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FinTech development and bank credit risk: Spatial spillovers and the role of financial system structures

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ABSTRACT

Rapid FinTech development is reshaping global financial systems, yet the understanding of its implications for the level of risk undertaken by banks remains ambiguous. This study examines the relationship between FinTech development and credit risk in the banking sector across 63 countries from 2013 to 2021. We distinguish between bank-based and market-based financial system structures, as well as between financially developed and underdeveloped economies within these two structures. Furthermore, we employ spatial models to account for cross-border spillovers in bank risk and adopt a novel measure of FinTech development that is based on FinTech investment activities. Our findings first reveal the existence of positive spatial dependence in bank credit risk across countries, highlighting the necessity of spatial analysis. Second, using the Spatial Durbin Model, which provides the best fit for our data, we show that FinTech development reduces bank credit risk both domestically and internationally. Third, such credit risk-mitigating effect of FinTech is concentrated in bank-based financial systems, whereas it is absent in market-based structures. Fourth, within bank-based economics, this effect is more pronounced in financially underdeveloped countries compared with those with well-developed financial markets. Finally, our robustness checks support these findings. This paper highlights FinTech's potential in mitigating bank credit risk and underscores the importance of considering financial structures and spatial interdependence in assessing bank risk.

1. Introduction

In the past two decades, Financial Technology (FinTech) has brought about profound changes to the infrastructure, provision, and delivery of financial services (Bussmann, 2017; Gomber et al., 2018). This transformation has sparked growing interest in how FinTech influences the level of risk undertaken by banks. One the one hand, competitive pressure from FinTech firms may incentivise banks to assume greater risk in order to preserve market share and profitability (Jiménez and Saurina, 2004; Guo, 2017). On the other hand, the bottom fishing strategy of many FinTech firms may attract relatively riskier customers away from banks (Cornaggia et al., 2018; De Roure et al., 2022), and the increasing adoption of FinTech innovations by banks (Al-Sowaidi, Faour., 2023; Xu et al., 2025) may enable them to benefit from improved screening technologies, enhanced operational efficiency, and better risk management (Ndwiga, 2020; Cheng and Qu, 2020; Jakšič and Marinč, 2019). Given these opposing effects, the overall impact of FinTech development on banks' risk-taking warrants careful investigation.

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While a growing body of research has analysed cross-country drivers of FinTech adoption (e.g., Frost, 2020), FinTech related regulatory arbitrage and shadow banking activities (e.g., Buchak et al., 2018), and bottom-fishing behaviour of peer-to-peer lending and its implications for banks (e.g., De Roure et al., 2022), limited attention has been devoted to how FinTech development affects risk at the level of the banking sector as a whole. Although some studies have examined how FinTech development influence the risk-taking behaviour of individual banks (e.g., Beck et al., 2016; Banna et al., 2021; Haddad and Hornuf, 2023), evidence on how the overall risk of a country's banking sector in its entirety (rather than that of individual banks) responds to FinTech development remains scarce.

To address this gap, this study investigates how FinTech development influences macro-level credit risk in a country's banking sector. Specifically, we examine the following first research question (*Q1*): "*Is FinTech development positively or negatively related to credit risk of the banking industry in its entirety*". This sector-wide perspective contributes to the existing literature by providing more direct and policy-relevant insights for central banks and other macroprudential authorities seeking to monitor the impact of FinTech on the banking industry. We focus on credit risk because, under competitive pressures such as those posed by FinTech firms, credit risk is typically the most affected aspect of banks' operations—particularly when banks respond by lending more aggressively (Jiménez et al., 2013; Berger et al., 2017; Cuestas et al., 2020).

Furthermore, previous studies have largely overlooked differences in financial market structures. In bank-based systems (e.g., Germany, Japan), banks dominate savings mobilisation, capital allocation and risk management, and they are often operating 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—can shape how FinTech affects bank risk. We thereby distinguish between the two systems and examine the following second research question (*Q2*): "*Does the relationship between FinTech development and bank credit risk vary between bank-based and market-based financial systems?*". Doing so not only addresses the omission of such an important distinction in the existing literature but also provides valuable information for international regulatory authorities in designing policies tailored to different financial market structures.

In addition, given the increasing interconnectedness amongst global financial markets (Bekaert et al., 2014; Caballero, 2015; Brunetti et al., 2019), developments in one country may generate spillover effects in others. Yet it is surprising that such cross-border spatial spillovers across banking sectors have largely been overlooked in previous analysis on the FinTech-bank risk nexus. To bridge this gap, this paper explicitly considers such cross-country spatial spillover effects and investigates the following third research question (*Q3*): "*Does spatial dependence affect the relationship between FinTech development and bank credit risk?*"

Moreover, various measures of FinTech development have been used in previous studies on the 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). However, they do not directly capture the actual scale of FinTech firms. We address this issue by employing the actual size of investment that flows to FinTech firms in each country as a measure of FinTech development. We collect these data from PitchBook and cover 63 countries (see Section 3.2).

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).

Our findings first reveal significant spatial dependence in bank credit risk, with positive spillover effects across countries. Second, FinTech has negative direct, indirect, and total effects on bank credit risk, suggesting that it lowers bank risk both domestically and across borders. Third, these effects are driven by economies with bank-based financial systems but are absent in market-based systems. Finally, within bank-based economies, FinTech's risk-mitigating effect is stronger in financially less developed countries than in those with more advanced financial markets.

The remainder of the paper is structured as follows. Section 2 reviews the theoretical and empirical literature and raises the research questions. Section 3 describes the data employed, while Section 4 outlines the methodological framework. Section 5 presents the empirical results, and Section 6 further examines whether different financial structure (i.e., bank-based versus market-based) affect the findings. Section 7 provides robustness checks. The final section concludes.

2. Literature review and research questions

2.1. Theoretical impact of FinTech development on bank credit risk

FinTech has risen as an alternative to traditional 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 lower cost and greater convenience exerts direct competitive pressure on banks over market share, customer base and profit levels (Nicoletti et al., 2017). A wide range of client groups are now 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 competing theories regarding whether the overall impact of the FinTech development on the banking sector is positive or negative. The "competition-fragility" hypothesis posits that greater competition in the financial system encourages increased risk-taking by individual financial institutions, thereby leading to an overall negative impact on the soundness of banks (Allen and Gale, 2004; Valencia and Bolaños, 2018; Elekdag et al., 2025). In the context of FinTech and bank credit risk, and in line with the "competition–fragility" hypothesis, banks facing competitive pressure from FinTech firms may seek to increase revenues through risk-shifting behaviour, such as relaxing lending standards and reducing screening and monitoring activities (Jiménez and Saurina, 2004; Guo, 2017). According to Chen et al. (2022), FinTech development leads to the squeeze of the net interest margin, which may increase banks' asset-side risk appetite. For instance, banks may lower credit requirements and reduce demands for collateral on loans to boost revenues. Balyuk (2016) shows that banks expand their credit supply in response to FinTech lending. It is argued that banks would increase loan supply to borrowers with a high propensity to seek credit from P2P channels by easing lending requirements. This behaviour exacerbates information asymmetries and moral hazards among borrowers who are associated with a higher probability of defaults (Agarwal and Hauswald, 2006; Dobbie and Skiba, 2013). Therefore, under competitive pressure 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).

Conversely, the “technology spillover theory”, or the “Schumpeter’s innovation theory”, suggests that FinTech innovations are likely to diffuse beyond their original creators, potentially leading to industry-wide improvements in efficiency and service quality (Ky et al., 2025). New technology may enable banks to enhance risk management, increase risk control capability and facilitate better portfolio diversification (see Liu et al. 2025 for a recent review of literature in this strand). Focusing on the FinTech and bank credit risk relationship, and in accordance with the “technology spillover theory”, 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; Al-Sowaidi, Faour., 2023; Xu et al., 2025). 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).

In addition, competition from FinTech may itself contribute to lower bank credit risk. For instance, given that FinTech platforms often operate with less stringent screening and lower borrowing costs, 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, Michalakopoulos., 2006; Jakšič and Marinč, 2019; Boot et al., 2021). Such strategic reorientation may further support improvements in overall credit risk management.

2.2. Empirical evidence

There has been increasing research interest in the relationship between FinTech development and bank credit risk, with empirical evidence showing support for both the competition-fragility channel and the technology spillover channel. In general, existing studies focus on bank credit risk measured by the non-performing loans ratio or on a broader measure of bank risk, such as the Z-score.

Anggreini and Singapurwoko (2019) find evidence supporting the competition-fragility channel in the case of 50 Indonesian rural banks over the period of 2013–2018. In their setting, rural banks and FinTech firms have almost the same market focus, both providing lending for SMEs and retail clients. Dividing the sample into the pre-FinTech period (2013–2015) and the post-FinTech period (2016–2018), they show that the more efficient provision of financial services by FinTech has attracted borrowers away from traditional rural banks. Having obtained new financing from FinTech companies, these borrowers seemed to become less willing to payback existing loans from rural banks, thereby increasing the credit risks in these banks. Also dividing sample into pre- (2003–3009) and post-FinTech entrance (2010–2017) period, Ndwiga finds that for the 31 Kenya banks, stronger market power raises bank risk in the post-FinTech period.

In contrast, several studies focusing on Chinese banks find that technology spillover in the forms of better technologies and increased efficiency caused a decrease of bank risk. Deng et al. (2021) demonstrate this effect using a sample of 155 small and medium-sized banks in the period of 2011–2016, Hu et al. (2022) analyse a panel of commercial banks during 2011–2020, and Cheng and Qu (2020) examine a panel of 60 commercial banks during the period of 2008–2017. Additional evidence supporting the technology spillover channel is provided by Safiullah and Paramati (2022) for Malaysian banks, Banna et al. (2021) for a sample of 534 banks across 24 Organisation of Islamic Cooperation (OIC) countries, and Haddad and Hornuf (2023) using data from financial institutions across 87 countries.

However, other studies suggest that the impact is more complex and depends on the type of FinTech considered. Zhao et al. (2023b) examine the impact of FinTech on bank risk-taking measured by the NPL ratio of 114 commercial banks in China over the period 2013–2020. Distinguishing among different types of FinTech technologies, their study reports varied effects: while payment and settlement technology, capital-raising technology and investment management technology are positively correlated with bank risk-taking, supporting the competition-fragility theory, market facility technology negatively correlates with bank risk-taking, indicating the technology spillover channel. Beck et al. (2016) analyse more than 2000 banks across 32 countries over the period 1996–2010 to assess the relationship between financial innovation, bank growth and fragility as well as economic growth. Their findings suggest that financial innovation increases bank growth and supports financial deepening. On the other hand, financial innovation that reduces information asymmetry may increase risk-taking, thereby supporting the competition-fragility channel.

