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Fintech and financial stability: Evidence from spatial analysis for 25 countries

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ABSTRACT

Fintech has experienced rapid advances in recent years. This study examines the impact of Fintech on financial stability for a group of 25 countries during 2013–2020. We adopt the novel Fintech-enabled financing volume to directly measure Fintech development. We utilise both the aggregate and disaggregated level of Fintech financing; the latter includes crowdfunding, business lending and consumer lending, each has a different funding process and default rates. We account for spatial dependence in financial stability across countries by employing various spatial models. Our findings first reveal that there is positive spatial dependence of financial stability across countries. It implies that financial stability has a positive spillover to neighbouring countries and validates the necessity of spatial analysis. Second, based on the Spatial Durbin Model which best describes our data, Fintech financing makes a positive local and cross-border contribution towards financial stability, irrespective of alternative weight matrices and sample sizes. Such positive impact is more profound in countries with smaller sizes of Fintech financing volume, and the cross-border effect is stronger with closer geographic proximity. Finally, crowdfunding enhances financial stability, whilst consumer lending has a contrasting destabilising effect.

1. Introduction

The world has experienced rapid developments in financial technology (Fintech) in recent years. Whilst Fintech can support potential economic growth and poverty alleviation by strengthening financial development and inclusion, it may pose risks to consumers and investors, and more broadly, to financial stability and integrity (World Bank, 2019). Regulatory stringency on Fintech is vital in protecting consumers and investors against financial misconduct and crime (e.g., fraud, tax evasion, money laundering, etc.), yet regulators must beware of not stifling financial innovation that responsibly and sustainably benefits the public (Lagarde, 2018). Notwithstanding the intense discussions by regulators, investors and researchers on the possible mechanisms between the proliferation of Fintech and the maintenance of financial stability (see details in Section 2.1), analysis empirically examining the impact of macro-level Fintech-enabled financing on financial stability is sparse (see discussion in Sections 2.2 and 2.3). Understanding the nature and magnitude of how Fintech financing influences financial stability would be an important input in determining regulators' attitude towards Fintech and investors' decision on asset allocation.

Against this backdrop, our study examines the macro-level relationship between Fintech and financial stability in the context of a group of 25 countries from 2013 to 2020. We first adopt the Fintech-enabled financing volume as a direct measure of Fintech development. We then further utilise the disaggregate levels of Fintech financing, namely crowdfunding, business lending and

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consumer lending, acknowledging their distinct funding process and default rates. We consider spatial dependence in financial stability across countries by employing various spatial models.

Our findings reveal positive spatial dependence of financial stability across countries, indicating that financial stability has a positive spillover effect on neighbouring countries. More importantly, based on the Spatial Durbin Model which best describes our data, our results show Fintech-enabled financing makes a positive local and cross-border contribution towards financial stability, regardless of alternative weight matrices and sample sizes. Such positive impact is more profound in countries with smaller sizes of Fintech financing volume. Finally, for the three main components of the aggregate Fintech-enabled financing, crowdfunding enhances financial stability, business lending also strengthens financial stability but only when the three Fintech financing leaders China, US and UK are excluded, whilst consumer lending has a contrasting destabilising effect.

