, 2016; Alt, Beck and Smits, 2018; Hughes et al., 2018).

The banking industry has yet to grow accustomed to the disruptive force exerted by FinTech. Faced with competitive pressure from FinTech firms, banks may change the level of risk that they take (Jiménez and Saurina, 2004; Guo, 2017). On the other hand, the bottom fishing strategy of many FinTech firms may attract riskier customers away from banks (Cornaggia et al., 2018; De Roure et al., 2022), and banks that embrace FinTech innovations may benefit from enhanced customer service efficiency and improved risk mitigation (Ndwiga, 2020; Cheng and Qu, 2020; Jakšič and Marinč, 2019). Therefore, the extent to which banks' credit risk is affected by FinTech is an issue which warrants careful investigation.

The objective of this research is to extend the existing understanding of the FinTech-bank risk relationship in several areas. First of all, although some recent studies have examined the impact of an economy's FinTech development on the risk-taking of individual banks (e.g., Beck et al., 2016; Banna et al., 2021; Haddad and Hornuf, 2023), analysis on how the risk of a country's banking sector in its entirety (instead of individual banks) is reacting to FinTech development is scarce. Focusing on the risk of the whole banking sector would provide more straightforward information for central banks and other macro policy makers in monitoring FinTech's impact on the banking industry. Therefore, this study analyses the risk-taking of the banking sector and how it is influenced by FinTech development. We focus on credit risk because, in the presence of competitive threats, such as FinTech firms, credit risk is usually the most affected in banks' survival efforts as banks are pressured to lend more aggressively (Jiménez et al., 2013; Berger et al., 2017; Cuestas et al., 2020).

Furthermore, previous studies have overlooked differences in financial market structures. In bank-based systems (e.g., Germany, Japan), banks dominate savings mobilisation, capital allocation and risk management, often under stricter regulation. In market-based systems (e.g., the United States, the United Kingdom), securities markets share these roles, with greater public disclosure due to investor demand. These structural differences—

banks' centrality, regulatory intensity and information asymmetry—affect FinTech's impact on bank risk, prompting our distinction between the two systems.

In addition, various measures for FinTech development in previous studies on FinTech-bank risk relationship (e.g., Beck et al., 2016; Okoli, 2020; Banna et al., 2021; Deng et al., 2021; Safiullah and Paramati, 2022; Haddad and Hornuf, 2023; Ochenge, 2023; Zhao et al., 2023) do not directly capture well the actual scale of FinTech firms. We fill this gap by employing the actual size of investment that flows to FinTech firms in each country to reflect the FinTech development. We collect these data from PitchBook, constructing a dataset covering 63 countries.

Moreover, we consider cross-country spatial dependence in the banking sector risk in our analysis. Given the increasing interconnectedness amongst global financial markets (Bekaert et al., 2014; Caballero, 2015; Brunetti et al., 2019), it is surprising that the spatial spillover across banking sectors in different countries is not accounted for in previous analysis on the FinTech-bank risk nexus.

Finally, as the banking industry is an important component of the financial market, this paper also contributes to the emerging literature on the FinTech-financial stability relationship (e.g., Fung et al., 2020; Daud et al., 2022).

The paper is structured as follows. In section 2, we argue for investigating the impact of FinTech on the credit risk of banks. In section 3, we give a short overview of the related literature, highlighting our main contributions. Section 4 describes the data used, and section 5 overviews the methodology adopted. Section 6 is dedicated to the empirical resultsThe final section concludes.

2. Potential Impact of FinTech on Bank Credit Risk

FinTech has risen as an alternative to banks and continues to break down the function of financial intermediation, which is cardinal to banking operations (Das, 2019). The ability of FinTech to unbundle banking products and services at a much cheaper and convenient cost puts a direct competitive pressure on banks over market share, customer base and profit levels (Nicoletti et al., 2017). Client groups are served with a myriad of alternative points of service and are more willing to transact with FinTech due to the low switching cost (Dapp et al., 2015; Hau et al., 2019).

There are several reasons why we focus on the impact of FinTech on credit risk. Faced with competition from FinTech, the desire of banks to increase revenues raises the threat of risk-shifting incentives to banks through reduced loan quality and decreased screening and monitoring (Jiménez and Saurina, 2004; Guo, 2017). FinTech development leads to the squeeze of the net interest margin, which may increase banks' asset-side risk appetite (Chen et al., 2022). For instance, banks may lower credit requirements and reduce demands for collateral on loans to boost revenues. Balyuk (2016) employ data from the US Prosper lending platform and shows that banks increase credit supply in reaction to FinTech lending. The study shows that banks would increase loan supply to borrowers with a high propensity to seek credit from P2P channels by easing lending requirements. This behaviour leads to increased information asymmetries and moral hazards among borrowers associated with a higher probability for defaults (Agarwal and Hauswald, 2006; Dobbie and Skiba, 2013). Therefore, in the presence of competitive threats from FinTech, credit risk is usually the most affected bank-related risk (Jiménez et al., 2013; Berger et al., 2017; Cuestas et al., 2020; Moudud-Ul-Huq, 2021; Adu, 2022).

However, competition from FinTech may hold benefits for lowering bank credit risk. For instance, as the cost and screening process of FinTech is relatively less stringent than that of banks, it is expected that banks would encounter less risky borrowers in their lending operations due to the greater appeal of FinTech lending platforms to adverse borrowers (Cornaggia et al., 2018; Di Maggio and Yao, 2021). Such bottom fishing of FinTech lending, as confirmed in De Roure et al (2022), enables banks to maintain much safer loan portfolios and helps reduce credit risk as banks have a pool of less risky borrowers to serve (Boyd and De Nicolo, 2005). Furthermore, faced with competition, banks may place greater focus on upscaling the most formidable business point of their operations (Boot and Thakor, 2000; Wagner, 2010). This includes focusing on improving relationship banking, service to institutional clients and wealthy customer groups while relinquishing sections such as small retail loan markets to FinTech platforms to safeguard profit levels (Blery et al., 2006; Jakšič and Marinč, 2019; Boot et al., 2021).

Furthermore, banks have increasingly embraced FinTech tools and technologies to modernise their operations and enhance their appeal to customers (Wang et al., 2021b; Kou et al., 2021). These advanced technologies play a key role in cutting operational costs, reducing errors, and streamlining inefficiencies in lending processes (Ndwiga, 2020). Technologies like blockchain and cloud computing provide banks with the means to manage data separation and resource distribution in real-time, boosting the effectiveness of their risk management processes (Cheng and Qu, 2020). By leveraging FinTech, banks can improve their data analysis and screening capabilities, helping to mitigate risks associated with adverse selection and ultimately lowering credit risk (Jakšič and Marinč, 2019).

3. Literature Review

To assess the impact of FinTech on banks' risk-taking, the development of FinTech should be captured first, which is usually not so straightforward. There are several different approaches in the literature. They include text mining on Baidu (China's largest search engine) in the case of China (e.g., Guo and Shen, 2016; Liu et al., 2017; Wang et al., 2021a; Chen et al., 2022; Zhao et al., 2023), text mining on Google trends for Kenya (e.g., Ochenge, 2023), digital financial inclusion index compiled by the Institute of Digital Finance at Peking University for China (e.g., Deng et al., 2021; Hu et al., 2022), FinTech-based financial inclusion consisting of access and usage indicator of mobile phone (e.g., Banna et al., 2021), the division of pre and post-FinTech entrance period (e.g., Anggreini and Singapurwoko, 2019; Ndwiga, 2020), banking industry's financial R&D intensity (e.g., Beck et al., 2016), the number of FinTech start-ups/firms (e.g., Safiullah and Paramati, 2022; Haddad and Hornuf, 2023; Ni et al., 2023), number of FinTech funding rounds (e.g., Haddad and Hornuf, 2023) and FinTech Index based on usage of ATM, mobile phone and internet (e.g., Okoli, 2020). These measures are often either based on text searches –the number of FinTech firms or funding rounds, access and usage of internet or mobile phone (which reflect more financial inclusion than FinTech), investment in financial research, a cut-off year for pre and post-FinTech entry–, or can be applied to a certain country only (e.g., the Peking University index for China).

The impact of FinTech on banks' risk taking is investigated in the literature mainly via country case studies, including different periods, numbers of banks or FinTech measures. A lot of studies find a U-shaped relationship (Guo and Shen, 2016; Wang et al, 2021a for China; Ochenge, 2023 for Kenya), while some of them declare an inverted U-shape impact (Liu et al, 2017; Chen et al, 2022 for China). Also, there is a large number of studies providing empirical evidence of FinTech reducing banks' risk taking (Cheng and Qu, 2020; Deng et al, 2021; Hu et al, 2022; Ni et al, 2023 for China; Anggreini and Singapurwoko, 2019 for Indonesia; Safiullah and Paramati, 2022 for Malaysia). But this impact may differ for different types of innovations (Zhao et al, 2023) or market power of banks. For instance, Ndwinga (2020), focusing on Kenya, showed that stronger market power raises bank risk in the period after FinTech entrance.

Only a few studies have provided cross-country analysis. Beck et al (2016) studied country-level financial innovation in 32 countries during 1996-2010 and found that it is linked to more aggressive bank risk-taking behaviour for over 2000 banks across these countries. For 24 Organisation of Islamic Cooperation countries, Banna et al (2021) found that a measure of financial inclusion controls the risk-taking behaviour for the 534 banks from these countries. Haddad and Hornuf (2023) show on a sample of 87 countries during 2005 – 2018 that FinTech does not impact their Z-score but reduces the volatility of stock returns and increases the marginal expected shortfall. The only paper focusing on the impact of FinTech on credit risk at the country level is Okoli (2020). He finds a U-shaped relationship for the BRICS[1] countries.

This paper aims to make four contributions to the existing literature in the area of FinTech and bank risk-taking. First, our review of the previous literature shows the overall limited cross-country analyses investigating the impact of FinTech on the risk-taking of the banking sector. To our knowledge, Okoli (2020) is the only exception which analyses how the risk-taking of the whole banking sector is affected by FinTech. However, the number of countries investigated can be expanded substantially. Therefore, we examine the macro-level relationship between FinTech development and the risk of the banking industry in its entirety, and we do so with a wide global coverage of 63 countries.

Second, we introduce a new measure of FinTech development to account for the size/scale of FinTech firms, which is usually lacking in the literature. We employ FinTech investment activities data from PitchBook, which directly reflects the actual volume of investment that flows into the FinTech industry.

Third, we distinguish between bank-based (e.g., Germany, Japan) and market-based (e.g., the United States, the United Kingdom) financial systems to assess whether FinTech's influence on bank risk varies between these two. In bank-based financial systems, banks play a leading role in mobilising savings, allocating capital, overseeing corporate investment decisions, and providing risk management tools. In contrast, market-based financial systems see other players, such as the securities markets, sharing prominence with banks in channelling savings, exerting corporate control, and facilitating risk management (Demirguc-Kunt and Levine, 1999). Consequently, bank supervision and regulatory frameworks differ significantly between the two systems (Levine, 2002; Lee, 2012), with bank-based economies typically subjecting banks to more stringent oversight due to their critical role in safeguarding financial stability (Narayan et al., 2023; Berger et al., 2022). Additionally, market-based systems are characterised by greater public information disclosure, driven by the demand for transparency from capital market participants to inform investment decisions (Uzunkaya, 2012; Boadi et al., 2019). These differences may have implications for FinTech's impact on bank risk.

[1] Brazil, Russia, India, China and South Africa.