Several studies suggest the relationship between FinTech development and bank risk evolves over time. In other words, the impact may depend on the length of time following FinTech adoption. Guo and Shen (2016), using a sample of 36 commercial banks in China from 2003 to 2013, find that the initial development of internet finance helped commercial banks reduce management costs and risk-taking, supporting the technology-spillover channel. Over time, however, internet finance raised capital costs and may have exacerbated risk-taking via the competition-fragility channel. Ochenge (2023), focusing on Kenya, finds that banks' risk-taking fell only initially and then the competition leads to increased risk-taking. The same is documented by Okoli (2020): the relationship between FinTech and credit risk among BRICS (Brazil, Russia, India, China and South Africa) reveals a U-shaped relationship. FinTech dampens credit risk in the short run, but beyond a certain adoption threshold its effect reverses, increasing credit risk in line with the competition-fragility hypothesis. Consistent with this finding, Okoli (2020) argues that greater collaboration between banks and FinTech firms should be encouraged.

Conversely, several studies, primarily focusing on Chinese banks, identify an inverted U-shaped relationship between FinTech development and bank risk. Wang et al. (2021a) find that banks' risk-taking initially increases but subsequently declines as FinTech further develops. They explain the initial rise in risk-taking by substantial initial fixed costs of FinTech adoption, the general increase in transaction, communication, coordination and operational costs and, by the impact of competition faced by banks from the usually more efficient FinTech companies. Similar evidence is provided by Chen et al. (2022) for 19 systemically important banks and by Ni et al. (2023) for 114 Chinese urban banks. These studies suggest that FinTech initially increases risk-taking because of adjustment costs and competitive pressures, but that, over time, the benefits associated with technology spillovers become dominant and contribute to lower financial risk.

2.3. Research questions

Following our review, this paper aims to make four key contributions to the existing literature on the impact of FinTech on bank risk-taking by addressing three research questions (*Q1*, *Q2* and *Q3*) and employing a novel dataset to capture FinTech development.

First, our review of the previous literature shows the overall mixed results and more importantly limited macro-level analyses investigating the impact of FinTech on the risk-taking of the banking sector as a whole. Specifically, the handful existing cross-country studies often combine country-level FinTech indicator with individual bank-level risk (e.g., Banna et al., 2021; Beck et al., 2016; Haddad and Hornuf, 2023). Concentrating on studies mentioned above that focus on bank credit risk (e.g., Anggreini and Singapurwoko, 2019; Cheng and Qu, 2020; Ndwiga, 2020; Zhao et al., 2023), they often employ bank-level analysis within one country. Compared to individual bank-level risk, risk level of the whole banking industry can provide further information for central banks and other macroprudential policy makers, and it presents a straightforward indicator for the monitoring of banking-sectoral impact of FinTech development. To our knowledge, Okoli (2020) is the only exception which analyses this impact at macro-level, but it is restricted for five BRICS countries. Given this, our study addresses this noteworthy gap in the existing literature by examining:

Q1. *Is FinTech development positively or negatively related to credit risk of the banking industry in its entirety?*

And we do so by employing a global coverage encompassing 63 economies worldwide. Moreover, we consider variations in financial market structure, incorporate spatial dependence and employ a novel FinTech dataset, as elaborated below.

Second, despite the growing research on the relationship between FinTech and bank risk, our review underscores that variations in financial market structure have been a dimension largely overlooked in the above literature. Following the analysis of market- and bank-based financial systems by Demirguc-Kunt and Levine (1999), this distinction in financial structure has been employed to better understand issues such as economic growth (Chakraborty and Ray, 2006) and international trade (Amissah et al., 2021). Bats and Houben (2020) link different financial system to systemic risk and show that bank-based financial structures are associated with higher systemic risk than market-based financial structures, signalling that market-based financial structures are more resilient to systemic risk. However, the distinction between market- and bank-based financial systems has received little attention in the FinTech-bank risk literature. This omission is notable, given that differing structural characteristics could shape the impact of FinTech on bank risk.

To bridge this gap, our analysis differentiates between bank-based financial system (e.g., Germany, Japan) and market-based system (e.g., the United States, the United Kingdom) to assess whether FinTech's influence on bank risk varies between these two. In a bank-based financial system, 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, Phan., 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). Accordingly, these differences—bank centrality, regulation intensity of banks, and levels of information asymmetry—have implications for FinTech's impact on bank risk. By considering different financial market system, our analysis would offer useful insights for international banking regulators in adopting differentiated regulatory approaches across financial market structures. We therefore proceed to examine:

Q2. *Does the relationship between FinTech development and bank credit risk vary between bank-based and market-based financial systems?*

Third, 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) illustrate 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, R.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., 2023a), 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.[1] More generally, Degryse et al. (2010) find that financial contagion is more widespread in closer geographical proximities.

Furthermore, FinTech development may contribute to the spatial spillover of credit risk through several channels. One of the most direct mechanisms operates through the adoption of FinTech technologies by multinational banking groups. Similar to the transmission of financial shocks and lending behaviour across multinational banks' global networks (de Haas and van Lelyveld, 2010; Jeon et al., 2013), FinTech investments in the headquarter country of the banking group can have implications for credit risk development in the countries where subsidiaries and branches operate. Even outside the same banking group, foreign bank ownership can also facilitate the cross-border transfer of organisational practices and technologies cross-border (Berger et al., 2004). In addition, external investment has been a key driver of the development of FinTech firms and is closely linked to scaling and international expansion of FinTech firms (Haddad and Hornuf, 2019). Bank investment in FinTech firms may therefore help accelerate the international diffusion of financial innovations, especially given that FinTech firms are keen to provide their services across borders (Sharma et al., 2021). By supporting the development and commercialisation of new technologies, such investments may enable FinTech firms to introduce similar products and services across multiple countries. Consequently, FinTech developments in one country may influence banking practices and credit risk in other countries, thereby creating a potential channel for cross-border spillover effects.

Therefore, our study investigates the relationship between FinTech and credit risk-taking in the banking sector by employing a range of spatial models to account for potential spillover effect:

Q3. *Does spatial dependence affect the relationship between FinTech development and bank credit risk?*

In addition to addressing the above three research questions, this study employs a novel measure of FinTech development to capture the size/scale of FinTech sector. In the above mentioned studies, the development of FinTech of a country has been captured in various ways including text mining on Baidu 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). Although these measures are intuitive, they are often based on text searches, 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). To better reflect the actual size of the FinTech sector, we employ FinTech investment activities data from the Pitchbook which directly reflects the actual volume of investment that flows into the FinTech industry and is comparable across countries. Further details of this dataset are provided in Section 3.2.

3. 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 GDP and global bank assets during the period of 2013–2021. Our sample period begins in 2013, by which time FinTech had moved beyond its initial emergence and entered a phase of expansion, gradually exhibiting signs of emerging maturity over the following decade (Milian et al., 2019; Kou et al., 2024). 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 Sections 4.1 and 5.1).

3.1. *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 loan (NPL) to the total loan ratio to indicate bank credit risk. However, it is important to point out that, unlike these studies, our study

[1] 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.

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
CAR	567	17.879	3.619	10.482	35.653

Note: See Appendix B for variable description and data source. 567 observations consist of 63 countries over the period 2013–2021.

Table 2
Correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(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	
(9) CAR	-0.076	-0.026	0.063	-0.124	-0.021	0.027	0.31	0.188	1.000

Note: See Appendix B for variable description and data source.

is at the macro-level, focusing on bank risk at the country level. The dataset of NPL (collected from the World Bank) is also used as a sub-indicator by the IMF Financial Soundness Indicators (FSI) which is widely employed to monitor 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.

3.2. The core explanatory variable: FinTech development in each country

As discussed in Section 2.3, FinTech development of a country has been captured using different ways (e.g., text searches, number of FinTech firms or funding rounds, access and usage of internet or mobile phone, investment in financial research, a cut-off year, or the Peking University index for China) in prior literature studying its impact on bank risk. However, they do not provide a direct indicator on the size or scale of FinTech firms. To achieve a more accurate assessment of the size of the FinTech sector, we use data on FinTech investment activities from PitchBook, which directly capture the actual volume of investment flowing into the FinTech industry. The global coverage of the data also makes it comparable across countries.

PitchBook's FinTech investment activities cover venture capital, private equity, and merger and acquisition transactions to FinTech firms.[2] 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 world 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 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

[2] PitchBook defines FinTech to include firms that operate to transform traditional financial services in the loans, payments and wealth management using technology. 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).

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.

For the analysis, we use the natural logarithm of FinTech Investment Activities as the main explanatory variable (*LFIA*, see Appendix B). By using the natural logarithm, we decrease the potentially large differences in the activities in different countries in absolute terms and the estimated coefficients give us a measure of the semi-elasticity of the changes in NPL ratios to the dynamics of these investment activities.

3.3. Control variables

Bank characteristics and macroeconomic conditions contribute to the risk levels of banks (Stiroh, Rumble., 2006; Haq, Heaney., 2012; Chaibi, Ftiti., 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). It measures the amount of liquid assets that 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, Jouini, 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). However, Vatansever, Hepsen., (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 higher NPL ratio if it leads to increased interest burdens for borrowers, potentially causing defaults (Panta, 2018; Ahmed 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, 2021; Liu and Zhang, 2021; Lu, Li, and Wu, 2024). Extant studies reveal 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 level of education measured as percentage of the population that have completed at least secondary school education as 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), 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).

3.4. 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. Looking at the data more closely, 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. Checking the data across the economies, 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.[3]

4. Methodology

4.1. 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 Demirgüç-Kunt and Levine, (2001).

Modifying the approach in Demirgüç-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.[4] 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 Demirgüç-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 Demirgüç-Kunt and Levine, (2001) employ the average of these three factors, we 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.

4.2. 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.,

[3] 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.

[4] Cave et al. (2020), Xu (2022); Beck and Levine (2004), 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.

the errors are correlated across space. Incorporating all three spatial interaction effects gives:

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

$$u_{it} = \lambda\sum\nolimits_{j=1}^{N} w_{ij}u_{jt} + \varepsilon_{it}, \tag{2}$$

$$-1 \leq \rho \leq 1, -1 \leq \lambda \leq 1, \tag{3}$$

where subscripts i and t denote spatial units (countries) and time, respectively. y_{it} and y_{jt} refer 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_{ij} denotes the (i,j)-th element of the spatial weight matrix W, an $N \times N$ non-negative matrix specifying the spatial arrangement of countries. X_{it} is a vector of explanatory variables for country i at time t, including our main variable of interest, namely the FinTech investment activities, as well as the control variables (the banking-sector variables, one socioeconomic variable and two macro factors mentioned above). β is a vector of coefficients associated with the explanatory variables. 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, respectively.[5] u_{it} denotes the spatially correlated error term, λ measures the correlated interaction effects and $\sum_{j=1}^{N} w_{ij}u_{jt}$ represents the spatial lag of the error term. ε_{it} denotes an independently and identically distributed error term.