This paper contributes to the existing literature in three key aspects. First, we account for spatial dependence in our analysis. Financial integration and increased global interconnectedness have led to amplified transmission of excess financial volatility through international capital flows (Tonzer, 2015; Agénor and Pereira da Silva, 2018). As a result, the financial stability of one economy is likely to be influenced by that of other economies. Thus, we employ several alternative spatial models to consider the spatial spillover effects in financial stability across countries. Second, we adopt a novel Fintech-enabled financing volume from the Cambridge Centre for Alternative Finance (CCAF) to directly gauge Fintech development. Benefitting from its extensive follow-up hand-collection procedure and wide coverage of Fintech platforms, this measure not only captures more accurately the actual size of Fintech-enabled financing volume for each country, but also offers a global dataset that is consistent and comparable (see discussion in Section 3.1 and Table 1). These two distinctive advantages render it a preferred measure in comparison to, for instance, the Google Fintech keyword search approach (e.g., Daud et al., 2022). The latter primarily captures online attention directed towards Fintech, rather than quantifying the actual volume of Fintech lending or investment; and Google's usage and popularity exhibit noticeable variations across different countries, introducing potential biases in the analysis. This is also the first time this unique set of data is adopted to examine the impact of Fintech on financial stability. Third, motivated by the different lending processes and, more importantly, distinct default rates associated with the three principal components of the Fintech financing volume, namely crowdfunding, business lending and consumer lending (Pierrakis and Collins, 2013; Chishti, 2016; Mollick and Robb, 2016; Schwartz, 2018; Wang et al., 2019), we conduct a disaggregated level analysis focusing on these constituents to evaluate to what extent these specific characteristics on lending process and default rate may translate to varied influence on financial stability. The findings would provide valuable insights into the necessity for policymakers to formulate tailored approaches and regulations corresponding to each component of Fintech lending. This aspect, however, has been hitherto overlooked in prior research endeavours.

The rest of the paper is organised as follows. Section 2 reviews the relevant literature and discusses our contributions in more detail. Section 3 describes the data. Section 4 outlines the spatial models. Sections 5 and 6 present empirical results using aggregate and

Table 1
Number of Fintech financing platforms included in CCAF (2013–2020).

Country	2013	2014	2015	2016	2017	2018	2019	2020
Argentina	5	7	8	13	17	21	21	22
Australia	11	19	27	36	37	41	38	38
Belgium	5	7	8	8	8	8	8	8
Brazil	11	16	26	34	43	47	49	51
Chile	1	4	4	7	7	7	8	8
China	24	68	87	95	98	99	100	102
Canada	12	15	22	24	25	26	26	26
Finland	4	5	5	5	5	5	5	5
France	25	37	46	50	50	50	51	54
Germany	21	27	33	39	41	43	43	45
India	28	43	77	130	170	193	213	240
Indonesia	2	5	13	26	34	51	59	62
Ireland	3	6	6	6	7	9	9	10
Israel	5	7	8	9	9	10	10	9
Mexico	11	18	30	41	44	49	51	58
Netherlands	12	15	18	23	25	27	28	28
Nigeria	1	1	3	5	9	12	15	21
Poland	1	2	3	3	4	5	5	5
Singapore	8	13	21	32	37	41	51	52
South Africa	5	8	10	11	13	14	14	13
South Korea	6	8	11	15	18	19	19	19
Spain	18	26	29	33	35	37	38	38
Sweden	5	6	9	10	11	12	12	13
United Kingdom	61	88	111	140	157	172	176	185
United States	131	182	220	245	255	267	278	286
Sum of the 25 sample countries	416	633	835	1040	1159	1265	1327	1398
Sum globally	508	766	1017	1268	1432	1592	1683	1771

Note: CCAF denotes Cambridge Centre for Alternative Finances. Data in the table is collected from the Cambridge Fintech Ecosystem Atlas, available at:
https://ccaf.io/atlas/visualisation/graph?country_field=op_hq&country=IN&segments=TMD3ALoYPC,WLS8F4XDuu&year=2019.

disaggregate Fintech financing, respectively. Section 7 concludes and discusses policy implications.

2. Literature review

2.1. How Fintech may influence financial stability

The exponential growth of Fintech has changed the economic and financial landscape. These changes come with benefits to the financial system and increased market efficiency but also a plethora of risk exposures (Wagner, 2005; Chan-Lau, 2008). Whether Fintech destabilises the financial markets or enforces its stability is an issue that has attracted the attention of researchers, regulators and investors.