Finally, previous studies do not consider the spatial dependence of bank risk in their investigation of the FinTech-bank risk relationship. Globalisation has greatly accelerated cross-country financial risk transmission (Bekaert et al., 2014; Caballero, 2015; Brunetti et al., 2019). Aldasoro and Ehlers (2017) and Choi (2022) show that there is a strong credit risk interdependence among countries, which ensures transmission of risk across banking sectors. Tonzer (2015) shows that countries that are linked to more stable banking systems abroad are significantly affected by positive spillover effects. On the other hand, in times of financial volatility, connections in the banking sectors can contribute to the spread of shocks across countries (Blasques et al., 2016; Pino et al., 2019; Dungey et al., 2020; Liu and Sun, 2022). The cross-country transmission of bank credit risks occurs via channels such as assets jointly held by banks (Lagunoff and Schreft, 2001; Kodres and Pritsker, 2002), competition incentive amongst banks (Cohen-Cole et al., 2015), interbank credit and international portfolio linkage (e.g., Allen and Carletti, 2006; Degryse and Nguyen, 2007; Boyson et al., 2008), cross-border lending (Ahrend and Goujard, 2015; Blasques et al., 2016; Zhao et al., 2023), the operations of cross-border banking groups (e.g., Popov and Udell, 2012) and interconnectedness of large international non-financial corporations (e.g., Fernandes and Artes, 2016; Agosto et al., 2019). Another factor contributing to spatial dependence could be the common regulatory and supervisory environment to which banking sectors are subject[2]. More generally, Degryse et al. (2010) find that financial contagion is more widespread in closer geographical proximities. However, despite the cross-border spatial spillover of bank risk having been confirmed in a number of analyses (e.g., Tonzer, 2015; Pino et al., 2019; Acedański and Karkowska, 2022), it has not been considered in the FinTech-bank risk relationship. With this factor in mind, our study investigates the linkage between FinTech and the banking sector risk-taking by employing a range of Spatial Models to account for the spatial spillover effect.

4. Data

This study employs annual data for 63 countries from 2013 to 2021. The data source includes the Pitchbook database and the World Bank's. The list of countries is summarised in Appendix A. These countries form a sound representation of global geographic locations, including major economies on all continents. According to the World Bank data, these countries accounted for, on average, 92.5% and 95% of the world's GDP and global bank assets during

[2] For instance, the Single Supervisory Mechanism, in operation since 2014, enforces a unified supervisory framework for all major banks within the Euro area. This mechanism is likely to influence risk management practices across these banking sectors.

the period of 2013-2020. A summary of variable measurement and data sources is presented in Appendix B. The descriptive statistics and correlation matrix are summarised in Tables 1 and 2, respectively. Data for the country classification were also collected from the World Bank and the Federal Reserve databases, and relevant variables are summarised in Appendix C (they are discussed in Section 5.1 and 6.1).

4.1 The dependent variable: Credit risk of the banking sector of each country

Following Anggreini and Singapurwoko (2019), Ndwiga (2020) and Zhao et al. (2023), we adopt the percentage of non-performing loans (NPL) to the total loan ratio to indicate bank credit risk. However, it is important to point out that, unlike these studies, our study is at the macro-level, focusing on bank risk at the country level. The dataset of NPL forms part of the IMF Financial Soundness Indicators (FSI), which monitors macro-prudential factors affecting the banking sector of an economy (Kasselaki and Tagkalakis, 2014; Agresti et al., 2008). This further supports the use of this ratio as a measure of credit risk.

4.2. The core explanatory variable: FinTech investment activities in each country

We employ the FinTech[3] investment activities of Pitchbook data as an indicator of FinTech development in each country. FinTech investment activities cover venture capital, private equity, and merger and acquisition transactions to FinTech firms.[4] These activities directly reflect the actual volume of investment that flows into the FinTech industry and thereby enable a more accurate evaluation of the impact of FinTech on the banking industry's risk taking. In addition, the global coverage of Pitchbook allows us to examine a wide range of 63 countries.

According to Pitchbook, the main investor types making these investments include investment banks, hedge funds, merchant banks, venture capital-backed companies, asset management firms, governments, corporations, venture capital firms, private equity buyouts, private equity-backed companies, limited partnerships, family offices, fund of fund firms, impact investors, lender/debt providers, accelerator/incubators, and angel investors both group and individuals. It is observed that the majority of investments sourced from many of these

[3] Pitchbook defines FinTech to include firms that operate to transform traditional financial services in the loans, payments and wealth management using technology.
[4] Venture deals are classified as equity investments to start-ups in the form of angel, early and late-stage corporate venture capitals. Mergers and acquisitions and private equity deals that acquire controlling interests or support growth expansion are included in the categorisation. Funding from family and friends, accelerator funding rounds, debt restructuring, and minority stake ownership transactions are excluded from the classification (KPMG, 2018; Cornelli et al., 2021).

investor types are more prevalent in countries with more advanced FinTech development, such as the US, UK, China, Australia and Canada, whilst many less financially developed economies, such as Bulgaria or Ghana, have less diverse investor types investing.

Pitchbook also records that the recipients of these investments are mainly composed of companies classified as financial services, cutting across capital markets and institutions, commercial banks and insurance companies. These recipients are also further classified according to their business status as profitable, revenue-generating, not-for-profit or as a start-up. The purpose of funding to these companies reflects a wide variety of reasons, such as for growth and expansion, early and late-stage angel and venture capital support, initial public offering, capitalisation, corporate investment, equity and product crowdfunding, grants, reverse mergers, mergers of equals and the broad classes of mergers and acquisition deals.

4.3. Control variables

Bank characteristics and macroeconomic conditions contribute to the risk levels of banks (Stiroh, 2006; Haq et al., 2012; Chaibi et al., 2015). We evaluate the impacts of bank characteristics, including liquidity, profitability and efficiency, as well as an important socioeconomic factor, financial literacy and macroeconomic factors, including real GDP growth rate and the global economic condition, as control variables.

Bank liquidity is measured as the liquidity ratio (LR). This variable measures the amount of liquid assets banks hold in relation to total assets. A high liquidity ratio communicates that banks are buoyant to withstand any emergency demands for cash. Additionally, liquid banks have enough held funds to support lending operations and are expected to undertake less risky lending practices. Therefore, it is expected for a high liquidity ratio to have a negative impact on bank credit risk (Leung et al., 2015; Godlewski 2005; Messai et al., 2013).

Bank profitability is measured as return on equity (ROE). The relationship between profits and bank credit risk can be both positive and negative, depending on the perspective of bank management of loan portfolios. Profitable banks usually have fewer incentives to undertake poor lending practices and may tend to have declining levels of non-performing loans (Louzis et al., 2012; Makri et al., 2014; Bikker et al., 2017). However, Vatansever et al. (2013) show that highly profitable banks have a lot of funds to administer more loans, exposing those banks to decreasing risk aversion and thus to increasing levels of non-performing loans in the event of loan defaults.

Bank efficiency is measured as net interest margin (NIM). Net interest margin reflects the difference between interest income and interest expense and shows how well banks efficiently manage intermediation cost (Almarzoqi and Naceur, 2015; Riyazahmed, 2021; Alnabulsi et al., 2023). The higher the net interest margin, the more banks are efficient at the lending business. While a higher NIM can indicate a bank's effective lending, it might also lead to a higher NPL ratio if it leads to increased interest burdens for borrowers, potentially causing defaults (Panta, 2018; Ahmad et al, 2021).

As a vital socioeconomic factor, financial literacy is expected to reduce credit risk as financially educated groups are better at financial management and take prudent actions to reduce loan defaults (Murta and Gama, 2022; Liu and Zhang, 2021; Lu, Li, and Wu, 2024). Extant studies reveal a close linkage between educational level and financial literacy (OECD, 2012; Baihaqqy and Sari, 2020). This is further evidenced by De Bassa Scheresberg (2013) who find that a third of postgraduate educated and close to half of college educated groups were more highly placed to answer financial literacy questions correctly than their uneducated counterparts respectively. In view of this, we employ the level of education measured as the percentage of the population that has completed at least secondary school education as an indicator for financial literacy.

Macroeconomic factors have a strong impact on bank riskiness (Bonfim, 2009; Zribi and Boujelbène, 2011; Aretz, Bartram, and Pope, 2010). Credit risk is expected to decline when GDP growth increases (Castro, 2013) due to the increased ability of borrowers to repay loans during buoyant economic periods (Goyal et al., 2023; Szarowska, 2018). However, Murumba (2013) and Artenisa and Hyrije (2023) find that non-performing loans increase with rising GDP due to high-risk projects invested in by borrowers during vibrant economic conditions in hopes of accruing high returns. The incidences of investment failures of these projects increase defaults among borrowers, increasing the levels of non-performing loans to banks. Following Ali and Daly (2010), Zribi and Boujelbene (2011) and Ghenimi et al. (2017), the annual real GDP growth rate is employed to capture the overall economic condition of a country.

The overall global terrain in which banks operate can affect their level of risk (Yang and Mallick, 2014). During periods of worldwide economic expansion, the income streams of both firms and households are generally sufficient to meet their debt obligations. Conversely, economic downturns diminish borrowers' capacity to service their debt (Chortareas et al., 2020). Consequently, NPL ratio tends to decline during economic upturns and increase during recessions. Following Ahmad et al. (2017) and Mazreku et al. (2018), we employ world exports as proxy for global economic conditions due to its role in driving specialism, global revenues and economic growth, exchange rates and facilitating global integration (Chit et al., 2010; Fontagné et al., 2017; Redmond and Nasir, 2020).

4.4. A brief overview of the data

There are 567 observations for 63 countries covering period 2013-2021. The descriptive statistics in Table 1 shows that on average, non-performing loans account for 4.122% of loans granted in our sample countries. Figure 1 further illustrates the NPL ratio for each country. Ghana exhibits the highest average ratio of 15.430% while South Korea records the lowest ratio of 0.369%. Overall, African countries have the highest NPL ratio, with a period average of 7.860%. That for the Europe region is 3.752%, followed by lower ratios in Asia (3.067%), South America (2.596%), Oceania (0.823%) and North America (0.913%) region.

The natural logarithm of FinTech Investment Activities (LFIA) has a mean of 17.438. Figure 2 demonstrates LFIA for our sample countries. The United States (US) shows the highest level of LFIA on average of 24.599, followed by the United Kingdom (UK) (23.046) and then China (22.741). On the other hand, Peru, Tanzania and Slovenia are at the lower end (12.584, 12.648 and 12.979, respectively). To gauge the relative size of FinTech investment activities, we calculated the ratio of investment activities in FinTech to banking sector profits of each country that we studied. Using the yearly cross-country mean of this ratio, we obtain a period average value of 16.88%. It implies that, on average, the volume of investment activities in FinTech is equivalent to around 16.88% of the bank profits in our sample countries during 2013-2021. North America, led by the United States, exhibits the highest country-period average ratio at 27.11%, closely followed by Europe at 26.31%, with the United Kingdom at the forefront. Oceania records a ratio of 13.08%, followed by South America at 12.98%. Despite the recent development of the digital economy in Asia, particularly in countries such as China, the region's ratio stands at 7.28% due to the scale of bank profit. Africa and the Middle East regions have the lowest ratios, at 5.00% and 3.22%, respectively.

Table 2 illustrates the correlation matrix. The highest correlation coefficient is observed between NIM and $Education$ (0.543). As such, the overall values of correlation coefficients do not raise any concern in the dataset.[5]

[5] As further confirmation, we employ the variance inflation factor (VIF) to investigate the presence of multicollinearity. The VIF test shows all variables individually have VIF values lower than 10. Net interest margin has the highest VIF value of 2 followed by Education with a value of 1.490 with an overall cumulative mean VIF value of 1.35 for all variables. This assures that there is no concern for multicollinearity among the employed variables.

5. Methodology

5.1. Country classification

Countries are categorised according to bank-based and market-based financial structures as well as their financial development as financially developed or underdeveloped, following Demirguc-Kunt and Levine (2001).