Although it is technically possible to estimate Eq. (1), 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 Eq. (1)) 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 Eq. (1), 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.

Eq. (1) can be rewritten as follows:

$$\mathrm{y} = (\mathrm{I} - \rho\mathrm{W})^{-1}(\mathrm{X}\beta + \mathrm{WX}\theta) + (\mathrm{I} - \rho\mathrm{W})^{-1}\varepsilon \tag{4}$$

where $(\mathrm{I} - \rho\mathrm{W})^{-1}$ 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., 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. 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,

[5] Both country- and time-fixed effects (μ_i and δ_t, respectively) were tested in our empirical analysis following Lee and Yu (2010) and Belotti and Hughes (2017). Since using only country-fixed effects allow us to retain the world exports variable to capture global economic conditions, we adopt country-fixed effects in our estimations. Using both country and time fixed effects affects the estimation results, probably due to a strong common time trend in FinTech investments. The estimation results in this regard are provided in Appendix G. While these additional results and the accompanying discussion support the use of country-fixed effects as our main specification, we also recognise the variation in the results when time effects are included.

2008). As such, we employ an inverse squared distance (distance decay) matrix for our empirical analysis.[6]

5. Empirical results

5.1. 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 4.1, 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 38 countries have cross-time averages lower than this value and are defined as financially underdeveloped, whilst the other 25 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 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 4.1), Austria is categorised as financially underdeveloped due to relatively a 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).

5.2. FinTech and bank credit risk: full sample direct, indirect and total effects

We start with examining the relationship between FinTech development and bank credit risk (*Q1*), while Section 6 further assesses the effects of different financial structure (*Q2*) on the relationship using country classification information in Section 5.1.

We first conduct a spatial autocorrelation test for the dependent variable, the *NPL* ratio, using the Moran's I test. As shown in Fig. 1, the test shows that *NPL* has a positive spatial autocorrelation of 0.370 at 1% significance level. Fig. 2 further illustrates that countries with similar level of NPL ratio are spatially clustered together. This conveys that the credit risk of banking sector is spatially correlated across jurisdictions. This indicates similarities among countries and provides evidence of spatial dependence among countries. It offers a positive response to *Q3*.

We also examine the stationarity properties of the two key variables, *NPL* and *LFIA*. we apply the Levin et al. (2002) method which tests the null hypothesis of unit root (assuming common unit root process across the cross-sections) against the alternative of no unit root. The results, summarised in Table 3, indicate that both NPL and LFIA follow an I(0) process.

Given that both series are stationary, we proceed to investigate 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. Results reported in Table 4 confirm a unidirectional causality running from LFIA to NPL, but not in the reverse direction.

Next, following the recommendation of Elhorst (2010), we proceed to estimate the SDM, SAR, SEM and SAC models to identify the best specification. The results presented in Table 5 indicates that the SDM is the most appropriate specification (see Appendix E for more detail about spatial model choice). We then 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 6.

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

[6] The inverse squared distance (distance decay) matrix is constructed using the geographical distances between countries in the sample. The geographic distance between two countries, *i* and *j* (d_{ij}) is calculated in kilometres based on the latitude and longitude coordinates of each country's geographical centre (geographical centroid). The diagonal elements are set to zero, ensuring that a country cannot be a neighbour to itself. The non-diagonal elements take the value of $1/d_{ij}^2$ and are row-standardised (Hu et al., 2021; Kopczewska et al., 2017). The squared distance term implies a stronger rate of decay, meaning that the influence between countries declines rapidly as distance increases. Consequently, geographically closer countries receive larger weights, while distant countries receive much smaller weights.

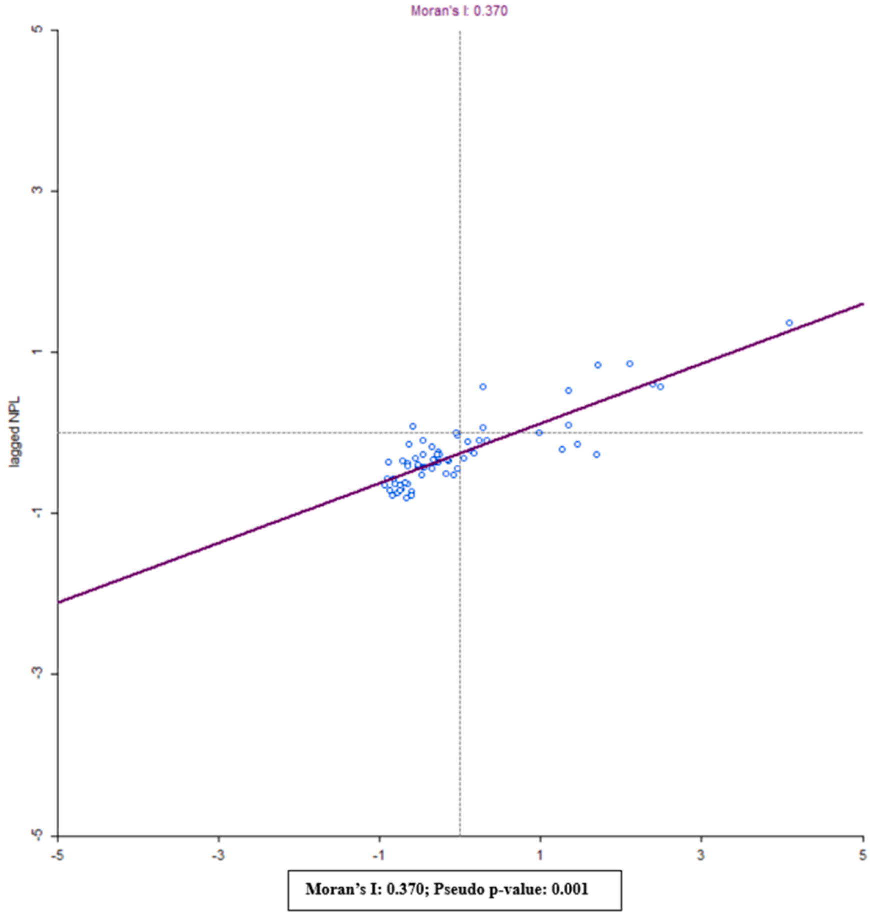

Fig. 1. Moran's I test for the non-performing loan (NPL) ratio. *Note:* Each dot represents the period (2013–2021) average value of NPL ratio of one of the 63 sample countries. See Appendix A for the list of 63 countries included in this study.

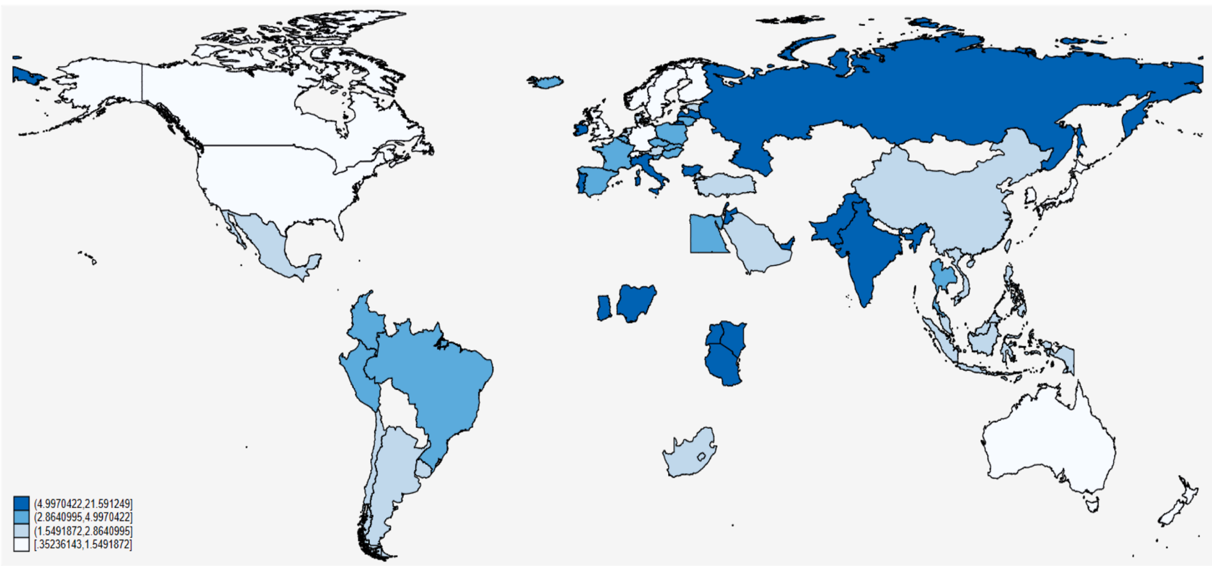

Fig. 2. Spatial distribution of the non-performing loan (NPL) ratio (Average of 2013–2021). *Note:* See Appendix A for the list of 63 countries included in this study.

Table 3
Panel Unit Root Tests for NPL and LFIA.

	NPL	LFIA
Levin, Lin and Chu Adjusted t	-13.0011***	-12.3370***

Note: NPL: non-performing loan ratio, LFIA: natural logarithm of fintech investment activities. Levin et al. (2002) unit root test is employed. The maximum lag length for the unit roots tests is set at 12. Lag length is chosen based on SIC. *** indicates statistical significance at 1% level.

Table 4
Panel causality NPL and LFIA.

	Dumitrescu and Hurlin (2012) non-causality test	
	Lag length	Stats ($\widetilde{Z}^b$)
LFIA→NPL	1	2.7598*** (0.0058)
NPL→LFIA	1	0.5308 (0.5956)

Note: NPL: non-performing loan ratio, LFIA: natural logarithm of fintech investment activities. P-values are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively. The optimal lag length is chosen based on AIC. *, ** and *** indicate 10%, 5% and 1% significance level, respectively.

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 they 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 6 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 6, 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 indicates that that FinTech investment activities in country *i* not only reduces bank credit risk level locally but also in neighbouring countries. The negative direct effects lend support to the argument that, under competitive pressure from FinTech firms, banks may also be motivated to focus more on institutional and wealthy clients in pursuit of stronger performance (Jakšič and Marinč, 2019; Boot et al., 2021). Furthermore, as banks increasingly adopt FinTech tools and technologies, the observed effects are also in line with prior research suggesting that such technologies can help minimise human error, enhance data processing and screening, and improve the efficiency of banks' risk management practices (Jakšič and Marinč, 2019; Cheng and Qu, 2020; Ntwiga, 2020). It is also consistent with the view that the bottom fishing strategy of FinTech lending may 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).