Many studies have posited the positive implications Fintech could introduce to financial stability through various channels. Aided by its diversity in operations and business models, Fintech promotes diversification and decentralisation of financial products and services, which mitigates the financial shocks arising from the failure of any individual financial institution (Financial Stability Board (FSB), 2017). Specifically, through increased bundling and specialisation of financial services into singular, specific and more efficient services, Fintech introduces increased market fragmentation and a scattered pool of many providers (Zalan and Toufaily, 2017; Nicoletti, 2017). This encourages diversification of risks across a wider spectrum and weakens risk correlations in the financial system, ensuring that the financial system does not suffer jeopardy of risk emanating from any particular institution (Gomber et al., 2017; Zetzsche et al., 2020). Another mechanism where Fintech enhances financial stability is by serving the financial system with efficiency and welfare benefits through speedy, innovative and less costly products and services. The widening accessibility to technological tools especially mobile phones has made financial service more convenient, encouraging the growth of open banking. The expeditious dissemination of information over multiple channels may yield advantages in fostering a more efficient capital market that reflects market information more accurately. This is anticipated to enhance capital allocation by diminishing overall search and transaction costs with superior and inclusive screening methods and thus offers a broader array of opportunities to investors and borrowers (Carney, 2017). In addition, given that information asymmetry significantly contributes to financial market failures and crashes, Fintech serves to reduce transaction costs, refine risk pricing, and advance data processing capabilities. This, in turn, mitigates information asymmetry and facilitates quick and fast-paced service provision (Gomber et al., 2018; Philippon, 2016; Omarova, 2018). As financial markets rely on greater efficiency and minimal information asymmetry for optimal operation, Fintech exerts a positive force for financial stability to thrive. From the view of the central banks, Fintech settlement processes with distributed ledger systems provide validity to actual funds and reserves of financial institutions, helping central banks to accurately track the health of institutions and detect fictitious off-balance sheet dealings (Milne, 2016).

On the other hand, the presence and continuous expansion of Fintech may exacerbate already existing financial risk or perhaps generate new risk exposures that adversely affect financial stability (Carney, 2017). Flawed with the need to reduce transaction costs as much as possible to attract customers, Fintech may be assigning low prices to high-risk projects, escalating the frequency of high-risk activities and ultimately leading to intensified incidences of defaults in the financial market (Philippon, 2016; Omarova, 2018). Elevated maturity mismatching stemming from suboptimal practices in alternative lending may engender significant credit shocks across the broader market, especially when heightened default rates impact the books of credit providers and market confidence (Classens et al., 2017). Regulatory risk is greater when Fintech activities are evolving at a fast pace and the legal and regulatory frameworks cannot adapt, or when Fintech platforms seek regulatory arbitrage as they are typically not subject to the same level of regulation as banks (FSB, 2017; Huang and Wang, 2023). Greater use of technology and digital solutions expand the range and number of entry points cyber hackers might target (Vučinić and Luburić, 2022). The underlying deficiencies of certain financial products (e.g., regulatory ambiguities that facilitate criminal activities and money laundering) can also make them highly speculative (OECD, 2020). Additionally, Fintech may further contribute to increased financial interconnectedness, pro-cyclicality and contagion that introduce excessive risk exposures (Lai, and Van Order, 2017; Xiang et al., 2017). This phenomenon is attributable to the pervasive integration of Fintech into the mainstream financial industry, amplifying both direct and indirect counterparty risk transmission factors (Vives, 2017). The accelerated expansion and daily reliance on Fintech services further elevate the interconnections between Fintech and financial markets (Arner et al., 2015; Chen et al., 2020). As pointed out by Navaretti et al. (2017), Fintech has the potential to disrupt the existing structure of the financial industry by blurring its boundaries and fostering strategic disintermediation. This exposes the financial system to increased interconnections and financial network complexities (Caccioli et al., 2014; Acemoglu et al., 2015). It can further spark contagion effects for other peripheral firms connected to the network (Billio and Caporin, 2010; Zhang et al., 2020). For instance, with the very few Fintech providers having massive access to a wealth of client data and financial information, incidents of cyber-attacks and data breaches could trigger significant contagion effects within the financial system with severe implications for financial instability (Fung and Halaburda, 2016; Engert and Fung, 2017), especially when the current regulations have not adequately addressed the ascendance of financial technology (Magnuson, 2018).