Modifying the approach in Demirguc-Kunt and Levine (2001), we classify a country as financially developed if both the level of development of its bank (private credit by deposit money banks to GDP ratio) and capital market (stock market total value traded to GDP ratio) are above the average of all the countries in our sample. The rest of the countries are regarded as financially underdeveloped. This avoids classifying countries with only a relatively developed bank or capital market as financially developed economies[6]. Also, we apply the principal component analysis (PCA) to the two ratios mentioned above to obtain a composite financial development indicator that encompasses both bank and capital markets development. This approach ensures a more simplified and definitive method to classifying the countries (Jolliffe and Cadima, 2016; Abdi and Williams, 2010; Karamizadeh et al., 2013). We then use the average of this indicator across country and time as a benchmark. The average for each country over-time is compared to this benchmark. If it is above the benchmark, this country is regarded as financially developed; it is financial underdeveloped if below.

Next, we construct the conglomerate index based on which countries are classified to be bank-based or market-based. The conglomerate index gives a single and definite score of whether a country's financial system is bank-based or market-based. Following Demirguc-Kunt and Levine (2001), we create the conglomerate index by calculating the financial structure score for each country using the indicator of relative size, activities and efficiency. Considering the banking sector, its size is measured as the deposit money banks' assets to GDP ratio. The level of activities is reflected using private credit by deposit money banks to GDP ratio. Efficiency is captured by the inverse of the overhead costs to total assets ratio, a higher value of which implies higher efficiency. For the capital market, size, activities and efficiencies are measured as stock market capitalisation to GDP ratio, total value traded to GDP ratio, and the stock market turnover ratio. respectively. Please see Appendix C for a summary of the above. While Demirguc-Kunt and Levine (2001) employ the average of these three factors, we

[6] Cave et al (2020), Xu (2022); Beck and Levine (2004), Cheng, S.Y. (2012), Wu et al. (2010) and Durusu-Ciftci et al (2017) also made modifications to the method introduced in Demirguc-Kunt and Levine (2001). The key reason is that according to the Global Financial Stability Report (2012) and Bhatia et al (2019), a well-functioning financial system typically requires both a robust banking sector and a deep, liquid capital market, and hence a significant imbalance in one area would indicate a lack of overall financial development.

use PCA to combine these factors. We then take the average of the outcome within the group of financially underdeveloped and developed countries respectively. These two averages are employed as a benchmark. Countries with a cross-time mean higher than the benchmark indicate stronger stock market development relative to the banking sector and are regarded as having a market-based financial system; if lower, a bank-based financial system is presumed.

5.2. Spatial models

With increasingly integrated financial markets, the level of credit risk in the banking sector of one economy is likely to be under the influence of other countries (Bekaert et al., 2014; Caballero, 2015; Tonzer, 2015; Brunetti et al., 2019; Pino et al., 2019; Acedański and Karkowska 2022). Therefore, we employ a range of spatial models to account for the spatial spillover effect.

Spatial models observe dependencies that exist across space and incorporate three types of spatial interaction effects: endogenous interaction effects, exogenous interaction effects and correlated effects (Elhorst, 2010). In the context of banking sector risk, an endogenous interaction effect is observed when a change in the risk of the banking industry in a country causes changes in neighbouring countries, i,e., there is a spatial dependence in bank risk across countries. Exogenous interaction effects refer to when the explanatory variables of banking sector risk in one country influence the bank risk in other countries. Correlated effects are related to unobserved and similar environmental factors across countries that affect banking sector risk in a similar way but are not observed, i.e., the errors are correlated across space. Incorporating all three spatial interaction effects gives:

$$y_{it} = \rho \sum_{j=1}^{N} W\, y_{jt} + X_{it}\beta + \sum_{j=1}^{N} W\, X_{jt}\theta + \mu_i + \delta_t + u_{it}, \quad i, j = 1, \ldots\ldots, N, \tag{4}$$

$$u_{it} = \lambda W u_{jt} + \varepsilon_{it}, \tag{5}$$

$$-1 \leq \rho \leq 1, \qquad -1 \leq \lambda \leq 1, \tag{6}$$

where subscripts *i* and *t* denote spatial units (countries) and time, respectively. y_{it} and y_{jt} refers to the credit risk of the banking sector in country *i* and *j* $(i \neq j)$ at time *t*, ρ measures endogenous interaction effects, or the impact of bank credit risk in countries other than country *i* on that in country *i*. W is a $N \times N$ non-negative matrix specifying the spatial arrangement of countries. X_{it} includes our main variable of interest, namely the FinTech investment activities and the control variables (the banking-sector variables, one socioeconomic variable and two macro factors mentioned above) in country *i* at time *t*. θ includes parameter estimates of the exogenous interaction effects (i.e., FinTech and control variables), or how bank credit risk of country i responds to changes in explanatory variables of country j. μ_i and δ_t represent country and time fixed effects. λ measures the correlated interaction effects (Wu) and ε_{it} denotes the error term.

Although it is technically possible to estimate Equation (4), it is problematic to interpret the result if all three spatial interaction effects are considered together (Elhorst, 2010). The Spatial Autoregressive Regression (SAR) model considers spatial dependence in the dependent variable (i.e., first item in Equation (4)) only, and the Spatial Error Model (SEM) allows only the correlated effects (i.e., $\lambda W u_{jt}$). The Spatial Auto Combined (SAC) model excludes spatially lagged independent variables in estimations but includes ρ and λ, and the Spatial Durbin Model (SDM) leaves out the correlated effects but captures the endogenous and exogenous interaction effects (i.e., first and third term in Equation (4), respectively). LeSage and Pace (2009) advocate models that can treat both the endogenous and exogenous interaction effects, as the omission of either (by assuming $\rho = 0$ or $\theta = 0$) or both (by assuming $\rho = 0$ and $\theta = 0$) leads to biased and inconsistent estimates while ignoring the presence of correlated effects results in loss of efficiency in estimates which is of relatively less concern. This clearly points to the SDM from alternative candidates of spatial models. Elhorst (2012) further indicates that the SDM yields unbiased coefficient estimates even if the true data generation process is an SEM, SAC or SAR.

Equation (4) can be rewritten as follows by dropping the subscripts:

$$y = (I - \rho W)^{-1}(X\beta + WX\theta) + (I - \rho W)^{-1}\varepsilon \tag{7}$$

where $(I - \rho W)^{-1}$ is the spatial multiplier. The spatial multiplier indicates that the spatial dependent variable (Wy) depends on the error term of other countries, leading to a correlation between Wy and the error term. Ordinary Least Squares (OLS) estimation will produce inconsistent estimates under this circumstance whilst the maximum likelihood (ML) estimation provides consistent and efficient parameter estimates (Anselin et al., 1988). Furthermore, the bias correction procedure by Lee and Yu (2010) ensures the consistency of fixed effect estimations of panel models.

To choose a model specification for a particular research setting, both the likelihood ratio (LR) and the Wald tests can be used to test the following hypotheses after the estimation of the SDM. As the SDM model nests the SEM and the SAR, the latter two are special cases of SDM. Providing $\rho \neq 0$, if tests do not reject the null $\theta = 0$, the SAR is the preferred model; if the tests do not reject $\theta + \rho\beta = 0$, the SEM is the appropriate model. If not, in both cases, the SDM is the selected model. Between SDM and SAC, as they are non-nested, the model with lower Akaike Information Criteria (AIC) is selected. For the decision on specific effects, the Hausman and J tests are suitable in spatial panel regression (Mutl and Pfaffermayr, 2011).

A spatial weight matrix is required to express the spatial dependence structure. Spatial weight matrices can take many forms, including contiguity, inverse distance, and nearest neighbour weight matrices (Qu and Lee, 2015). The contiguity matrix requires spatial entities to share boundaries, making it not applicable for our study, and it captures only the local spillover effects arising from immediate neighbours. Similarly, although the nearest neighbour weight matrix does not require common borders, it also captures only local spatial interactions (Getis and Aldstadt, 2004). The inverse distance matrix, using linear distance (d_{ij}) where weights are equal to $(1/d_{ij})$, concerns global spatial interaction that cumulates across all units[7]. Allowing for non-linear distance relationships, the inverse squared distance (distance decay) matrix builds on $(1/d_{ij}^2)$ and assumes that strength of spatial relationships decays at a faster rate proportional to distance. Therefore, it captures both local and global spatial interactions (Kopczewska et al., 2017; Lu and Wong, 2008). As such, we employ an inverse squared distance (distance decay) matrix for our empirical analysis.

6. Empirical Results

6.1. Country classification

The country classification results are summarised in Appendix D. We classify the countries according to the level of financial development before further classifying them into bank-based and market-based to ensure the disparities in financial development levels are well accounted for in our classification.

Based on the method described in Section 5.1, we first calculate the cross-country and time mean using the PCA-based composite indicator for both bank and capital market development (the mean is very close to zero). The bank and capital market development are respectively measured using the private credit by deposit money banks to GDP ratio and the stock market total value traded to GDP ratio. We find that 40 countries have cross-time averages lower than this value and are defined as financially underdeveloped, whilst the other 23 economies have higher values and are classified as financially developed. We are aware that some European countries in the top left panel in Appendix D, such as Austria and Luxembourg, are not usually considered as financially underdeveloped. Looking at bank and stock market

[7] Distance is measured as the political boundary lines between countries based on the Esri (Environmental Systems Research Institute) shapefile format (Esri, 2010; Venter et al., 2022). The use of political boundaries as distance is observed to help optimize draw performance and improve the effectiveness of measurement (Esri, 2010).

development separately for Austria, while the bank development (private credit by deposit money banks to GDP ratio) is higher than the cross-time average of the sample countries, the capital market development (stock market total value traded to GDP ratio) is below. As both bank and stock market development need to be above the average to be deemed as financially developed for a country (as explained in section 5.1), Austria is categorised as financially underdeveloped due to a relatively less developed capital market. The same applies to Luxembourg.

Following this, we move on to classify countries as bank-based or market-based. We apply PCA to the relative size, activity and efficiency of the capital markets to the banking sector to form a composite score. The average value for the group of financially underdeveloped and developed economies is -0.61 and 0.76, respectively. The higher/lower the value, the more important the capital market/banking sector is. Amongst the 38 financially underdeveloped countries, 24 have cross-time averages that are lower than -0.61 and 14 higher. They are thus defined as bank-based financially underdeveloped and market-based financially underdeveloped countries, respectively. Likewise, for the 25 financially developed nations, 16 have a cross-time average lower than 0.76 and 9 higher, and hence are classified as bank-based financially developed and market-based financially developed countries, respectively.

As summarised in Appendix D, we now have four classifications: 1) bank-based financially underdeveloped (upper-left panel), 2) bank-based financially developed (upper-right panel), 3) market-based financially underdeveloped (lower-left panel), and 4) market-based financially developed economies (lower-right panel). Naturally, the bank-based countries in the two upper panels have much lower averages (i.e., -0.91 and -0.09) than that for the market-based countries in the two lower panels (-0.03 and 0.76).

6.2. Direct, indirect and total effects – Full sample

We confirm the necessity of adopting spatial models and show that the SDM is the most appropriate specification in Appendix E. We estimate the direct, indirect and total effects of FinTech investments and control variables on bank credit risk captured by the NPL ratio. The results are presented in Table 4.

According to LeSage and Pace (2009), spatial parameters should be viewed and interpreted as partial derivatives of the effects of the changes in a variable. In the case of the SDM model, direct effects refer to the impact of changes in an explanatory variable in country i on NPL ratio of the same country (country i). Indirect effects, on the other hand, capture the effects of changes in an explanatory variable in country i on the NPL ratio of the rest of the countries in the sample. Furthermore, impacts brought by a change in an explanatory variable in country i pass through to other countries and come back to the original location. These are called feedback effects and explain the differences between the coefficient estimates of the SDM model and the direct effects. The total effects are the summation of the direct and indirect effects.

Following Kopczewska et al. (2017), we exclude insignificant spatially lagged independent variables and re-estimate with the significant ones in the SDM in Column (2) in Table 3 to make sure that our results are not driven by any collinearity between insignificant and significant spatially lagged independent variables. This also applies to the rest of this paper.