The negative indirect effect of FinTech on bank risk implies that FinTech development also reduce bank credit risks in neighbouring countries. This finding is consistent with the observation that, although many FinTech firms initially operate within a single economy, their successful business models are often imitated in other markets or gradually expanded across borders (Frost, 2020). Such cross-border expansion may generate knowledge spillovers and intensify competition in financial services. In this context, local banks' integration with foreign FinTech firms could enhance efficiency through cost reductions, improved service delivery, and more effective risk management (Claessens et al., 2018; Wang et al., 2021; Yuan and Yan, 2022). In addition, competition induced by foreign FinTech firms may incentivise local banks to improve service quality, refine product offerings, and manage costs more effectively to remain competitive (Borauzima et al., 2021; Gondwe et al., 2024). These mechanisms are consistent with the cross-border credit risk–reducing effects associated with FinTech investment activities observed in our analysis.

Furthermore, the size of the indirect effects (0.457) is noticeably bigger than that of direct effects (0.107), suggesting that FinTech development has far reaching impact on neighbouring jurisdictions in reducing their bank risks. This pattern accords with the rapid global expansion of FinTech firms observed over the past two decades. Prior research notes that the rise of FinTech in many markets was facilitated by regulatory gaps that allowed new entrants to operate with relatively limited regulatory burdens (Feyen et al., 2021). This also applies to the international expansion of FinTech firms to countries with minimal regulation where they can launch innovative products and services with 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.

Therefore, we found consistent evidence that FinTech development is negatively related to credit risk in the banking sector (*Q1*), and that spatial spillover plays a role in this relationship as such risk-mitigation effect takes place not only locally but also in neighbouring economies, with the latter being even stronger (*Q3*).

We now move to control variables. In the case of profitability, *ROE* has a significantly negative direct (-0.165), indirect (-0.123) and

Table 5
Model selection: Full sample.

	(1)	(2)	(3)	(4)	(5)
	OLS	SDM	SAR	SEM	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 $\theta=0$		283.91***			
Waldtest $\theta+\beta\rho=0$		284.87***			
Lrtest $\theta=0$		281.85***			

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. Distance decay weight matrix is adopted. See Appendix B for variable description and data source. Full sample means all 63 countries (see Appendix A) are included. Country fixed effects are employed when Hausman test indicates significance at least at 1% level; otherwise, random effects are employed. As discussed in Section 4.2, 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). Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

total effects (-0.288) on *NPL* ratio, all at 1% significance level. The negative direct effect is consistent with 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 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 significantly positive direct, indirect and total impact on *NPL* ratio across all weights at 1% level (0.219,

Table 6
Direct, indirect and total effects: Full sample.

Based on the SDM model Table 5 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. Distance decay weight matrix is adopted. See Appendix B for variable description and data source. Full sample means all 63 countries (see Appendix A) are included. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

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 of 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 of diversifying their loan portfolios, their aggressive approach at 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, 2021). 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 maximize investment returns. The prudence and discipline at 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).

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), who 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 of *GDP* on bank credit risk.

6. Does financial structure matter?

6.1. 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 to examine *Q2*. As discussed in Section 5.1, 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 (2)-(5) and Column (7)-(10) for bank-based and market-based economies, respectively, in Table 7.

When we focus on bank-based economies, Columns (2)-(5) of Table 7 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 5 (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* shows 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-

Table 7
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 $\theta+\beta\rho$=0		182.93***					6.61***			
Lrtest θ=0		244.98***					72.03***			

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. Distance decay weight matrix is adopted. See Appendix B for variable description and data source. See Appendix D for the list of 40 bank-based economies and 23 market-based economies. Country fixed effects are employed when Hausman test indicates significance at least at 1% level; otherwise, random effects are employed. As discussed in Section 4.2, 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). Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

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.

The above shed insights on *Q2*, illustrating that FinTech's mitigating impact on banking sector credit risk occurs in bank-based but not in market-based financial system, indicating difference in financial structure does have implications on such risk-reduction effect.

6.1.1. Why does the relationship between FinTech and bank risk differ between bank-based and market-based financial systems?

Results in Table 7 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 et al., 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, Phan., 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

Table 8
Direct, indirect and total effects: Bank-based economies.

Based on the SDM model Table 7 Column (2)			
	(1) Direct effects	(2) Indirect effects	(3) 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. Distance decay weight matrix is adopted. See Appendix B for variable description and data source. See Appendix D for the list of 40 bank-based economies. Only bank-based economies are included as LFIA is insignificant across columns (7)-(10) in the right panel of Table 7. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

adverse selection (Ugurlu-Yildirim, Ordu-Akkaya., 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, Reggi Pecora., 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.

6.1.2. *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 7). Columns (1)-(3) in Table 8 summarise the direct, indirect and total effects estimates based on the SDM specification in Column (2) in Table 7.

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 6 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 6 (-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, combined with our findings in Table 7 that FinTech does not significantly affect bank risk in market-based economies, suggest that the credit risk mitigating impact of FinTech for banks are mainly driven by economies with bank-based financial system, as explained in Section 6.1.1.

In terms of the control variables in Table 8, similar to the full-sample results in Table 6, *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* remain insignificant as in Table 6. 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, informing *Q3*. It also confirms that FinTech reduces the level of bank credit risk, shedding light on *Q1*. 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. This provides clear insights confirming the issue raised in *Q2*. 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.

6.2. *Further analysis on bank-based financially underdeveloped versus financially developed economies*

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. Intrigued by our findings in Section 6.1, 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 not only by the scant research in this area, but also 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, 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., 2015) 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.

6.2.1. *Bank-based financially developed versus underdeveloped economies - direct, indirect and total effects*

As mentioned in Section 5.1, 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).

Again, we show that the SDM is the most appropriate specification in Table 9 (see detailed discuss in Appendix F). Columns (1)-(3) and Columns (4)-(6) in Table 10 summarise the direct, indirect and total effects estimates based on the SDM specification in Column (1) and Column (5) in Table 9 for bank-based financially underdeveloped and developed economies, respectively. In the case of the former, in Columns (1)-(3) in Table 10, *LFIA* continues to have negative direct (-0.224), indirect (-0.603) and total effects (-0.828) on

Table 9
Model selection: Bank-based financially underdeveloped vs Bank-based financially developed economies.

	Bank-based financially underdeveloped economies				Bank-based financially developed economies			
	(1) SDM	(2) SAR	(3) SEM	(4) SAC	(5) SDM	(6) SAR	(7) SEM	(8) 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 $\theta=0$	114.82***				81.46***			
Waldtest $\theta+\beta\rho=0$	111.79***				20.20***			
Lrtest $\theta=0$	192.99***				95.15***			

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. Distance decay weight matrix is adopted. See Appendix B for variable description and data source. See Appendix D for the list of 24 bank-based financially under-developed economies and 16 bank-based financially developed economies. Country fixed effects are employed when Hausman test indicates significance at least at 1% level; otherwise, random effects are employed. As discussed in Section 4.2, 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 OLS 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). Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

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 6 and the bank-based economies in Table 8. 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 8 for all bank-based countries.

For bank-based countries that are financially developed in Columns (4)-(6) in Table 10, 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 10 (-0.224, −0.603 and −0.828, respectively), they are less negative than in the overall bank-based economies results in Table 8 (-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 8 for all 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 6.

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. The above findings directly inform *Q1* and *Q3* and provide valuable insights on *Q2* in the context of economies with bank-based financial structure.

7. Robustness checks

7.1. Economic-based spatial weight matrix

To validate the robustness of our findings, we carry out five sets of additional investigation in this section. First, while the distance decay weight matrix employed in the main results capture the geographic dimension of spatial dependence, we further consider an alternative channel through which the spillover effects could propagate – the real economic links. To this end, we follow the method of Debarsy et al., (2018) and constructed an economic spatial weight matrix ($ew_{ij,t}$) for the 63 countries included in our sample:

$$ew_{ij,t} = \frac{M_{ij,t} + X_{ij,t}}{GDP_{i,t} + GDP_{j,t}}$$

where i and j are our sample countries ($i \neq j$), $GDP_{i,t}$ and $GDP_{j,t}$ are the nominal gross domestic products of the country $i$and$j$, respectively, and $M_{ij,t}$ and $X_{ij,t}$ are the bilateral total import and export, respectively. This measure captures the contribution of the bilateral trade to the wealth of the countries. To construct our interaction matrix, and following Debarsy et al., (2018), we average this

Table 10
Direct, indirect and total effects: Bank-based financially underdeveloped vs Bank-based financially developed economies.

	Bank-based financially underdeveloped economies Based on the SDM model Table 9 **Column (1)**			**Bank-based financially developed economies Based on the SDM model** Table 9 **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. Distance decay weight matrix is adopted. See Appendix B for variable description and data source. See Appendix D for the list of 24 bank-based financially under-developed economies and 16 bank-based financially developed economies. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

measure over our sample period 2013–2021.

We collected annual data on bilateral total trade flows between all countries using the International Trade in Goods (by partner country) (IMTS), provided by the IMF. The data represents the total amount in US Dollars of import (export) from (to) one country to (from) another country. The nominal GDP data are collected from the World Economic Outlook database from the IMF.

Having obtained this real economic links-based spatial weight matrix, we apply it in place of the geographic location-based distance decay matrix and re-estimate the main results in Tables 5–10. To conserve space we report the direct, indirect and total effects in Tables 11–13.

The full-sample results using the economic spatial weight matrix in Table 11 are highly consistent with the main results based on the distance decay weight matrix in Table 6, showing that the direct, indirect, and total effects are all negative and significant at least at the 5% level, with the indirect effect having a larger magnitude (i.e., more negative) than the direct effect. When considering the different financial structure, and consistent with the main results in Table 8, the direct, indirect, and total effects remain negative and significant at least at the 5% level for bank-based economies (as shown in Table 12), while they are insignificant for market-based economies (results for market-based economies are omitted here for brevity but are available upon request), which is again consistent with the main results. One slight difference is that the magnitude of the indirect effect changes from being larger (more negative) than the direct effect in Table 8 to slightly smaller (less negative) in Table 12. Nevertheless, all effects remain negative and significant, confirming both the local and cross-border credit risk mitigation effects of FinTech on the banking sector. In Table 13, bank-based economies are further divided into financially underdeveloped (left Columns (1)–(3)) and developed economies (right Columns (1)–(3)). The results are once again broadly similar to the main results in Table 10, except that in Table 13 the indirect effect is less negative than the direct effect for bank-based underdeveloped economies, and the direct effect for bank-based developed economies is negative but insignificant. Despite these differences, all effects retain a negative sign, confirming the credit risk–reducing impact of FinTech. Overall, the results based on the economic spatial weight matrix are consistent with the main findings using the distance decay weight matrix, supporting the local, cross-border, and overall credit risk mitigation effects of FinTech.