2.2. Empirical studies on the impact of Fintech on financial stability

In addition to the heated discussion surrounding the potential positive and negative influence Fintech may exert on the financial system, empirically rooted evidence on this subject has also started to grow. Some studies focus on a specific type of Fintech lending or Fintech-related product and analyse their impact on other aspects of the economy. Braggion et al. (2018) analyse P2P lending in China and reveal that it undermines regulation in the credit market and may lead to excessive household debt. Fuster et al. (2018) show that Fintech based mortgage lenders in the US adjust supply more elastically than do other lenders in response to exogenous mortgage demand shocks. Narayan et al. (2019) analyse Bitcoin price growth in Indonesia and find that it leads to inflation growth, currency appreciation, and a reduction in money velocity.

From the perspective of the banking sector, Banna et al. (2021) show that an elevated level of Fintech-based financial inclusion exerts control over the risk-taking behaviour of 534 banks across 24 countries in the Organization of Islamic Cooperation (OIC). Concentrating on Chinese banks, Lai and Van Order (2017) model the interconnections and network linkages of Fintech finance and the banking sector in China. By examining the impact of the growing numbers of Fintech-bank collaborations on the evolving structure of financial networks in China, the study reveals that a ring-fencing network offers a viable environment for isolating Fintech financing from the broader banking sector. This provides a channel of mitigation and separation of failures from Fintech to banks and *vice versa*. Also in the context of China, Li et al. (2022) find that a bank's Fintech innovation diminishes its risk-taking, whilst Wang et al. (2021) show Fintech development initially heightens, but subsequently weakens, a bank's risk-taking tendencies.

Studies empirically examining the relationship between Fintech and financial stability did not emerge until more recently including Fung et al. (2020) and Daud et al. (2022). Employing panel data from 1375 banks across 84 countries, Fung et al. (2020) capture Fintech using the Fintech regulatory sandboxes that represent a shock to Fintech innovations. In practice it is measured using dummy variables corresponding to the year the sandboxes were implemented in each country. As there were no Fintech regulatory sandboxes prior to 2016, the study reflects the impact of Fintech after 2016, despite that the sample period covers 2010–2017. Financial stability is represented using the Z-score which reflects each bank's fragility. The panel regression results show that when the market characteristics are ignored, promoting Fintech has no effect on the stability of financial institutions, and that banks in emerging markets experience greater financial stability after the introduction of a regulatory sandbox.

Daud et al. (2022) investigate the Fintech-financial stability relationship for 63 countries from 2006 to 2017. They develop a Fintech index by applying data mining methods and technologies. Fintech is defined as the application of emerging technologies in the banking sector, namely artificial intelligence, blockchain, cloud computing and data technology. The yearly total number of released articles on Fintech based on the Google keyword search is calculated as the Fintech index. Similar to Fung et al. (2020), bank Z-score is employed to measure financial stability of each country. Using the dynamic panel system Generalised Method of Moments method, their results indicate that Fintech is positively and significantly correlated with financial stability and such relationship is stronger when there is greater market concentration.

Whilst not directly examining the relationship between Fintech and financial stability, Franco et al. (2020) and Li et al. (2020) investigate the risks Fintech firms might bring to the financial system. Franco et al. (2020) apply the Conditional Value at Risk (CoVaR) method to stock market return data for 75 Fintech firms and market indices for the US and Europe during period 2010–2017. They find that Fintech companies do not contribute greatly to the systemic risk of the financial system. Also using stock returns data, Li et al. (2020) estimate pairwise risk spillovers between Fintech firms and traditional financial institutions in the US using the Granger causality test across quantiles and build spillover networks. They find evidence that the spillover from Fintech could affect traditional financial institutions' systemic risk. More recently, Haddad and Hornuf (2023) demonstrate that Fintech start-up formations decrease the systemic risk exposure of financial institutions for a sample of financial institutions from 87 countries.