In Column (1) of Table 4, the results show that $LFIA$ has a negative direct impact (-0.108) on NPL ratio at 5% significance level. Indirect (-0.457) and total effect (-0.564) are also significantly negative, with the level of significance rising to 1%. Negative direct and indirect effects indicate that FinTech investment activities in country i not only reduce bank credit risk level locally but also in neighbouring countries. The negative direct effects confirm that competition from FinTech holds benefits for lowering bank credit risk, as the bottom fishing of FinTech lending attracts sub-prime customers away from the formal banking sector (Cornaggia et al., 2018; Banna et al., 2021; Di Maggio and Yao, 2021; De Roure et al., 2022; Marcelin et al., 2022). Pressured by FinTech competition, banks may also be motivated to focus more on institutional and wealthy clients for stronger performance (Jakšič and Marinč, 2019; Boot et al., 2021). Furthermore, as banks themselves have increasingly embraced FinTech tools and technologies, these technologies can contribute to lowering costs, minimising human errors, enhancing data processing and screening and improving the efficiency of risk management of banks (Jakšič and Marinč, 2019; Cheng and Qu, 2020; Ntwiga, 2020).

The negative indirect effect of FinTech on bank risk implies that FinTech investment activities also reduce bank credit risks in neighbouring countries. It reflects the fact that while many FinTech firms start by focusing on one economy, their successful FinTech business models were soon imitated in different markets, or they themselves gradually engage in cross-border expansion (Frost, 2020). The expansion of FinTech beyond borders creates knowledge spillover and cross-border competition in financial services. Local banks' integration with foreign FinTech firms can improve these banks' efficiency by reducing costs, enhancing service delivery, and improving risk management (Claessens et al., 2018; Wang et al., 2021; Yuan and Yan, 2022). Cross-border competition induced by foreign FinTech firms forces local banks to focus more on their service quality, improve their product offerings, and manage costs more effectively to stay competitive against international rivals (Borauzima et al., 2021; Gondwe et al., 2024). These factors contribute to a credit risk-reduction effect of FinTech investment activities on banks to go beyond the borders.

Finally, the size of the indirect effects (0.457) is noticeably bigger than that of the direct effects (0.107). It shows that FinTech has far far-reaching impact on neighbouring jurisdictions in reducing their bank risks. It captures the fast global expansion of FinTech firms the world has witnessed in the past two decades. The rapid rise of FinTech was facilitated in many markets by regulatory gaps that allowed new service providers to enter and operate with minimal regulatory burden (Feyen et al., 2021). This also applies to the global expansion of FinTech firms to countries with minimal regulation, where they can launch innovative products and services facing fewer bureaucratic hurdles, potentially giving them a competitive edge in the market. FinTech firms also expand across borders to reach scale with their existing product offering (Frost, 2020). This characteristic of FinTech's cross-border activities intensifies FinTech's mitigating impact on the neighbouring banking sector's credit risk level.

In the case of profitability, ROE has a significantly negative direct (-0.165), indirect (-0.123) and total effects (-0.288) on NPL ratio, all at 1% significance level. The negative direct effect is consistent with the theoretical expectation that banks with high return on equity have lesser incentives to engage in poor lending practices or risky practices (Athanasoglou et al., 2008; Ly, 2015; Boadi et al., 2016). The negative indirect effect implies that higher returns in banks in country i are also beneficial to banks in country j in lowering their risk level. Since these banks tend to be counterparties to similar contracts and transactions or hold shared loan liabilities, the safety of one banking sector stemming from its high profitability reduces the credit risk of its neighbouring banks (Chen and Liao, 2011; Aldasoro and Ehlers, 2017; Song et al., 2023).

NIM on the other hand, has a significantly positive direct, indirect and total impact on NPL ratios across all weights at 1% level (0.219, 0.163 and 0.682 respectively). Although a high net interest margin signifies an excellent level of bank efficiency, it can also increase banks' tendency toward risky lending, with the understanding that they have accumulated enough buffer and reserves to be able to increase the riskiness of their loan portfolios (Hamadi and Awdeh, 2012; Islam and Nishiyama, 2016). It is further expected that when such efficient banks extend their businesses to other countries in efforts to diversify their loan portfolios, their aggressive approach to risk-taking would further contribute to increasing the credit risk levels in those jurisdictions through foreign country operations and subsidiaries (Buch et al., 2010; Adzobu et al., 2017; Le et al., 2020).

The socioeconomic factor $Education$ has highly significant (at 1% significance level) negative direct, indirect and total effect on NPL ratio (-0.058, -0.044 and -0.102, respectively). This is expected as the more clients are financially literate, the more prudent they are in taking decisions that ensures the proper management of funds and projects that will enable them payback acquired loans thereby reducing bank credit risk exposure (Nkundabanyanga et al., 2014; Murta and Gama, 2022). This effect is also relevant for spillover, as financially educated clientele groups are also likely to diversify their investment across multiple jurisdictions in efforts to maximise investment returns. The prudence and discipline in personal financial management would likewise ensure that transacting overseas banks are not at risk of borrower defaults, thereby reducing the credit risk of these banks (Abreu and Mendes, 2010; Nguyen et al., 2023; Zhang et al., 2023).

In terms of the macroeconomic factors, GDP has significantly negative direct effects on the NPL ratio. This is consistent with the studies of Boadi et al. (2016) and Abdelaziz et al. (2018), who both found a strongly significant negative relationship between economic growth and bank credit risk. This is attributable to the high-yielding profitability of investable projects that usually arise in good economic periods (Mpofu and Nikolaidou, 2018; Naili and Lahrichi, 2022). While high GDP growth of a nation indicates a stable and possibly wealthy economic environment that can help to retain capital within the country (Ndikumana and Boyce, 2011), it may also attract economic and financial resources away from neighbouring countries (Kohlscheen et al., 2020), pushing banks in these economies to engage in risker lending activities. The opposite sign of direct and indirect effects leads to an insignificant total effect GDP on bank credit risk.

7. Does Financial Structure Matter?

7.1. Bank-based versus market-based financial systems

In this section, we separate our full sample into bank-based and market-based economies to evaluate whether FinTech's influence on bank credit risk varies between these two financial systems. 40 countries are categorised as bank-based (the top panel of Appendix D) and 23 as market-based (the bottom panel of Appendix D). The spatial module choice results are presented in Columns (1)-(4) and Column (5)-(8) for bank-based and market-based economies, respectively, in Table 5.

When we focus on bank-based economies, Columns (2)-(5) of Table 5 show a positive and significant ρ at the 1% significance level for SDM and SAR specifications and a positive and significant λ at the 1% significance level for SEM, which is similar to the findings of the full sample in Table 3 (Columns (2)-(5)). This reaffirms the positive spatial correlation in bank risk among neighbouring countries. At the bottom of Column (2), the hypotheses $\theta = 0$ and $\theta + \rho\beta = 0$ are both rejected at 1% significance level, suggesting that SDM is the most appropriate specification compared to SAR and SEM. The lower AIC statistic of the SDM compared to the SAC coupled with the insignificant ρ and λ of SAC also confirms appropriateness of SDM for our specification. Under the SDM in Column (2), both $LFIA$ and the spatial lag $WLFIA$ show a negative sign at -0.113 and -0.274 and are significant at 10% and 5%, respectively.

When we move to the market-based economies in Column (7)-(10), we notice that ρ and λ are insignificant in all cases, suggesting a lack of spatial dependence. To further evaluate this finding, we employ two alternative weight matrices, inverse distance and the 5-nearest neighbour weight matrices, but the results remain unchanged (results are not reported here to save space but are available upon request). Therefore, although many studies have suggested spatial dependence of bank risk, this seems to take place predominately in bank-based financial systems. Such spatial dependence does not have a strong presence in economies with market-based financial systems, which could be due to the lack of bank dominance in these economies, which restricts the strength of their spillover to other countries. We also notice that the main effect of $LFIA$ is insignificant across Columns (7)-(10). Given the insignificance of ρ and λ, we run a panel regression for market-based economies in Column (6), which illustrates that, although ROE, NIM and $Education$ show significant influence, FinTech investment activities ($LFIA$) do not seem to have any significant impact on bank credit risk in market-based financial systems.

7.1.1. Why does FinTech affect bank risk differently in bank-based versus market-based financial systems?

Results in Table 5 show that while FinTech has a mitigating effect on bank credit risk in countries operating a bank-based financial system, such effects are missing in countries with a market-based financial system. A number of factors could have contributed to such an intriguing finding.

First, in both bank-based and market-based financial systems, banks play a crucial role in raising and distributing financial resources to viable sectors of the economy (Barattieri et al., 2020; Aloulou et al., 2024). However, the dominance of banks in the process of capital mobilisation and allocation is far more pronounced in the former compared to the latter. This is because, in bank-based systems, banks serve as the primary source of external funds for both institutions and households. In contrast, in market-based systems, capital allocation is primarily driven by capital markets and stock exchanges (Ergungor, 2004; Moradi et al., 2016). Given this distinction, the emergence and operation of FinTech in bank-based systems have a significantly more competitive impact on banks than in market-based systems due to the larger substitution gap that FinTech fills in the former (Cornaggia et al., 2018; De Roure et al., 2022). By offering parallel financial products, lower service costs, and less stringent requirements, FinTech platforms are able to cater to the outstanding segments of the capital allocation market, often composed of sub-prime groups, shifting high-risk borrowers away from banks (Cornaggia et al., 2018; Tang, 2019). Although FinTech platforms perform similar functions in market-based systems, the gap they fill is relatively smaller, as market-based systems already offer a wide range of alternative channels for raising capital (Uzunkaya, 2012). As a result, there has been no significant reduction in bank credit risk in market-based systems.

Second, bank-based systems are characterised by significant banking sector concentration (Beck et al., 2003). This renders banks in such systems as systemically important, in contrast to market-based systems, where financial institutions are more widely diversified (Yao, 2017; Bats and Houben, 2020; Liu et al., 2022). Consequently, the systemic importance of banks necessitates stringent banking supervision and regulation in bank-based systems to safeguard financial stability (Narayan et al., 2023; Berger et al., 2022). Even if one assumes a similarly strict banking regulation in a market-based economy compared to a bank-based country, the regulatory perimeter is significantly lower in the former, and thus the overall impact of the regulation on the banking sector is less burdensome. The regulatory requirements imposed on banks, which are far stricter than those applied to FinTech firms, create significant regulatory arbitrage, allowing FinTech operations in bank-based systems to function with greater flexibility compared to their counterparts in market-based systems (Buchak et al., 2018; Murinde et al., 2022). This difference in the regulatory perimeter benefits FinTech platforms in bank-based financial system by enabling them to expand credit supply without the asset-liability matching constraints imposed on traditional banks. As such, FinTech firms are able to assume greater risk, while banks reduce their risk exposure, thereby lowering overall bank credit risk (Deng et al., 2021; Jia, 2024).

Third, the level of information disclosure varies between bank-based and market-based systems (Mertzanis, 2020). Market-based systems are characterised by greater public information disclosure due to the broader demand for information by capital market participants to inform investment decisions (Uzunkaya, 2012; Boadi et al., 2019). In contrast, in bank-based economies, despite of the increasing information disclosure requirements, these requirements are more concentrated on the details of portfolios and financial situation and less so on the creditors and borrowers (Levine, 2002; Odhiambo, 2011; Guillemin, 2015). As such, compared to market-based systems, banks in bank-based economies encounter substantial information asymmetry and heightened exposure to adverse selection (Ugurlu-Yildirim et al., 2022). Given the powerful data acquisition and processing capabilities of FinTech, it provides more readily accessible and comprehensive data to stakeholders, including financial institutions, analysts, investors, regulators (Bartlett et al., 2022; Grennan and Michaely, 2021). The rapid advancement of FinTech has notably alleviated the information asymmetry challenges of the financial market (Zhou and Li, 2024). Hence, the adoption and operation of FinTech tools in bank-based systems are expected to have a greater impact on reducing credit risk levels. Additionally, the intensity of information asymmetry creates higher transaction charges by banks in bank-based systems, creating stronger incentives for clients to switch to more cost-effective FinTech alternatives (Yan et al., 2015; Ornelas et al., 2022). As a greater proportion of high-risk customers migrate to FinTech platforms, banks in bank-based systems are expected to experience a decline in adverse selection and credit risk exposure.