7.2. Lagged independent variables

Second, to evaluate if there is any lagged effect and to address potential endogeneity issues, we replace the independent variables by their one-period lags in Eq. (4). Compared with the 2013–2021 sample period in the main results in Sections 5 and 6, we collected data for NPL for year 2022 and use NPL's sample period of 2014–2022, whilst data for independent variables (LFIA and control variables) remained at 2013–2021, so we do not lose any number of observations.

We start with re-estimating the spatial models using the full sample, bank-based vs market-based economies, and bank-based financially underdeveloped vs developed economies. Specifically, we continue to observe spatial dependence in bank credit risk across countries and SDM as the most appropriate specification. To conserve space, the model selection tables are not reported here, as they are quite long, but are available upon request. We report the corresponding direct, indirect and total effects of FinTech on bank credit risk based on SDM specification in Table 14 (full sample), 15 (bank-based vs market-based) and 16 (bank-based financially underdeveloped vs developed), all estimated using one-year lagged independent variables denoted by (-1). The results are comparable to the main results presented in Tables 6, 8, and 10, respectively, and they are consistent with the main results. In particular, the results reaffirm the strong negative direct, indirect, and total effects of FinTech on bank credit risk, both locally and globally across

Table 11
Robustness checks: Direct, indirect and total effects - Full sample but using economic spatial weight matrix instead of the distance decay weight matrix.

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA	-.119**	-.687**	-.805***
	(.052)	(.294)	(.302)
LR	.017	.189**	.205**
	(.013)	(.094)	(.099)
ROE	-.158***	-.238**	-.397***
	(.023)	(.095)	(.108)
NIM	.257***	.39*	.647**
	(.085)	(.203)	(.27)
GDP	-.1***	.299***	.199**
	(.038)	(.093)	(.092)
Exports	-.006	-.009	-.016
	(.009)	(.015)	(.023)
Education	-.067***	.11	.042
	(.012)	(.093)	(.093)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. The economic spatial weight matrix is adopted. See Appendix B for variable description and data source. Full sample means all 63 countries (see Appendix A) are included. Estimates are based on the SDM specification which was identified as the most appropriate model and the spatial ρ (rho) for the SDM specifications remain positive and significant at 1% significance level (the model selection table is not included to conserve space but is available upon request). Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Table 12
Robustness checks: Direct, indirect and total effects - Bank-based economies but using economic spatial weight matrix instead of the distance decay weight matrix.

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA	-.175**	-.162**	-.338**
	(.069)	(.077)	(.133)
LR	.02	.125*	.145*
	(.016)	(.076)	(.081)
ROE	-.152***	-.147**	-.299***
	(.03)	(.059)	(.08)
NIM	.161	.323	.485
	(.115)	(.769)	(.814)
GDP	-.107**	.232**	.126
	(.049)	(.099)	(.095)
Exports	-.003	-.003	-.007
	(.011)	(.011)	(.022)
Education	-.093***	-.089**	-.182***
	(.018)	(.035)	(.047)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. The economic spatial weight matrix is adopted. See Appendix B for variable description and data source. See Appendix D for the list of 40 bank-based economies. Only bank-based economies are included as LFIA is insignificant for market-based economies (market-based economies table is not included to conserve space but is available upon request). Estimates are based on the SDM specification which was identified as the most appropriate model and the spatial ρ (rho) for the SDM specifications remain positive and significant at 1% significance level (the model selection table is not included to conserve space but is available upon request). Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Table 13
Robustness checks: Direct, indirect and total effects - Bank-based financially underdeveloped vs Bank-based financially developed economies but using economic spatial weight matrix instead of the distance decay weight matrix.

	Bank-based financially underdeveloped economies			**Bank-based financially developed economies**		
	(1)	(2)	(3)	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
LFIA	-.212**	-.114*	-.326**	-.093	-.278**	-.371***
	(.098)	(.063)	(.151)	(.065)	(.133)	(.134)
LR	.012	.006	.018	.007	.127***	.134***
	(.025)	(.015)	(.04)	(.013)	(.04)	(.043)
ROE	-.199***	-.113**	-.312***	-.052*	-.015	-.067
	(.042)	(.054)	(.087)	(.031)	(.018)	(.044)
NIM	.22	2.047***	2.268***	.33**	.086	.416**
	(.169)	(.631)	(.696)	(.133)	(.091)	(.188)
GDP	-.006	-.004	-.01	.07**	.017	.087**
	(.05)	(.031)	(.08)	(.035)	(.018)	(.044)
Exports	-.035	-.018	-.054	-.029	-.007	-.036
	(.042)	(.025)	(.065)	(.025)	(.012)	(.033)
Education	-.147***	-.083**	-.23***	-.101***	-.024	-.125***
	(.029)	(.036)	(.056)	(.037)	(.024)	(.047)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. The economic spatial weight matrix is adopted. See Appendix B for variable description and data source. See Appendix D for the list of 24 bank-based financially under-developed economies and 16 bank-based financially developed economies. Estimates are based on the SDM specification which was identified as the most appropriate model and the spatial ρ (rho) for the SDM specifications remain positive and significant at 1% significance level (the model selection table is not included to conserve space but is available upon request). Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

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. Therefore, our findings remain robust regardless of whether the lagged or unlagged versions of the independent variables are employed.

7.3. An alternative credit risk measure

The third set of robustness tests involves employing capital adequacy ratio (CAR) as an alternative to banking sector credit risk. The capital adequacy ratio is a key indicator of the overall financial health and stability of the banking sector, particularly from a regulatory perspective. By enabling banks to improve credit assessment, strengthen risk management, and enhance operational efficiency

Table 14
Robustness checks: Direct, indirect and total effects - Full sample but using lagged independent variables.

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA(-1)	-.115**	-.502***	-.617***
	(.048)	(.133)	(.142)
LR(-1)	.007	.004	.011
	(.012)	(.009)	(.021)
ROE(-1)	-.127***	-.279***	-.406***
	(.021)	(.087)	(.094)
NIM(-1)	.19**	.131**	.321**
	(.08)	(.064)	(.139)
GDP(-1)	-.156***	.283***	.127**
	(.035)	(.062)	(.056)
Exports(-1)	-.001	-.001	-.002
	(.008)	(.006)	(.014)
Education(-1)	-.063***	-.044***	-.107***
	(.011)	(.014)	(.023)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. All independent variables enter a one-year lag indicated by (-1). See Appendix B for variable description and data source. Full sample means all 63 countries (see Appendix A) are included. Estimates are based on the SDM specification which was identified as the most appropriate model; distance decay weight matrix is adopted as in the main results; and the spatial ρ (rho) for the SDM specifications remain positive and significant at 1% significance level (the model selection table is not included to conserve space but is available upon request). Compared to the sample period of 2013–2021 in the main results in Table 6, as we employ one year lagged independent variables, we collect data for the dependent variable NPL for year 2022 and use NPL's sample period of 2014–2022, whilst the data for independent variables (LFIA and control variables) remain at 2013–2021, so we achieve using lagged independent variables without losing any number of observations. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

(Ndwiga, 2020; Cheng and Qu, 2020; Jakšič and Marinč, 2019), FinTech development can reduce risk-weighted assets and thereby strengthen banks' capital buffers. Higher CAR correspond to better financial resilience, as banks possess a larger buffer to absorb potential losses, and *vice versa* (Berger and Bouwman, 2013; Demirguc-Kunt et al., 2013). Deterioration in credit risk can erode bank profitability and, ultimately, weaken capital positions. Accordingly, examining FinTech's impact on the capital adequacy ratio offers valuable insights into its broader implications for the stability and soundness of the banking sector. We adopt the risk-based capital requirements for credit risk (Bank for International Settlements., 2025), which capture a bank's capital adequacy relative to its risk-weighted assets.

Replacing the NPL ratio with the risk-based capital adequacy ratio, we re-estimate the SDM, SAR, SEM and SAC specifications for (i)

Table 15
Robustness checks: Direct, indirect and total effects - Bank-based economies but using lagged independent variables.

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA(-1)	-.142**	-.369**	-.51***
	(.061)	(.146)	(.153)
LR(-1)	.001	.082**	.082*
	(.015)	(.041)	(.046)
ROE(-1)	-.112***	-.063**	-.175***
	(.027)	(.025)	(.047)
NIM(-1)	.17	1.21***	1.381***
	(.108)	(.467)	(.502)
GDP(-1)	-.125***	.202***	.077
	(.043)	(.065)	(.06)
Exports(-1)	-.037	-.02	-.057
	(.025)	(.015)	(.04)
Education(-1)	-.121***	.028	-.093
	(.02)	(.056)	(.065)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. All independent variables enter a one-year lag indicated by (-1). See Appendix B for variable description and data source. See Appendix D for the list of 40 bank-based economies. Only results for bank-based economies are included as LFIA in the case of market-based economies is insignificant across all spatial model specifications. Estimates are based on the SDM specification which was identified as the most appropriate model; distance decay weight matrix is adopted as in the main results; and the spatial ρ (rho) for the SDM specifications remain positive and significant at 1% significance level (the model selection table is not included to conserve space but is available upon request). Compared to the sample period of 2013–2021 in the main results in Table 8, as we employ one year lagged independent variables, we collect data for the dependent variable NPL for year 2022 and use NPL's sample period of 2014–2022, whilst the data for independent variables (LFIA and control variables) remain at 2013–2021, so we achieve using lagged independent variables without losing any number of observations. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

the full sample, (ii) bank-based vs market-based economies, and (iii) bank-based financially underdeveloped vs bank-based financially developed economies. In all cases, the SDM continue to emerge as the most appropriate model, with the spatial ρ remaining positive and statistically significant at 1% level. This confirms the validity and necessity of employing spatial models (To conserve space, these results are not presented here but are available upon request). The subsequent estimates of the direct, indirect and total effects for the three cases are summarised in Table 17–19, respectively

Compared with the main results in Table 6, which employ the NPL ratio, the coefficients of LFIA in Table 17 remain significant at least at 10% level across the direct, indirect and total effects. Note that as a higher risk-based capital ratio signifies stronger ability to absorb losses and to meet financial obligations, the positive coefficients of LFIA in Table 17 indicate that FinTech contributes to the overall soundness and stability of the banking sector. This finding aligns with our earlier result in Table 6, which shows that FinTech reduces banks' credit risk (addressing *Q1*) As previously discussed, FinTech's "bottom fishing" strategy may lead banks to acquire less risky customers (Cornaggia et al., 2018; De Roure et al., 2022), thereby reducing their risk-weighted assets. In addition, this capital enhancing effect may stem from FinTech's ability to improve credit risk assessment and management (Fuster et al., 2019; Tan et al., 2024), its role in facilitating more efficient equity financing (Vismara, 2022), and its technological spillovers to banks (Shen and Guo, 2015), which can transform business models (Drasch et al., 2018) and enhance profitability (Tong and Yang, 2025), thereby strengthening banks' capital positions.