2.3. Discussions and our contributions

Our review of the existing literature underscores that, despite the increasing body of work on Fintech and its impact on the financial system, there remains a limited amount of empirically grounded studies addressing the specific nexus between Fintech and financial stability. More importantly, there is an absence of investigations examining the impact of macro-level Fintech-enabled financing on financial stability. This gap in research is particularly striking in light of the extensive discourse among regulators regarding the potential implications of Fintech on financial stability and the intensified financial interconnectedness instigated by Fintech, as discussed earlier. Consequently, this research gap provides a strong motivation for our research, wherein we aim to make three substantial contributions to the extant literature.

Our first contribution lies in the consideration of spatial dependence of financial stability. In a world of integrated financial markets, a reduction of financial risks in one country contributes to financial stability in others (positive externality), whereas an inadequate response by a national regulator to home financial risks may increase the likelihood of financial instability spreading to other countries (negative externality) (Agénor and Pereira da Silva, 2018). Tonzer (2015) shows that countries that are linked to more stable banking systems abroad through foreign borrowing or lending positions are significantly affected by positive spillover effects. Engel (2016) finds that effective domestic macroprudential policy that helps contain systemic risks in one economy promotes financial stability elsewhere. On the other hand, in times of financial volatility, connections in the financial markets can contribute to the spread of shocks destabilising the financial system across countries (MacDonald et al., 2018). Prevailing stability issues in other economies may be transmitted as externalities associated with bilateral transactions, network loops or similarities in market structures (Schoenmaker and Wagner, 2011). Degryse et al. (2010) find that financial contagion is more widespread in closer geographical proximities. Therefore, financial stability of one economy is likely to be under the influence of other countries. However, although there had been a number of analyses examining the spatial spillover effect of interbank risks and stock market volatility (e.g., Liedorp et al., 2010; Tonzer, 2015; Zhang et al., 2020), studies on spatial dependence of financial stability are sparse. With this factor in mind, our study investigates the linkage between Fintech and financial stability by employing a range of spatial models to consider the spatial spillover effect.

Second, we employ a novel Fintech-enabled financing volume dataset from the CCAF to directly gauge Fintech development. This is the first time this unique dataset is utilised to examine the relationship between Fintech and financial stability.[1] It has two distinctive advantages compared with measures adopted in previous studies, making it ideally suited for this study. To start with, in relation to the two studies most closely linked to ours, Fung et al. (2020) and Daud et al. (2022), the former adopts Fintech regulatory sandboxes and the latter employs data mining based on Google Fintech keyword search to indicate Fintech development. The Fintech regulatory sandboxes (measured using dummy variables) represent a shock to Fintech innovations, and hence it may not capture the dynamic evolution of Fintech of a country over time. Also, this approach does not encompass years preceding 2016, as regulatory sandboxes in the Fintech domain were not established prior to that year. The Google Fintech keyword search by Daud et al. (2022) is intuitive, but how well it reflects the actual extent of Fintech development is contingent upon the varied level of usage and popularity of Google in different countries. For instance, Google has very restricted usage (less than 5 % in 2023) in China, one of the world's largest Fintech lending countries; in South Korea, Naver has over 60 % in terms of share of search engine compared to Google's share of less than 30 % in 2022 (based on data from Statista). Also, the number of searches may reflect online attention to Fintech but does not translate directly into the actual amount of Fintech lending or investment. For other studies, the number of Fintech start-ups employed by Haddad and Hornuf (2023) does not consider the size of these firms and the CoVaR of Fintech firms used by Franco et al. (2020) and Li et al. (2020) focus on stock markets only. In contrast, the CCAF data provides a reliable global coverage of the actual volume of Fintech-enabled financing. Facilitated by a thorough follow-up hand-collection procedure, the survey-based CCAF data has very high response rate from Fintech financing platforms (e.g., 77 % in Europe), and it includes all large platforms in each country and almost 100 % of their market volume (Rau, 2020). Table 1 further shows the large number of Fintech financing platforms covered by CCAF for our 25 sample countries and globally. Additionally, as the same data collection method (see Section 3.1 for details) is applied to all countries, the dataset is consistent and comparable across nations which is an important requirement for our cross-country analysis. Fig. 1 shows the global distribution of countries analysed in our study. These nations present a sound geographic inclusion, covering key markets in Asia, Africa, North America, South America, Europe, and Australia. Therefore, the CCAF data not only capture more accurately the actual size of Fintech-enabled financing volume for each country, but also offer a global dataset that is consistent and comparable.