7.1.2. Bank-based financial system – Direct, indirect and total effects

In this section, we focus our attention on estimating the direct, indirect and total effects for countries with bank-based financial system, as FinTech does not appear to significantly influence bank credit risk in market-based economies (as shown in Table 5). Columns (1)-(3) in Table 6 summarise the direct, indirect and total effects estimates based on the SDM specification in Column (2) in Table 5.

We first notice that $LFIA$ remains negative and significant at least at 5% significance level for direct (-0.164), indirect (-0.538) and total effects (-0.702). This is highly consistent with the full sample findings in Table 4 that the development of FinTech leads to the reduction of bank risk level not only locally, but also cross-border. Furthermore, what also catches our attention is that these coefficients are consistently more negative than ones in Table 4 (-0.108, -0.457 and -0.564, respectively), implying that in bank-based financial system, the credit risk reduction effect of FinTech for banks are more pronounced than for the full-sample when both bank- and market-based systems are considered. This confirms our findings in Table 5 that FinTech does not significantly affect bank risk in market-based countries. Therefore, the credit risk mitigating impact of FinTech for banks are mainly driven by economies with bank-based financial system, as explained in Section 7.1.1.

In terms of the control variables, similar to the full-sample results in Table 4, ROE and $Education$ continue to have highly significant (at 1% significance level) negative direct, indirect and total effects on bank credit risk. Due to the opposite sign of direct and indirect effects, the total effects of GDP become insignificant as in Table 4. On the other hand, NIM, although remains to have positive coefficients, they have turned insignificant. Finally, despite not having a direct effect, LR shows positive indirect effect which leads to a positive total effect, both at 10% level of significance. More liquid banks are more able in extending credits internationally and hence, the spillover effect (Goldsmith-Pinkham and Yorulmazer, 2010; Ji et al., 2018). Excessive liquidity spreading into neighbouring countries can induce risk-taking behaviour on the part of bank managers and also lead to asset bubbles in these economies (Acharya and Naqvi, 2012), leading to higher level of bank credit risk.

To summarise, the analysis in this section demonstrates spatial dependency in bank credit risks among economies with bank-based financial system. It also confirms that FinTech reduces the level of bank credit risk. However, neither of these findings hold for countries with market-based financial system, for which we found no evidence of significant spatial spillover effects of bank credit risk or of FinTech's risk-mitigating impact. Furthermore, the magnitude of FinTech's risk-reducing effect is greater in bank-based nations than in the full sample, which includes both bank- and market-based countries. This suggests that the full sample results are primarily driven by bank-based economies.

7.2. Bank-based: Financially underdeveloped versus financially developed economies

Given our findings in Section 7.1, we move one step further analysing that within bank-based economies, whether the level of financial development influences the strength of the credit risk-reducing impact of FinTech on banks. It is motivated by the different level of financial regulation and information asymmetry between financially developed and underdeveloped countries. Financial regulation may be weaker in financially underdeveloped countries compared to developed nations, due to factors such as limited regulatory capacity, lower adherence to international standards, and weaker institutional frameworks (Brownbridge and Kirkpatrick, 2002; Klomp and de Haan, 2014; Jones, 2020). Furthermore, information asymmetry in financial markets tends to be more severe in these economies, characterised by less transparent financial reporting, the absence of robust bankruptcy procedures and contract enforcement mechanisms, and weaker regulatory oversight (Anayotos, 1994; Alao, 2018).

Less stringent financial regulation reduces compliance burdens on FinTech firms, facilitating their expansion (Arner et al., 2016) and strengthening their ability to attract riskier customers away from the banking sector. More pronounced information asymmetry in the financial market means greater marginal impact of FinTech in mitigating these asymmetries through enhancing transparency and information dissemination (Yan et al., 2015). Therefore, amongst bank-based countries, FinTech is expected to have a stronger risk-reducing effect on banks in financially underdeveloped economies, as it has a better environment for expansion and subsequently attracts more high-risk clients away from banks and exerts a stronger marginal effect in reducing the barrier of asymmetric information faced by banks.

However, given the lack of prior analysis on how financial market structure (i.e., bank-based or market-based) affects the relationship between FinTech and bank risk, studies on the impact of the level of financial development are non-existent. As mentioned in Section 7.1, 40 countries are categorised as bank-based (the top panel of Appendix D). Amongst them, 24 are classified as financially developed (left-top panel) and 16 as financially underdeveloped (right-top panel).

7.2.1. Direct, indirect and total effects

Again, we show that the SDM is the most appropriate specification in Appendix F. Columns (1)-(3) and Columns (4)-(6) in Table 8 summarise the direct, indirect and total effects estimates based on the SDM specification in Column (2) and Column (6) in Table 7 for bank-based financially underdeveloped and developed economies, respectively. In the case of the former, $LFIA$ continues to have negative direct (-0.224), indirect (-0.603) and total effects (-0.828) on bank credit risk, and they are significant at least at 5% significance level. This is in line with the results for the full sample in Table 4 and the bank-based economies in Table 6. It reaffirms FinTech's credit risk-reduction effect on banks located both locally and in neighbouring countries. Interestingly, we also observe that the direct, indirect and total effects are all more negative than what is found in the overall bank-based economies results in Table 6 (-0.164, -0.538 and -0.702, respectively). This implies that within countries adopting bank-based financial systems, FinTech's risk-mitigating impact is stronger in financially underdeveloped markets than its overall impact on all bank-based nations. In terms of the control variables, the results are very similar to ones in Table 6 for all the bank-based countries.

For bank-based countries that are financially developed in Columns (4)-(6) in Table 8, we again observe that $LFIA$ has negative direct (-0.126), indirect (-0.277) and total effects (-0.403) on bank risk, and they are significant at least at 10% significance level. In contrast to these effects of the bank-based financially underdeveloped economies in Columns (1)-(3) in Table 8 (-0.224, -0.603 and -0.828, respectively), they are less negative than in the overall bank-based economies results in Table 6 (-0.164, -0.538 and -0.702, respectively). This suggests that, although FinTech's credit risk-mitigating impact is present in both bank-based financially underdeveloped and developed economies, it is relatively weaker in the latter than in the former. Regarding control variables, the results are overall comparable to the ones in Table 6 for all the bank-based countries, except that NIM has positive direct and total effect and LR turns to have no effects on bank risk, which is similar to the full sample results in Table 4.

Therefore, the analysis in this section demonstrates that there is a positive spatial spillover in bank credit risk among countries with a bank-based financial system, regardless of whether they are financially underdeveloped or developed. It also confirms that FinTech reduces the level of bank credit risk. We also find that the magnitude of FinTech's risk-reducing effect on bank risk is greater in bank-based financially underdeveloped than developed nations. This intrigue finding confirms our expectation that amongst bank-based countries, FinTech has a stronger credit risk-mitigating effect on banks in financially underdeveloped economies, where it is more effective in attracting high-risk clients away from banks and weakening asymmetric information that banks experience[8].

To validate the robustness of our findings, we conduct additional tests in which the independent variables are replaced by their one-period lags in Equation (4). We re-estimate the models using the full sample, bank-based vs market-based economies, and bank-based financially underdeveloped vs developed economies. The results remain consistent with those presented in Tables 3, 5 and 7, respectively. Specifically, we continue to observe spatial dependence in bank credit risk across countries and SDM as the most appropriate specification.

[8] As explained in Section 6.1, some European economies including Austria and Luxembourg are categorised as finally underdeveloped due to their relatively lagged stock market development. To be cautious we re-run our estimations for bank-based financially underdeveloped countries (in the top left panel in Appendix D) but this time removing Austria and Luxembourg. We found that compared to results in the left panel in Table 8 when these two countries were included, the re-estimation shows consistent signs and level of significance for direct, indirect and total effects of LFIA and the control variables, except that these effects of LFIA had slightly larger magnitude at -0.257, -0.827 and -1.084, respectively. We also re-estimated for bank-based financially developed countries (in the top right panel in Appendix D) but now adding Austria and Luxembourg to this group. Again, the results are very similar to ones in the right panel in Table 8 when these two countries were not included. Therefore, these two countries do not seem to change the conclusions of this paper. These results are available upon request.

Furthermore, the results reaffirm the strong negative direct, indirect, and total effects of FinTech on bank credit risk, both locally and globally across neighbouring countries. These negative effects are more pronounced in the bank-based sample compared to the full sample, are absent in the market-based sample, and are stronger in financially underdeveloped bank-based economies relative to their developed counterparts. Although these robustness results are not presented here for reasons of space, they are available upon request. Overall, our findings remain robust regardless of whether the lagged or unlagged versions of the independent variables are employed.

8. Conclusions and Policy Implications

In this paper, we examine the impact of FinTech on bank credit risk in 63 countries during the period 2013-2021. We differentiate between bank-based and market-based financial systems. The structural differences between these two systems—banks' centrality, regulatory intensity and perimeter on banks, and the level of information asymmetry—affect FinTech's impact on bank credit risk, yet these distinctions have been overlooked by previous studies in this area. We adopt a novel measure based on FinTech investment activities from Pitchbook to directly capture FinTech development. Our analysis accounts for spatial dependence in bank credit risk across countries by utilising various spatial models.

Our findings can be summarised as follows. First, our spatial model analysis strongly validates the consideration of spatial dependence in bank credit risk across countries, showing that bank credit risk has a positive spillover effect to neighbouring countries. The SDM specification is found to be the most appropriate spatial model for our data. Second, FinTech shows negative direct, indirect and total effects on bank credit risk, which demonstrates that FinTech reduces bank risk not only domestically, but also in neighbouring countries. Third, these negative direct, indirect and total effects of FinTech are stronger in bank-based economies compared to the full-sample results. They are, however, absent in market-based countries. Therefore, the credit risk-reducing effect of FinTech is primarily driven by economies with bank-based financial systems. Finally, our analysis demonstrates that within bank-based countries, the credit risk-mitigating impact of FinTech is more pronounced in financially underdeveloped economies than in those with well-developed financial markets.

Our findings have important policy implications. The credit risk-reducing effect of FinTech, both domestically and cross-border, underscores the need for the development of regulatory frameworks that support both FinTech innovation and its adoption. This is particularly crucial in countries operating under bank-based financial systems, where we find

FinTech exerts a stronger credit risk-lowering effect on banks. The power FinTech holds in alleviating information asymmetry (Bartlett et al., 2022; Grennan and Michaely, 2021; Zhou and Li, 2024) in bank-based economies—where such asymmetries are more pronounced than in market-based financial systems—needs to be promoted, as it can serve as an effective means of mitigating the risks assumed by banks. However, as FinTech reduces bank credit risk via the possible channel of shifting risker customers from traditional banks to FinTech lending platforms, it is imperative that this displacement of riskier borrowers is carefully monitored and regulated to ensure that it not only redistributes risk away from banks but also contributes to a reduction in the overall risk within the financial system.

Furthermore, the risk-reducing effect of FinTech on bank risk is particularly strong in bank-based economies with underdeveloped financial markets. Therefore, it is vital that these economies harness such beneficial effects of FinTech not only by having their own national strategies supporting FinTech development, but also by being more open in allowing and adopting FinTech from the international market. However, as countries with underdeveloped financial markets may lack comprehensive regulatory frameworks, FinTech firms may take advantage of substantial regulatory arbitrage, potentially leading to illegal activities and failure in implementing adequate safeguards to protect consumers (Boeddu and Chien, 2022; Omarova, 2021), a trade-off that needs to be carefully managed by the financial regulators in these countries.

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Appendix A. List of countries

The 63 developing countries included in this paper are: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Czech Republic, Denmark, Egypt, Estonia, Finland, Germany, Ghana, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Kenya, Latvia, Lebanon, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, South Africa, South Korea, Spain, Sweden, Switzerland, Tanzania, Thailand, Turkey, Uganda, United Arab Emirates, United Kingdom, United States, Uruguay, and Vietnam.