In Table 18, we focus on bank-based economies. Although the direct effect is statistically insignificant, the indirect effect is positive and significant (at the 1% level), resulting in a strong positive total effect. This suggests that FinTech makes a positive contribution to the improvement of banks' capital adequacy ratios in bank-based markets, thereby enhancing their resilience. Although not shown here for brevity, a similar pattern of direct, indirect and total effects is observed for market-based economies, but with smaller size of the effect. These results corroborate the conclusion in Section 6.1 (Table 8)—that FinTech reduces bank credit risk more substantially in bank-based economies (*Q2*)— which may, in turn, reduce risk-weighted assets and increase profitability, both of which contribute to higher capital adequacy ratios. Collectively, these findings underscore the importance of considering financial system structure when assessing FinTech's impact on the banking sector.

Table 19 further demonstrates that the contribution of FinTech to the capital adequacy ratio is more pronounced in financially underdeveloped bank-based economies. This finding reinforces the result reported in Section 6.2 (Table 10), which indicates that banks in financially underdeveloped markets benefit more from FinTech in mitigating credit risk compared with those in more developed markets. Consequently, banks in such economies are likely to experience a reduction in risky assets. Moreover, technological spillovers from FinTech are expected to generate larger positive marginal effects in less developed financial systems by enabling cost savings and profit growth, thereby strengthening these banks' capital bases.

Furthermore, the consistently significant (at the 1% level) coefficients of the indirect effects across Tables 17-19, together with the significant spatial ρ, provide strong evidence of spatial dependence, thereby confirming the relevance of spatial interactions highlighted in *Q3*.

7.4. Country classification

For the fourth set of robustness checks, as explained in Section 5.1, some European economies including Austria and Luxembourg are categorised as financially 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. Starting with spatial model section, the SDM continue to be the most appropriate model, and the spatial ρ remaining positive and statistically significant at 1% level. To conserve space, the module selection results tables are not included in the paper (but they are available upon request). The subsequent estimates of the direct, indirect and total effects are summarised in the left panel of Table 20. We found that compared to results in the left panel in Table 10 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. The direct, indirect and total effects are reported in the right panel of Table 20. Again, the results are very similar to ones in the right panel in Table 10 when these two countries were not included.

Therefore, these two countries do not seem to alter the conclusions of this paper. And as such, the above three sets of robustness check firmly support the main results in Sections 5 and 6.

7.5. Additional robustness checks

In the fifth set of robustness checks, we replace NPL, which reflects bank credit risk, with the broader Z-score that captures stability of the banking sector and Sovereign CDS spreads that represent country risk. We also employ scaled measures in which the FinTech investment is divided by GDP and total bank assets.

The original Z-score is transformed using $-1*\ln(1+Z)$ to address the skewed distribution and the presence of zero values. A minus sign is added so that a higher/lower value indicates higher/lower bank risk. Overall, the results indicate an absence of FinTech's impact on the transformed Z-score, with the only exception of bank-based economies where only the indirect and total effects are significant (the results are not presented here for brevity but are available upon request). One possible explanation is that NPLs and the Z-score capture different dimensions of banking sector risk. NPL measures the share of impaired loans, providing a direct indicator of asset quality and credit risk, which motivates its use as the primary measure in this study. In contrast, the Z-score reflects the overall

Table 16
Robustness checks: Direct, indirect and total effects - Bank-based financially underdeveloped vs Bank-based financially developed economies with lagged independent variables.

	(1)	(2)	(3)	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
LFIA(-1)	-.244***	-.117**	-.361***	-.138*	-.046	-.185*
	(.087)	(.056)	(.134)	(.071)	(.03)	(.096)
LR(-1)	-.003	-.001	-.004	.016	.005	.021
	(.022)	(.011)	(.033)	(.015)	(.005)	(.019)
ROE(-1)	-.135***	-.066**	-.201***	-.009	-.003	-.013
	(.037)	(.029)	(.062)	(.034)	(.013)	(.046)
NIM(-1)	.122	1.416***	1.538***	.038	.015	.053
	(.147)	(.444)	(.492)	(.153)	(.057)	(.207)
GDP(-1)	-.134**	.193**	.059	-.133**	.166**	.033
	(.055)	(.086)	(.085)	(.066)	(.074)	(.057)
Exports(-1)	-.037	-.016	-.053	-.012	-.004	-.016
	(.038)	(.02)	(.056)	(.01)	(.004)	(.013)
Education(-1)	-.129***	-.063**	-.192***	-.073***	-.025**	-.097***
	(.027)	(.026)	(.047)	(.02)	(.011)	(.028)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. All independent variables enter a one-year lag indicated by (-1). See Appendix B for variable description and data source. See Appendix D for the list of 24 bank-based financially under-developed economies and 16 bank-based financially developed economies. Estimates are based on the SDM specification which was identified as the most appropriate model; distance decay weight matrix is adopted as in the main results; and the spatial ρ (rho) for the SDM specifications remain positive and significant at 1% significance level (the model selection table is not included to conserve space but is available upon request). Compared to the sample period of 2013–2021 in the main results in Table 10, as we employ one year lagged independent variables, we collect data for the dependent variable NPL for year 2022 and use NPL's sample period of 2014–2022, whilst the data for independent variables (LFIA and control variables) remain at 2013–2021, so we achieve using lagged independent variables without losing any number of observations. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Table 17
Robustness checks: Capital adequacy ratio as the alternative dependent variable to NPL: Direct, indirect and total effects – Full sample.

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA	.069*	.583***	.652***
	(.042)	(.112)	(.113)
LR	.026**	-.106***	-.08**
	(.012)	(.036)	(.039)
ROE	-.053***	-.035**	-.088***
	(.019)	(.015)	(.032)
NIM	.244***	.163**	.406***
	(.076)	(.067)	(.136)
GDP	-.023	-.015	-.038
	(.021)	(.014)	(.035)
Exports	.041**	.027**	.067**
	(.018)	(.014)	(.031)
Education	.026**	.017**	.043**
	(.013)	(.009)	(.02)

Note: Dependent variable: Capital adequacy ratio (ratio of total regulatory capital to its risk weighted assets) instead of the NPL ratio. See Appendix B for variable description and data source. Full sample means all 63 countries (see Appendix A) are included. Estimates are based on the SDM specification which was identified as the most appropriate model; distance decay weight matrix is adopted as in the main results; and the spatial ρ (rho) for the SDM specifications remain positive and significant at 1% significance level (the model selection table is not included to conserve space but is available upon request). Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

probability of banking system default by combining capitalisation, returns, and their volatility, and is therefore widely interpreted as a measure of broader financial stability (e.g., Beck et al., 2013; Ferreira, 2023; Cevik, 2024). This distinction is also supported by the weak negative correlation between the two variables in our sample (−0.1035). The missing FinTech-Z score link is consistent with literature highlighting credit risk as the most responsive dimension to FinTech (Jiménez et al., 2013; Berger et al., 2017; Cuestas et al., 2020; Moudud-Ul-Huq, 2021; Adu, 2022) and with Cevik (2024), who finds no significant effect of FinTech on Z-scores.

We also employ 5-year sovereign CDS spread data (*SCDS*), a measure for country risk (Debarsy et al., 2018; Heinz and Sun, 2014; Galariotis, et al., 2016; Raimbourg and Salvadè, 2021) as an alternative dependent variable. The 5-year CDS spread is chosen due to its high liquidity and heavy trading volumes relative to spreads with other term structure (Mihai and Neagu, 2011; Pan and Singleton, 2008). We find that, overall, FinTech reduces the spreads (including for market-based economies) except in the case of bank-based

Table 18
Robustness checks: Capital adequacy ratio as the alternative dependent variable to NPL: Direct, indirect and total effects – Bank-based economies.

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA	.071	.617***	.688***
	(.047)	(.096)	(.095)
LR	.007	-.145***	-.138***
	(.011)	(.027)	(.029)
ROE	-.046**	-.012	-.059**
	(.021)	(.008)	(.027)
NIM	.299***	.08*	.379***
	(.084)	(.042)	(.115)
GDP	.032	-.098**	-.065*
	(.034)	(.047)	(.038)
Exports	0	0	0
	(.02)	(.006)	(.025)
Education	.062***	.197***	.259***
	(.015)	(.033)	(.037)

Note: Dependent variable: Capital adequacy ratio (ratio of total regulatory capital to its risk weighted assets) instead of the NPL ratio. See Appendix B for variable description and data source. See Appendix D for the list of 40 bank-based economies. Only results for bank-based economies are included as LFIA in the case of market-based economies is insignificant across all spatial model specifications. Estimates are based on the SDM specification which was identified as the most appropriate model; distance decay weight matrix is adopted as in the main results; and the spatial ρ (rho) for the SDM specifications remain positive and significant at 1% significance level (the model selection table is not included to conserve space but is available upon request). Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Table 19
Robustness check: Capital adequacy ratio as the alternative dependent variable to NPL: Direct, indirect and total effects – Bank-based financially underdeveloped vs Bank-based financially developed economies.