Appendix B. Variable description and data source

Variables	Symbols	Description	Expected Sign	Data Source
Dependent variable: Non-performing loan ratio	NPL	The ratio of bank nonperforming loans to total gross loans (%).		World Bank Database
Main explanatory variable: Investment activities in FinTech	$LFIA$	Private equity, venture deals and M&A investments in FinTech and it is in natural logarithm.	-	Pitchbook Data

Control Variables

Category	Variables	Symbols	Description	Expected Sign	Data Source	Supporting Literature
Bank specific factors	Liquidity	LR	The ratio of bank liquid reserves to bank total assets (%)	+	WB	Leung et al. (2015); Almarzoqi et al. (2015); Brei et al. (2018); Louzis et al. (2012)
	Profitability	ROE	Commercial banks' after-tax net income to yearly average equity (%)	-	WB	Naili and Lahrichi (2022); Chaibi et al. (2015); Louzis et al., (2012); Brei et al. (2018); Makri et al. (2014)
	Efficiency	NIM	Bank's net interest revenue as a share of its average interest-bearing (total earnings) assets (%)	-	WB	Islam and Nishiyama (2016); Delis and Kouretas (2011); Godlewski (2005); Messai et al. (2013); Leung et al. (2015); Almarzoqi et al. (2015); Brei et al. (2018)
Socioeconomic factor	Financial literacy	$EDUCATION$	Percentage of population that have completed at least secondary school education (%)	-	WB	Nkundabanyanga et al. (2014); Olaniyi (2017) and Adeola and Evans (2017)
Macroeconomic factors	Economic Growth	$GDPG$	Real Gross Domestic Product growth rate (%)	+	WB	Ghenimi et al. (2017); Brei et al. (2018); Cucinelli (2013)
	Global factor	$EXPORTS$	Exports of goods and services as percentage of total GDP (%)	-	WB	Besedeš, Kim, and Lugovskyy (2014); Clichici, and Colesnicova (2014); Mileris (2014); Koju, Koju, and Wang (2020)

Appendix C. Country classification method

	Variables	Description	Data Source
Banking sector			
Size	Bank assets per GDP	The ratio of deposit money banks' assets to GDP (%) Deposit money banks' assets are total assets held by deposit money banks	World Bank
Activity	Private credit by deposit money banks per GDP	The ratio of private credit to deposit money banks divided by GDP (%)	World Bank
Efficiency	The inverse of the Overhead cost	The inverse of the (bank's overhead costs/total assets (%))	World Bank, FRED
Capital Market			
Size	Stock market capitalization to GDP	Total value of all listed shares in the stock market as a percentage of GDP (%)	World Bank, FRED
Activity	Stock market total value traded to GDP	Total value of all traded shares in the stock market exchange as a percentage of GDP	World Bank, FRED
Efficiency	Stock market turnover ratio	Total value of shares traded divided by the average market capitalization (%)	World Bank, FRED
	Financially developed and underdeveloped classification		
Banking sector indicator	Private credit by deposit money banks to GDP (%)		World Bank, FRED
Capital market indicator	Stock market total value traded to GDP (%)		World Bank, FRED
	Financial Structure Index		
Size	Market capitalization vs Banking	Stock market capitalization to GDP divided by money banks' assets to GDP	World Bank, FRED
Activity	Trading vs Bank credit	Stock market total value traded per GDP divided by Private credit by deposit money banks per GDP	World Bank, FRED
Efficiency	Trading vs The inverse of the Overhead Cost	Stock market total value traded per GDP divided by the inverse of the overhead cost (or multiplied by overhead cost)	World Bank, FRED

Note: The country classification method follows Demirguc-Kunt and Levine's (2001). Please see Section 5.1 for discuss of the method.

Appendix D. Country classification

Financially underdeveloped economies		Financially developed economies	
Bank-based economies	**Structure index**	**Bank-based economies**	**Structure index**
Argentina	-0.86	Australia	-0.05
Austria	-0.89	Canada	0.48
Bulgaria	-1.02	China	0.68
Columbia	-0.65	Denmark	-0.63
Czech Republic	-1.05	France	0.11
Egypt	-0.90	Germany	-0.15
Estonia	-0.91	Japan	0.48
Ghana	-0.99	Malaysia	-0.09
Hungary	-0.75	Netherlands	0.17
Ireland	-0.63	New Zealand	-0.96
Jordan	-0.78	Norway	-0.62
Kenya	-0.88	Portugal	-0.64
Latvia	-0.96	Singapore	0.22
Lebanon	-1.12	Spain	-0.19
Lithuania	-1.01	Thailand	0.56
Luxembourg	-0.73	Vietnam	-0.85
Malta	-0.99		
Nigeria	-0.78		
Pakistan	-0.84		
Poland	-0.63		
Slovakia	-1.17		
Slovenia	-1.05		
Tanzania	-1.08		
Uruguay	-1.17		
Group mean	**-0.91**	**Group mean**	**-0.09**
Market-based economies	**Structure index**	**Market-based economies**	**Structure index**
Belgium	-0.39	Finland	2.15
Brazil	0.68	Iceland	2.85
Chile	-0.34	Italy	4.46
India	0.68	South Africa	3.54
Indonesia	-0.10	South Korea	1.35
Israel	-0.27	Sweden	1.08
Mexico	-0.27	Switzerland	1.57
Peru	-0.60	United Kingdom	0.88
Philippines	-0.08	United States	5.78
Russia	-0.37		
Saudi Arabia	1.01		
Turkey	0.28		
Uganda	0.01		
United Arab Emirates	-0.59		
Group mean	**-0.03**	**Group mean**	**2.63**
Financially underdeveloped economies mean	**-0.61**	**Financially developed economies mean**	**0.76**
Mean of the whole sample	**-0.18**		

Note: The classification method builds on Demirguc-Kunt and Levine’s (2001) conglomerate index method. Please see Section 5.1 for discuss of the method. Note that given the effects of outliers, we use the 5% trimming to calculate the means (see for example Cots et al. (2003), Wu and Zuo (2009) and Sullivan (2021) who also employ trimming for their data). Data employed for the classification are collected from the World Bank and FRED Databases for the 63 countries in our sample for the sample period 2013-2021.

Appendix E. Spatial model choice – Full sample

We first conduct a spatial autocorrelation test for the dependent variable, the NPL ratio, using the Moran's I test. As shown in Figure 3, the test shows that NPL has a positive spatial autocorrelation of 0.370 at 1% significance level. Figure 4 further illustrates that countries with similar levels of NPL ratio are spatially clustered together. This conveys that the credit risk of the banking sector is spatially correlated across jurisdictions. This indicates similarities among countries and provides evidence of spatial dependence among countries.

We also examine the stationarity properties of the two key variables, NPL and LFIA. To this end, we apply the Levin et al. (2002) method, which tests the null hypothesis of unit root. The result indicates that both NPL and LFIA follow an I(0) process. As both series are stationary, we proceed to analyse the causal relationship between them. We employ the Dumitrescu and Hurlin (2012) panel causality test, which allows for heterogeneity in coefficients across cross-sectional units. The test confirms a unidirectional causality running from LFIA to NPL, but not in the reverse direction. The results are not presented here to save space but are available upon request.

In conformity with the recommendation of Elhorst (2010), we proceed to estimate the SDM, SAR, SEM and SAC models and process them for testing for the best model. Columns (2)-(5) in Table 3 presents the estimation results of Equation (4) with distance decay matrix. At the bottom of the table, we report the diagnostic test results along with AIC scores. OLS results are summarised in Column (1) for comparison.

In Columns (2), (3) and (5), the spatial dependence denoted by rho (ρ) is positive and significant at 1% significance level, suggesting that the NPL ratio in a given country tends to move in the same direction as that of its surrounding neighbours. SEM estimates the spatial error ($lambda$), which is also significant at 1% level matrix (Column (4)).

As the SAR and SEM are nested models of the SDM, we conduct a Likelihood ratio (LR) test and a Wald test to identify if the SDM can be simplified into either of these two models. If the null hypothesis that the spatially lagged independent variables are jointly insignificant (θ=0) is not rejected, SDM can be simplified into SAR. As the hypothesis $\theta = 0$ was rejected at 1% significance level, SAR is not the appropriate model. Similarly, the null of $\theta + \rho\beta = 0$ was rejected at 1% significance level, suggesting SEM is not the preferred model either. As the SAC is not nested in the SDM, the Akaike Information Criteria (AIC) is used to decide between the SAC and SDM. Here, although the AIC of the SDM model is not lower than that of SAC, SDM is chosen over SAC as spatial error ($lambda$) is insignificant in Column (5) Therefore, results in Columns (2)-(5) in Table 3 suggest that the SDM is the most appropriate model.

Given the above results, we focus our attention on the SDM model in Column (2). Random effect is adopted based on Hausman test. Both $LFIA$ and the spatially lagged value $WLFIA$ have a negative sign and are significant at 10% and 1% significance level, respectively. This communicates that an increase in FinTech investment activities in country i leads to reduction in NPL ratio in banks, not only within country i but also in neighbouring countries.

For control variables, ROE, GDP and Edu have negative coefficients whilst NIM shows a positive sign, all significant at 1% level. Their spatial lags are, however, only significant in the case of $WGDP$, which changes sign to positive.

To sum up, it is essential to highlight that ρ consistently exhibits a positive and highly significant presence across all specifications (when estimated) in Table 3. It confirms propositions articulated by prior studies (discussed in Section 3.2) that banking sector credit risk in one country is influenced by that of other economies. It underscores the necessity of employing spatial models, as demonstrated in our study, to account for such dependence.

Appendix F. Spatial model choice, bank-based financially developed and underdeveloped economies

For bank-based financially underdeveloped economies, Columns (1)-(4) of Table 7 show a positive ρ for SDM and SAR models and a positive λ for SEM, all at 1% level of significance, confirming the positive spatial dependence in bank credit risk among neighbouring nations. Statistics at the bottom of Column (2) suggest that the hypotheses $\theta = 0$ and $\theta + \rho\beta = 0$ are both rejected at 1% significance level. ρ and λ are both insignificant in the case of the SAC, and AIC statistic of the SDM is lower than that of the SAC. A such, again, SDM is the most appropriate across all four specifications. Under the SDM in Column (1), both $LFIA$, and its spatial lag $WLFIA$ show a negative sign at -0.168 and -0.299 and are significant at 10% and 1%, respectively.

For bank-based financially developed economies in Columns (5)-(8), we notice that ρ is positive and significant in all cases when estimated, suggesting spatial dependence. At the bottom of Column (5), the statistics suggest that both hypotheses $\theta = 0$ and $\theta + \rho\beta = 0$ are rejected at 1% significance level, nominating SDM as the best specification compared to SAR and SEM. Between SDM and SAC, the AIC of SAC is lower than that of the SDM. However, as SDM yields unbiased coefficient estimates even if the true data generation process is a SEM, SAC or SAR (Elhorst, 2012), we also adopt SDM in this case for consistence. In the SDM in Column (5), both $LFIA$ and its spatial lag $WLFIA$ have negative coefficient, -0.109 and -0.237, at 10% and 5% significance level, respectively.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
NPL	567	4.122	3.957	.129	22.717
LFIA	567	17.438	3.157	9.21	25.895
LR	567	24.647	12.359	.537	67.085
ROE	567	9.335	5.511	-8.205	31.223
NIM	567	3.332	2.584	.311	14.401
GDP	567	2.642	3.772	-21.464	25.176
Exports	567	48.9	38.514	8.222	213.223
Education	567	61.908	22.917	3.028	103.99

Table 2. Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) NPL	1.000							
(2) LFIA	-0.347	1.000						
(3) LR	0.197	-0.138	1.000					
(4) ROE	-0.011	-0.118	0.161	1.000				
(5) NIM	0.273	-0.307	0.244	0.453	1.000			
(6) GDP	0.032	-0.033	0.074	0.187	0.054	1.000		
(7) Exports	-0.069	-0.052	0.050	-0.201	-0.394	0.119	1.000	
(8) Education	-0.372	0.271	-0.184	-0.230	-0.543	-0.113	0.269	1.000

Table 3: Model selection: Full sample

	(1) OLS	(2) SDM	(3) SAR	(4) SEM	(5) SAC
LFIA	-.19***	-.098*	-.121**	-.088*	-.093**
	(.053)	(.05)	(.048)	(.051)	(.047)
LR	.014	.017	.011	.011	.008
	(.016)	(.013)	(.013)	(.014)	(.014)
ROE	-.142***	-.154***	-.15***	-.143***	-.15***
	(.026)	(.023)	(.023)	(.023)	(.022)
NIM	.285***	.274***	.219**	.227**	.257***
	(.105)	(.092)	(.087)	(.09)	(.091)
GDP	.005	-.115***	-.021	-.086**	-.001
	(.029)	(.04)	(.026)	(.036)	(.028)
Exports	-.064***	-.004	-.001	-.003	-.048**
	(.024)	(.009)	(.009)	(.009)	(.021)
Education	-.091***	-.066***	-.063***	-.066***	-.081***
	(.016)	(.012)	(.012)	(.012)	(.014)
cons	16.214***	11.227***	8.772***	10.389***	
	(1.803)	(3.031)	(1.368)	(1.39)	
Wx					
Wx:LFIA		-.297***			
		(.098)			
Wx:LR		.023			
		(.028)			
Wx:ROE		-.061			
		(.054)			
Wx:NIM		-.183			
		(.235)			
Wx:GDP		.192***			
		(.051)			
Wx:Exports		-.001			
		(.017)			
Wx:Education		.043			
		(.03)			
ρ (rho)		.434***	.479***		.517***
		(.063)	(.056)		(.125)
λ (lambda)				.546***	-.051
				(.061)	(.195)
(sigma2_e)		3.613***	3.75***	3.693***	3.671***
		(.232)	(.241)	(.238)	(.214)
(lgt_theta)		-1.196***	-1.216***		
		(.126)	(.126)		
(ln_phi)				.781***	
				(.208)	
N	567	567	567	567	567
R^2	.176	.291	.188	.186	.101
Between R^2	.127	.316	.204	.207	.108
Within R^2	.176	.233	.166	.141	.18
Log likelihood	-1185.1	-1269.6	-1283.21	-1283.69	-1152.938
AIC	2386.2	2603.2	2616.419	2589.381	2353.875
Hausman test	24.76***	18.081	8.258	7.217	
Waldtest θ=0		283.91***			
Waldtest θ+βρ=0		284.87***			
Lrtest θ=0		281.85***			

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. As discussed in Section 5.2, the distance decay weight matrix is adopted for the spatial models. Hausman test is not reported for the SAC model as the fixed effect variant of the model is largely favoured in literature and the random effect option can be written as a special form of SAR model (Mutl and Pfaffermayr, 2011; Belotti et al., 2017). t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

Table 4: Direct, indirect and total effects: Full sample

	Based on the SDM model Table 3 Column (2)		
	(1) Direct effects	(2) Indirect effects	(3) Total effects
LFIA	-.108**	-.457***	-.564***
	(.051)	(.144)	(.153)
LR	.019	.014	.033
	(.013)	(.01)	(.023)
ROE	-.165***	-.123***	-.288***
	(.023)	(.033)	(.048)
NIM	.219***	.163**	.382**
	(.085)	(.074)	(.152)
GDP	-.121***	.212***	.092
	(.036)	(.065)	(.058)
Exports	0.000	0.000	0.000
	(.009)	(.007)	(.016)
Education	-.058***	-.044***	-.102***
	(.012)	(.014)	(.025)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

Table 5: Model selection: Bank-based vs Market-based economies

	Bank-based Economies					Market-based Economics				
	(1) OLS	(2) SDM	(3) SAR	(4) SEM	(5) SAC	(6) OLS	(7) SDM	(8) SAR	(9) SEM	(10) SAC
LFIA	-.295***	-.113*	-.201***	-.147**	-.129	-.057	.005	-.051	-.036	-.039
	(.068)	(.068)	(.064)	(.07)	(.082)	(.066)	(.07)	(.065)	(.069)	(.074)
LR	.021	.008	.018	.009	.004	.002	-.004	0	-.003	.02
	(.017)	(.017)	(.016)	(.016)	(.019)	(.032)	(.032)	(.032)	(.031)	(.038)
ROE	-.128***	-.164***	-.138***	-.136***	-.139***	-.151***	-.162***	-.152***	-.157***	-.151***
	(.033)	(.029)	(.03)	(.029)	(.029)	(.035)	(.035)	(.034)	(.035)	(.034)
NIM	.16	.198	.153	.141	.16	.282**	.281**	.278**	.287**	.318**
	(.123)	(.121)	(.114)	(.115)	(.125)	(.129)	(.133)	(.127)	(.129)	(.134)
GDP	-.012	-.092*	-.023	-.073	-.045	.001	-.049	.001	-.006	.003
	(.039)	(.051)	(.036)	(.047)	(.062)	(.034)	(.053)	(.033)	(.037)	(.04)
Exports	-.006	-.047*	-.001	-.006	-.059**	.004	.006	.005	.008	-.005
	(.01)	(.027)	(.01)	(.011)	(.027)	(.023)	(.023)	(.022)	(.022)	(.037)
Education	-.093***	-.12***	-.089***	-.095***	-.127***	-.028*	-.024	-.028*	-.027*	-.027
	(.017)	(.021)	(.017)	(.016)	(.024)	(.016)	(.016)	(.015)	(.015)	(.018)
cons	15.913***		12.194***	14.157***		6.356***	6.604	6.069***	5.93***	
	(1.833)		(1.84)	(1.852)		(2.051)	(4.289)	(2.075)	(2.059)	
Wx										
Wx:LFIA		-.274**					-.227*			
		(.118)					(.121)			
Wx:LR		.064*					.047			
		(.033)					(.066)			
Wx:ROE		.021					.067			
		(.056)					(.075)			
Wx:NIM		.112					-.093			
		(.333)					(.26)			
Wx:GDP		.153**					.073			
		(.064)					(.067)			
Wx:Exports		.032					-.02			
		(.055)					(.048)			
Wx:Education		.031					.03			
		(.041)					(.038)			
ρ (rho)		.387***	.423***		.124		.06	.067		-.015
		(.072)	(.063)		(.318)		(.12)	(.114)		(.282)
λ (lambda)				.5***	.389				.147	.139
				(.071)	(.315)				(.127)	(.304)
(sigma2_e)		3.838***	4.64***	4.53***	4.536***		2.113***	2.204***	2.19***	2.185***
		(.291)	(.376)	(.371)	(.347)		(.224)	(.231)	(.229)	(.195)
(lgt_theta)			-1.103***				-1.438***	-1.406***		
			(.17)				(.217)	(.199)		
(ln_phi)				.647**					.999***	
				(.272)					(.33)	
N	360	360	360	360	360	207	207	207	207	207
R^2	.282	.206	.256	.236	.164	.140	.145	.143	.152	.108
Between R^2	.33	.212	.291	.268	.187	.149	.146	.153	.169	.108
Within R^2	.204	.308	.217	.191	.208	.111	.149	.11	.109	.113
Log likelihood	-789.395	-759.041	-850.119	-850.508	-768.576	-363.317	-409.194	-412.973	-412.498	-362.861
AIC	1594.79	1578.083	1750.238	1723.016	1585.153	742.635	882.388	875.945	846.995	773.723
Hausman test	9.88	48.55***	8.608	10.88		2.35	11.808	4.164	3.808	
Waldtest θ=0		182.16***					7.56***			
Waldtest θ+βρ=0		182.93***					6.61***			
Lrtest θ=0		244.98***					72.03***			

distance decay weight matrix is adopted for the spatial models. Hausman test is not reported for the SAC model as the fixed effect variant of the model is largely favoured in literature and the random effect option can be written as a special form of SAR model (Mutl and Pfaffermayr, 2011; Belotti et al., 2017). t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

Table 6. Direct, indirect and total effects: Bank-based economies

	Based on the SDM model Table 5 Column (1)		
	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA	-.164**	-.538***	-.702***
	(.068)	(.162)	(.175)
LR	.021	.08*	.101*
	(.016)	(.046)	(.052)
ROE	-.165***	-.09***	-.255***
	(.03)	(.031)	(.053)
NIM	.175	.096	.27
	(.111)	(.069)	(.175)
GDP	-.1**	.191***	.092
	(.046)	(.073)	(.069)
Exports	.002	.001	.003
	(.011)	(.006)	(.017)
Education	-.091***	-.05***	-.141***
	(.017)	(.017)	(.031)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

Table 7: Model selection: Bank-based financially underdeveloped vs Bank-based financially developed economies

	Bank-based financially underdeveloped economies				Bank-based financially developed economies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC
LFIA	-.168*	-.249***	-.147	-.192*	-.109*	-.145**	-.132*	-.068**
	(.097)	(.095)	(.102)	(.108)	(.065)	(.067)	(.069)	(.031)
LR	.021	.015	.002	.008	.002	.014	.005	0
	(.025)	(.025)	(.024)	(.027)	(.015)	(.014)	(.015)	(.008)
ROE	-.208***	-.165***	-.162***	-.173***	-.072**	-.059*	-.056*	-.023
	(.041)	(.043)	(.04)	(.042)	(.032)	(.034)	(.034)	(.018)
NIM	.019	.013	-.046	.032	.355**	.236	.29*	.099
	(.169)	(.16)	(.156)	(.174)	(.143)	(.153)	(.15)	(.074)
GDP	-.086	-.035	-.079	-.038	-.085	.018	.016	.017
	(.068)	(.051)	(.063)	(.066)	(.068)	(.038)	(.045)	(.013)
Exports	-.025	-.003	-.009	-.061	-.021	-.013	-.035	-.009
	(.044)	(.016)	(.015)	(.042)	(.025)	(.01)	(.026)	(.014)
Education	-.129***	-.099***	-.104***	-.135***	-.101**	-.07***	-.106***	-.009
	(.029)	(.023)	(.022)	(.028)	(.04)	(.02)	(.033)	(.013)
cons		15.188***	17.075***			9.586***		
		(2.723)	(2.67)			(1.816)		
Wx								
Wx:LFIA	-.299*				-.237**			
	(.158)				(.097)			
Wx:LR	.117**				.027			
	(.05)				(.025)			
Wx:ROE	.076				.088			
	(.065)				(.057)			
Wx:NIM	.368				-.341			
	(.379)				(.276)			
Wx:GDP	.183**				.15**			
	(.088)				(.072)			
Wx:Exports	-.129				-.01			
	(.111)				(.039)			
Wx:Education	0				.052			
	(.059)				(.044)			
ρ (rho)	.355***	.384***		.222	.174**	.24***		.861***
	(.083)	(.076)		(.214)	(.088)	(.083)		(.035)
λ (lambda)			.472***	.254			.221**	-.96***
			(.081)	(.241)			(.099)	(.055)
(sigma2_e)	5.392***	6.686***	6.47***	6.594***	1.082***	1.386***	1.238***	.467***
	(.529)	(.705)	(.686)	(.572)	(.128)	(.174)	(.147)	(.065)
(lgt_theta)		-1.108***				-1.107***		
		(.218)				(.258)		
(ln_phi)			.52					
			(.341)					
N	216	216	216	216	144	144	144	144
R^2	.053	.17	.153	.131	.407	.379	.316	.343
Between R^2	.047	.175	.15	.151	.446	.439	.37	.448
Within R^2	.337	.224	.201	.229	.305	.207	.188	.149
Log likelihood	-492.578	-549.989	-548.472	-501.067	-210.734	-251.462	-220.834	-195.722
AIC	1045.155	1149.978	1118.944	1050.133	481.469	552.925	459.667	439.444
Hausman test	61.132***	6.297	3.983		5964.48***	13.241	37.014***	
Waldtest θ=0	114.82***				81.46***			
Waldtest θ+βρ=0	111.79***				20.20***			
Lrtest θ=0	192.99***				95.15***			