	Bank-based financially underdeveloped economies			Bank-based financially developed economies		
	(1)	(2)	(3)	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
LFIA	.065	.62***	.685***	.203***	.102***	.305***
	(.065)	(.123)	(.129)	(.06)	(.035)	(.089)
LR	.002	-.125***	-.123***	.001	-.194***	-.193***
	(.017)	(.041)	(.048)	(.013)	(.027)	(.032)
ROE	-.023	-.006	-.029	-.072**	-.037**	-.11**
	(.028)	(.008)	(.035)	(.029)	(.019)	(.046)
NIM	.216*	.056	.273*	.213*	.11	.323*
	(.112)	(.043)	(.147)	(.126)	(.073)	(.195)
GDP	.053	-.171***	-.117**	.003	.001	.004
	(.044)	(.063)	(.053)	(.032)	(.017)	(.049)
Exports	.056**	.014	.07*	-.059**	-.03**	-.089**
	(.029)	(.011)	(.037)	(.023)	(.015)	(.036)
Education	.049**	.195***	.244***	.198***	.1***	.298***
	(.02)	(.045)	(.054)	(.033)	(.024)	(.045)

Note: Dependent variable: Capital adequacy ratio (ratio of total regulatory capital to its risk weighted assets) instead of the NPL ratio. See Appendix B for variable description and data source. See Appendix D for the list of 24 bank-based financially under-developed economies and 16 bank-based financially developed economies. Estimates are based on the SDM specification which was identified as the most appropriate model; distance decay weight matrix is adopted as in the main results; and the spatial ρ (rho) for the SDM specifications remain positive and significant at 1% significance level (the model selection table is not included to conserve space but is available upon request). Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

financial underdeveloped economies. This could be due to that country risk in financially underdeveloped economies is more strongly driven by global and regional risk premia rather than domestic economic and political factors (Fender et al., 2012; Pan et al., 2024), limiting the extent to which domestic FinTech developments can exerts its influence. As sovereign CDS spreads capture broader macro-financial conditions rather than bank-specific risk alone, in market-based systems where banks, capital markets, and other financial institutions all play important roles, the impact of FinTech is likely to extend beyond the banking sector, affecting overall financial conditions and, consequently, sovereign risk perceptions. These findings confirm the risk-mitigation effect of FinTech,

Table 20
Robustness checks: Direct, indirect and total effects - Bank-based financially underdeveloped (Austria and Luxembourg removed) vs Bank-based financially developed economies (Austria and Luxembourg added).

	Bank-based financially underdeveloped (Austria and Luxembourg removed)			Bank-based financially developed economies (Austria and Luxembourg added)		
	(1) Direct effects	(2) Indirect effects	(3) Total effects	(1) Direct effects	(2) Indirect effects	(3) Total effects
LFIA	-.257**	-.827***	-1.084***	-.161***	.011	-.15**
	(.101)	(.261)	(.303)	(.061)	(.015)	(.059)
LR	.087***	.062**	.149***	.001	0	.001
	(.029)	(.029)	(.055)	(.011)	(.001)	(.01)
ROE	-.181***	-.128***	-.308***	-.053*	.004	-.05*
	(.043)	(.046)	(.082)	(.031)	(.005)	(.03)
NIM	.036	.023	.059	.151	-.01	.142
	(.152)	(.113)	(.263)	(.142)	(.02)	(.133)
GDP	-.071	-.051	-.122	.018	-.001	.017
	(.051)	(.041)	(.089)	(.034)	(.004)	(.032)
Exports	-.003	.279***	.277***	-.012*	.001	-.011
	(.02)	(.074)	(.079)	(.007)	(.001)	(.007)
Education	-.153***	-.109***	-.262***	-.073***	-.04	-.113***
	(.025)	(.036)	(.056)	(.02)	(.029)	(.03)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. See Appendix B for variable description and data source. See Appendix D for the list of 24 bank-based financially under-developed economies and 16 bank-based financially developed economies. However, estimates in this Table is based on that Austria and Luxembourg are excluded from the left panel (bank-based financially under-developed economies) and these two countries are moved to be included the right panel (bank-based financially developed economies) to see if the results remain consistent with the main results in Table 10. Estimates are based on the SDM specification which was identified as the most appropriate model; distance decay weight matrix is adopted as in the main results; and the spatial ρ (rho) for the SDM specifications remain positive and significant at 1% significance level (the model selection table is not included to conserve space but is available upon request). Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

although from a more broader country risk perspective.[7]

As discussed in Section 3.2, we employ *LFIA* (log of FinTech investment) to capture the dynamic link between credit risk and FinTech growth. Using the alternative scaled measures: the ratio of FinTech investment to GDP (*FIAgdp*) and to total bank assets (*FIAba*), we find they have negative and significant indirect and total effects on credit risk for the full sample (for both *FIAgdp* and *FIAba*) and bank-based economies (for *FIAgdp* only), although these effects are considerably smaller in magnitude (i.e., less negative coefficients) than those obtained using *LFIA*, and both alternative measures become insignificant for bank-based underdeveloped and developed sub-samples, as well as for market-based economies. The results are reported in Appendix H for the ratio of FinTech investment to GDP (*FIAgdp*) and in Appendix I for the ratio of FinTech investment to total bank assets (*FIAba*). This likely reflects the small scale of FinTech—around 0.1% of GDP and around 0.1% of bank assets in our sample countries—limiting level-based measures, as also noted by Cevik (2024). However, despite its relatively small size, FinTech exerts a substantial impact on the financial sector due to its rapid growth and disproportionately strong effect on bank competition and lending behaviour (Thakor, 2020; Feyen et al., 2021). Compared to these two scaled measures, our main measure, *LFIA*, which embodies the relationship between changes in credit risk and FinTech investment growth, is shown to be more effective in capturing such effects.

8. Conclusions and policy implications

In this paper, we examine the relationship between FinTech and bank credit risk in 63 countries during the period 2013–2021 (*Q1*). We differentiate between bank-based and market-based financial systems *(Q2)*, as the structural differences between these two systems (i.e., banks' centrality, regulatory intensity and perimeter on banks, and the level of information asymmetry) may affect this relationship. Our analysis accounts for spatial dependence in bank credit risk across countries by utilising various spatial models *(Q3)*. We adopt a novel measure based on FinTech investment activities from PitchBook to directly capture FinTech development.

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. This supports the prevalence of the "technology spillover" hypothesis and the "bottom fishing" over the "competition-fragility" hypothesis. 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

[7] While these findings are informative, sovereign CDS spread measures is more closely aligned with sovereign (country) default risk rather than the credit risk of the banking sector and therefore analysing it fully would require a broader framework beyond the scope of this paper, suggesting a promising avenue for future research.

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 robustness checks confirm the findings above and show that, given the still generally small amount of FinTech investment (albeit fast growing) relative to the size of the real economy and the banking sector in the respective countries, it is the dynamics of these investments, rather than their relative size, that drive these results.

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 mitigates 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 systemic risk within the financial system.

While the proper oversight of embedding new FinTech in the banking sector – including monitoring credit risk with a potential broadening of the supervisory scope – is important in bank-based financial systems, in market-based system the regulatory oversight is naturally also more focused on non-bank players. It is therefore crucial to foster innovation and competition among new non-bank players to manage potential systemic risks arising from the interconnectedness of capital markets and to promote operational resilience of the financial system (Bats and Houben, 2020; World Bank, 2022).

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 advantages 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.

CRediT authorship contribution statement

Kefei You: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Barbara Koranteng:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ján Klacso:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of Competing interest

Manuscript title: FinTech Development and Bank Credit Risk: Spatial Spillovers and the Role of Financial System Structures

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Appendix A. List of countries

The 63 countries included in this paper are: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Czech Republic, Denmark, Egypt, Estonia, Finland, France, 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, Slovenia, 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

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Variables	Symbols	Description	Expected Sign	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: FinTech Investment Activities	*LFIA*	Private equity, venture deals and M&A investments in FinTech firms. It is in natural logarithm.	-	PitchBook Data

Control Variables

	Variables	Symbols	Description	Expected Sign	Data Source	Supporting Literature
Bank specific factors	Liquidity	*LR*	The ratio of bank liquid reserves to bank total assets for the banking sector of a country (%)	-	The World Bank (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 for the banking sector of a country (%)	+/-	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 for the banking sector of a country (%)	+/-	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*	Global exports of goods and services as percentage of total world GDP (%)	-	WB	Besedeš, Kim, and Lugovskyy (2014); Clichici, and Colesnicova (2014); Mileris (2014); Koju, Koju, and Wang (2020)

Variable for Robustness check	Symbol	Description	Data Source
An alternative dependent variable: Capital adequacy ratio	*CAR*	It is a ratio of total regulatory capital to its assets held, weighted according to risk of those assets.	World Bank Database
A broader bank risk measure: the transformed Z-score	*Z* – score	It is $-1*\ln(1+Z)$ where Z is the original Z-score data collected from the World Bank.	World Bank Database
A broader country risk measure: Sovereign Credit Default Spread (CDS)	*SCDS*	5-year Sovereign Credit Default Spread (CDS)	Bloomberg
A scaled measure of FinTech: scaled by GDP	*FIAgdp*	FinTech Investment Activities divided by nominal GDP of a country	World Bank Database
A scaled measure of FinTech: scaled by total bank assets	*FIAba*	FinTech Investment Activities divided by total bank assets of a country	World Bank Database

Note: According to the World Bank, Liquidity Ratio (LR): Ratio of bank liquid reserves to bank assets is the ratio of domestic currency holdings and deposits with the monetary authorities to claims on other governments, nonfinancial public enterprises, the private sector, and other banking institutions; Profitability (ROE): Return on Equity: Commercial banks' after-tax net income to yearly averaged equity. Numerator and denominator are aggregated on the country level before division; Efficiency (NIM): Net Interest Margin: Accounting value of bank's net interest revenue as a share of its average interest-bearing (total earning) assets. Numerator and denominator are aggregated on the country level before division.

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

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(*continued*)

	Variables	Description	Data Source
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 4.1 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

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Financially underdeveloped economies		Financially developed economies	
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 4.1 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 et al., 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

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 Eq. (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 2.3) 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* shows 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 also 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.

Appendix G. Direct, indirect and total effects employing both country and time fixed effects

While the main results employ country-fixed effects (including the world exports variable), here we also report the results for the direct, indirect, and total effects when employing both country and time fixed effects, with the country-invariant world exports variable omitted. Table G1 below presents the results for the full sample, Table G2 for bank-based economies, and Table G3 for market-based economies.

Across all three tables, LFIA retains a negative sign for the full sample (Table G1) and the bank-based economies sample (Table G2), but the coefficient is insignificant in all three Tables across direct, indirect and total effects. These results are likely driven by common time trend in LFIA, with country and time fixed effects together explaining more than 75% of its variation and time fixed effects significantly explain the development of LFIA throughout the whole period (see Table G4 below). In contrast, this common trend is less pronounced in the NPL series, at least over the 2014–2017 period. As such, given the strong increase in FinTech development across countries over the sample period, the including of time fixed effects may absorb part of this common variation, contributing to the loss of statistical significance in its estimated relationship with bank credit risk. In other words, time fixed effects may remove some of the economically relevant variation in FinTech development. Since this study intends to analyse the relationship between FinTech development and bank credit risk over time, we focus on the findings from the main specification that accounts for country fixed effects, while also recognising the importance of considering both country and time fixed effects and acknowledging the variation in the results when time fixed effects are included.