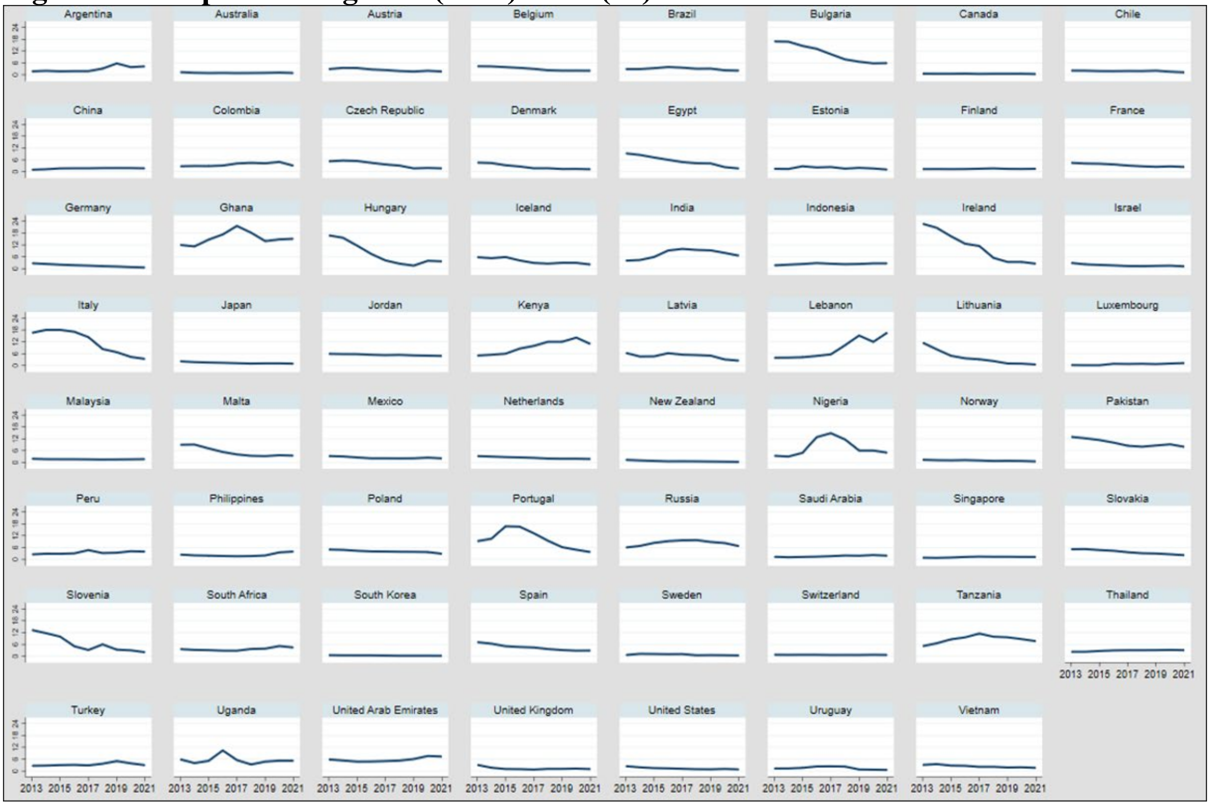
Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. As discussed in Section 5.2, the distance decay weight matrix is adopted for the spatial models. Hausman test is not reported for the SAC model as the fixed effect variant of the model is largely favoured in literature and the random effect option can be written as a special form of SAR model (Mutl and Pfaffermayr, 2011; Belotti et al., 2017). Panel regression results also show negative and highly significant coefficient for LFIA in both cases but are not included here to save space (they are available upon request). t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

Table 8. Direct, indirect and total effects: Bank-based financially underdeveloped vs Bank-based financially developed economies

	Based on the SDM model Table 7 Column (1)			Based on the SDM model Table 7 Column (5)		
	(1) Direct effects	(2) Indirect effects	(3) Total effects	(1) Direct effects	(2) Indirect effects	(3) Total effects
LFIA	-.224**	-.603***	-.828***	-.126*	-.277***	-.403***
	(.093)	(.204)	(.225)	(.066)	(.099)	(.115)
LR	.035	.162**	.197**	.013	.003	.016
	(.025)	(.066)	(.079)	(.014)	(.004)	(.017)
ROE	-.209***	-.103***	-.312***	-.072**	-.016	-.088**
	(.041)	(.039)	(.071)	(.032)	(.012)	(.04)
NIM	.086	.037	.123	.274*	.062	.335*
	(.165)	(.085)	(.246)	(.141)	(.048)	(.178)
GDP	-.073	.184*	.111	-.068	.14**	.072
	(.06)	(.098)	(.095)	(.063)	(.071)	(.048)
Exports	-.047	-.022	-.069	-.013	-.003	-.016
	(.041)	(.022)	(.062)	(.01)	(.003)	(.013)
Education	-.139***	-.069**	-.208***	-.059***	-.013	-.072***
	(.03)	(.028)	(.051)	(.021)	(.009)	(.027)

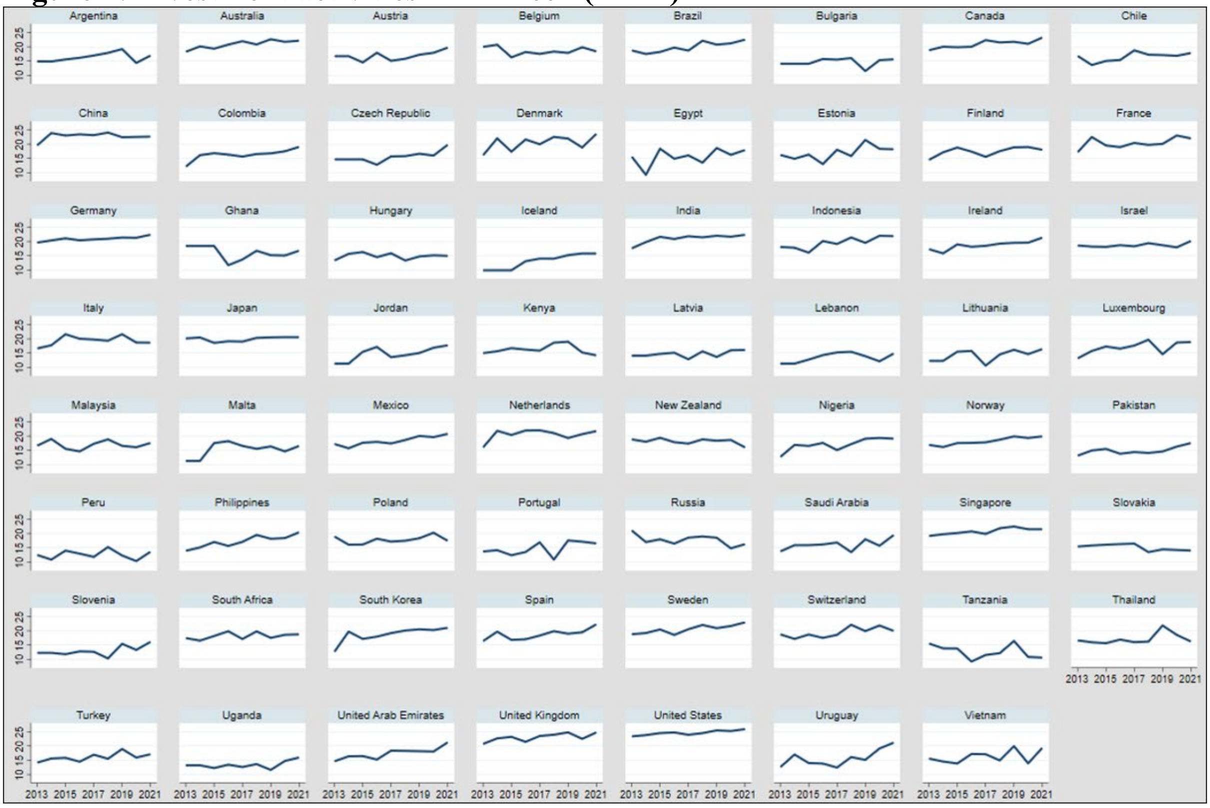
Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively.

Figure 1. Non-performing loan (NPL) ratio (%)



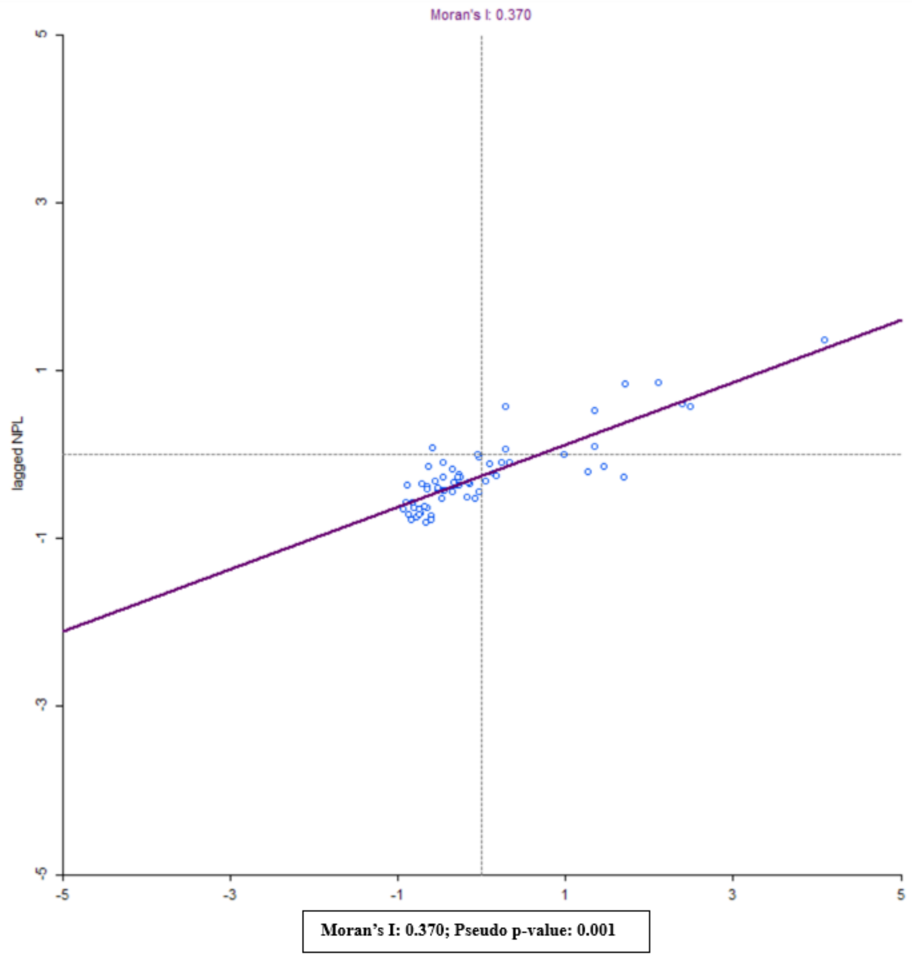
Note: It is the non-performing loans to total loans ratio (%) in each country. See Appendix A for the list of 63 countries included in this study. Time period covered is 2013-2021.

Figure 2: Investment activities in FinTech (LFIA)



Note: The investment activities in FinTech is in natural logarithm (LFIA). See Appendix A for the list of 63 countries included in this study. Time period covered is 2013-2021.

Figure 3: Moran's I test for the non-performing loan (NPL) ratio



Note: Each dot represents the period (2013-2021) average value of NPL ratio of one of the 63 sample countries. See Appendix A for the list of 63 countries included in this study.

Figure 4: Spatial distribution of the non-performing loan (NPL) ratio (Average of 2013-2021)

Note: See Appendix A for the list of 63 countries included in this study.

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