Table G1
Direct, indirect and total effects: Full sample with country and time fixed effects

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA	-.048	-.028	-.077
	(.054)	(.033)	(.086)
LR	.007	.004	.011
	(.014)	(.009)	(.022)
ROE	-.186***	-.315***	-.5***
	(.023)	(.09)	(.101)
NIM	.207**	.12**	.328**
	(.092)	(.06)	(.146)
GDP	-.157***	-.093***	-.249***
	(.037)	(.034)	(.065)
Education	-.066***	-.039***	-.104***
	(.015)	(.014)	(.026)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. Distance decay weight matrix is adopted. See Appendix B for variable description and data source. Full sample means all 63 countries (see Appendix A) are included. SDM is used as it is the best specification. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively. The global factor (i.e., the country-invariant world exports) is omitted when time fixed effects are included.

Table G2
Direct, indirect and total effects: Bank-based sample with country and time fixed effects

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA	-.101	-.043	-.144
	(.071)	(.034)	(.103)
LR	.012	.103**	.115**
	(.016)	(.045)	(.051)
ROE	-.171***	-.073***	-.245***
	(.03)	(.026)	(.048)
NIM	.142	.059	.201
	(.119)	(.054)	(.17)
GDP	-.136***	-.059**	-.194**
	(.051)	(.029)	(.077)
Education	-.115***	-.049***	-.164***
	(.022)	(.017)	(.034)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. Distance decay weight matrix is adopted. See Appendix B for variable description and data source. See Appendix D for the list of 40 bank-based economies. SDM is used as it is the best specification. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively. The global factor (i.e., the country-invariant world exports) is omitted when time fixed effects are included.

Table G3
Direct, indirect and total effects: Market-based sample with country and time fixed effects

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA	.061	-.003	.058
	(.077)	(.012)	(.073)
LR	.024	-.001	.023
	(.035)	(.005)	(.034)
ROE	-.159***	.007	-.152***
	(.031)	(.018)	(.035)
NIM	.221	-.012	.209
	(.138)	(.027)	(.131)
GDP	-.082	-.193*	-.276**
	(.051)	(.117)	(.122)
Education	-.01	0	-.009
	(.018)	(.002)	(.018)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. Distance decay weight matrix is adopted. See Appendix B for variable description and data source. See Appendix D for the list of 23 market-based economies. SDM is used as it is the best specification. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively. The global factor (i.e., the country-invariant world exports) is omitted when time fixed effects are included.

Table G4
Further information

	LFIA Time Fixed Effects	NPL Time Fixed Effects
(Intercept)	14.796***	3.700***
	p = <0.001	p = <0.001
Year2014	0.700*	-0.231
	p = 0.012	p = 0.559
Year2015	1.092***	-0.329
	p = <0.001	p = 0.404
Year2016	1.099***	-0.323
	p = <0.001	p = 0.413
Year2017	1.344***	-0.627
	p = <0.001	p = 0.113
Year2018	1.878***	-1.082**
	p = <0.001	p = 0.006
Year2019	2.392***	-1.356***
	p = <0.001	p = <0.001
Year2020	2.025***	-1.439***
	p = <0.001	p = <0.001
Year2021	2.980***	-1.779***
	p = <0.001	p = <0.001
Country fixed effects	Yes	Yes
Obs.	567	567
R^2	0.786	0.725
R^2 Adj.	0.756	0.687

Appendix H. Direct, indirect and total effects estimated using the ratio of FinTech investment to GDP (*FIAgdp*) as the explanatory variable for each country

Table H1
Direct, indirect and total effects: Full sample

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
FIAgdp	0	-.023**	-.023**
	(.002)	(.009)	(.01)
LR	.02	.018	.038
	(.013)	(.013)	(.026)
ROE	-.163***	-.149***	-.312***
	(.023)	(.037)	(.054)
NIM	.236***	.215**	.451***
	(.086)	(.089)	(.169)
GDP	-.115***	.229***	.114*

(*continued on next page*)

Table H1 (*continued*)

	(1)	(2)	(3)
	(.036)	(.07)	(.065)
Exports	.001	.001	.002
	(.009)	(.009)	(.018)
Education	-.064***	-.058***	-.122***
	(.012)	(.017)	(.028)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. See Appendix B for variable description and data source. Full sample means all 63 countries (see Appendix A) are included. Estimates are based on the SDM specification which was identified as the most appropriate model (the model selection table is not included to conserve space but is available upon request). The distance decay weight matrix is adopted as in the main results. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Table H2
Direct, indirect and total effects: Bank-based economies

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
FIAgdp	.001	-.026***	-.025**
	(.006)	(.009)	(.01)
LR	-.016	0	-.016
	(.031)	(.004)	(.032)
ROE	-.146***	-.003	-.149***
	(.032)	(.018)	(.039)
NIM	.253**	.006	.258**
	(.118)	(.035)	(.127)
GDP	.006	0	.006
	(.031)	(.004)	(.032)
Exports	.008	0	.008
	(.021)	(.003)	(.022)
Education	-.022	0	-.023
	(.016)	(.003)	(.016)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. See Appendix B for variable description and data source. See Appendix D for the list of 40 bank-based economies. Only bank-based economies are included as *FIAgdp* is insignificant in the case of market-based economies. Estimates are based on the SDM specification which was identified as the most appropriate model (the model selection table is not included to conserve space but is available upon request). The distance decay weight matrix is adopted as in the main results. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Table H3
Direct, indirect and total effects: Bank-based financially underdeveloped vs Bank-based financially developed economies

	Bank-based financially underdeveloped economies			**Bank-based financially developed economies**		
	(1)	(2)	(3)	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
FIAgdp	-.002	-.001	-.004	.001	0	.001
	(.004)	(.003)	(.007)	(.003)	(.001)	(.003)
LR	.031	.113	.144	.018	.08***	.097***
	(.026)	(.077)	(.092)	(.014)	(.024)	(.029)
ROE	-.184***	-.112***	-.296***	-.071**	-.02	-.09**
	(.043)	(.042)	(.078)	(.033)	(.014)	(.044)
NIM	.028	.014	.042	.377***	.103	.48**
	(.162)	(.103)	(.262)	(.144)	(.065)	(.193)
GDP	-.11*	.192*	.082	-.054	.144**	.089*
	(.062)	(.111)	(.112)	(.063)	(.07)	(.049)
Exports	-.005	-.003	-.008	-.028	-.007	-.035
	(.017)	(.011)	(.027)	(.026)	(.009)	(.034)
Education	-.1***	-.061**	-.161***	-.143***	-.038**	-.18***
	(.026)	(.025)	(.047)	(.033)	(.017)	(.041)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. See Appendix B for variable description and data source. See Appendix D for the list of 24 bank-based financially under-developed economies and 16 bank-based financially developed economies Estimates are based on the SDM specification which was identified as the most appropriate model (the model selection table is not included to conserve space but is available upon request). The distance decay weight matrix is adopted as in the main results. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Appendix I. Direct, indirect and total effects estimated using the ratio of FinTech investment to bank assets (*FIAba*) as the explanatory variable for each country

Table I1
Direct, indirect and total effects: Full sample

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA	-.078	-2.768**	-2.846**
	(.318)	(1.2)	(1.347)
LR	.02	.019	.039
	(.013)	(.013)	(.026)
ROE	-.164***	-.151***	-.315***
	(.023)	(.038)	(.055)
NIM	.238***	.22**	.457***
	(.086)	(.09)	(.17)
GDP	-.112***	.227***	.114*
	(.036)	(.071)	(.066)
Exports	.001	.001	.001
	(.009)	(.009)	(.018)
Education	-.064***	-.059***	-.124***
	(.012)	(.018)	(.028)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. See Appendix B for variable description and data source. Full sample means all 63 countries (see Appendix A) are included. Estimates are based on the SDM specification which was identified as the most appropriate model (the model selection table is not included to conserve space but is available upon request). The distance decay weight matrix is adopted as in the main results. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Table I2
Direct, indirect and total effects: Bank-based economies

	(1)	(2)	(3)
	Direct effects	Indirect effects	Total effects
LFIA	-.181	-.123	-.304
	(.38)	(.278)	(.653)
LR	.027*	.123**	.15***
	(.016)	(.05)	(.056)
ROE	-.153***	-.11***	-.263***
	(.03)	(.035)	(.059)
NIM	.182	.129	.311
	(.114)	(.088)	(.198)
GDP	-.096**	.201**	.105
	(.047)	(.084)	(.081)
Exports	.001	0	.001
	(.011)	(.008)	(.019)
Education	-.099***	-.071***	-.171***
	(.018)	(.022)	(.035)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. See Appendix B for variable description and data source. See Appendix D for the list of 40 bank-based economies. Only bank-based economies are included as *FIAba* is insignificant in the case of market-based economies. Estimates are based on the SDM specification which was identified as the most appropriate model (the model selection table is not included to conserve space but is available upon request). The distance decay weight matrix is adopted as in the main results. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Table I3
Direct, indirect and total effects: Bank-based financially underdeveloped vs Bank-based financially developed economies

	Bank-based financially underdeveloped economies			Bank-based financially developed economies		
	(1) Direct effects	(2) Indirect effects	(3) Total effects	(1) Direct effects	(2) Indirect effects	(3) Total effects
LFIA	-.355	-.21	-.566	.188	.053	.241
	(.49)	(.31)	(.791)	(.644)	(.196)	(.826)
LR	.031	.116	.147	.017	.08***	.097***
	(.026)	(.077)	(.092)	(.014)	(.024)	(.028)
ROE	-.184***	-.112***	-.296***	-.071**	-.02	-.091**
	(.043)	(.042)	(.078)	(.033)	(.014)	(.044)
NIM	.025	.012	.037	.376***	.103	.479**
	(.162)	(.103)	(.262)	(.142)	(.065)	(.19)
GDP	-.111*	.198*	.087	-.054	.143**	.089*
	(.062)	(.112)	(.113)	(.063)	(.07)	(.049)
Exports	-.005	-.003	-.008	-.028	-.007	-.035
	(.017)	(.011)	(.027)	(.026)	(.009)	(.034)
Education	-.099***	-.061**	-.16***	-.143***	-.038**	-.181***
	(.026)	(.025)	(.046)	(.033)	(.017)	(.041)

Note: Dependent variable: Banking sector credit risk indicated by the NPL ratio. See Appendix B for variable description and data source. See Appendix D for the list of 24 bank-based financially under-developed economies and 16 bank-based financially developed economies Estimates are based on the SDM specification which was identified as the most appropriate model (the model selection table is not included to conserve space but is available upon request). The distance decay weight matrix is adopted as in the main results. Standard errors are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively.

Data Availability

Data will be made available on request.

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