Third, we further analyse the sub-components within the aggregate Fintech-enabled financing volume in each nation to evaluate whether their impact on financial stability varies. It is motivated by that, although they all contribute to the total volume of Fintech lending, these components (i.e., crowdfunding, business lending and consumer lending) are also characterised by different lending process and more notably, distinct default rate (Pierrakis and Collins, 2013; Chishti, 2016; Mollick and Robb, 2016; Schwartz, 2018; Wang et al., 2019) (see more detailed discussion in Section 3.2). In the subset of Fintech lending, particularly those with a lower default rate (e.g., crowdfunding), there is a potential for a diminished adverse impact on financial stability and an increased likelihood of contributing to its enhancement. Conversely, for segments characterised by a higher default rate (e.g., consumer lending), the opposite effect may be observed. This concern holds significant importance, as addressing it could yield valuable insights into whether policymakers should adopt differentiated approaches for various constituents of Fintech lending. Remarkably, this aspect has not been investigated in any previous studies. Therefore, employing CCAF data for each component, we conduct a disaggregated level analysis focusing on subsets within Fintech lending to shed light on this issue.

3. Data

We employ annual data for 25 countries (see Appendix A) during period 2013–2020 from the Cambridge Centre for Alternative Finance (CCAF), World Bank, International Monetary Fund (IMF), Thomson Reuters DataStream and the Federal Reserve Economic Data. Detailed variable measurement and data source are summarised in Appendices B and C. The sample period is 2013–2020 as 2020 is currently the latest available year for Fintech-enabled financing data and 2013 is the earliest when a sensible number of countries (i.e., 25) start to report this data.

3.1. The aggregate level of Fintech-enabled financing

As discussed earlier, to measure Fintech, we adopt CCAF's concept of 'Alternative Finance' which includes digital finance activities outside of the banking systems and traditional capital markets and occurs online. In other words, it captures various lending, investment, and non-investment models that enable individuals, businesses, and other entities to raise funds via an online digital marketplace (CCAF, 2021). There are on average 2225 Fintech financing platforms being surveyed each year across 191 countries. The average survey response rates for the platforms contacted in the final sample regionally comprise 62 % in UK, 60 % in the Americas, 46 % in Asia and 77 % in Europe. Benefitting from the extensive follow-up hand-collection procedure,[2] these survey-captured platforms include all of the largest Fintech financing platforms in each country; in other words, although it is possible that the survey missed the smallest platforms, the survey volume data is close to 100 % of the market volume for all large platforms in each country (Rau, 2020).

[1] In Section 3.1, we provide a brief review of previous papers that have employed the CCAF data to measure Fintech. However, as mentioned above, our paper marks the first utilisation of the CCAF data on Fintech lending volume to study the impact of Fintech on financial stability.

[2] As explained in Rau (2020), it is plausible that particular types of platforms are more likely to respond to the survey than others. For example, non-financial crowdfunding platforms might lack both resources and time to respond to the survey. Hence, significant efforts were made to manually follow up with non-responding platforms, a labour-intensive process, to collect the CCAF data.

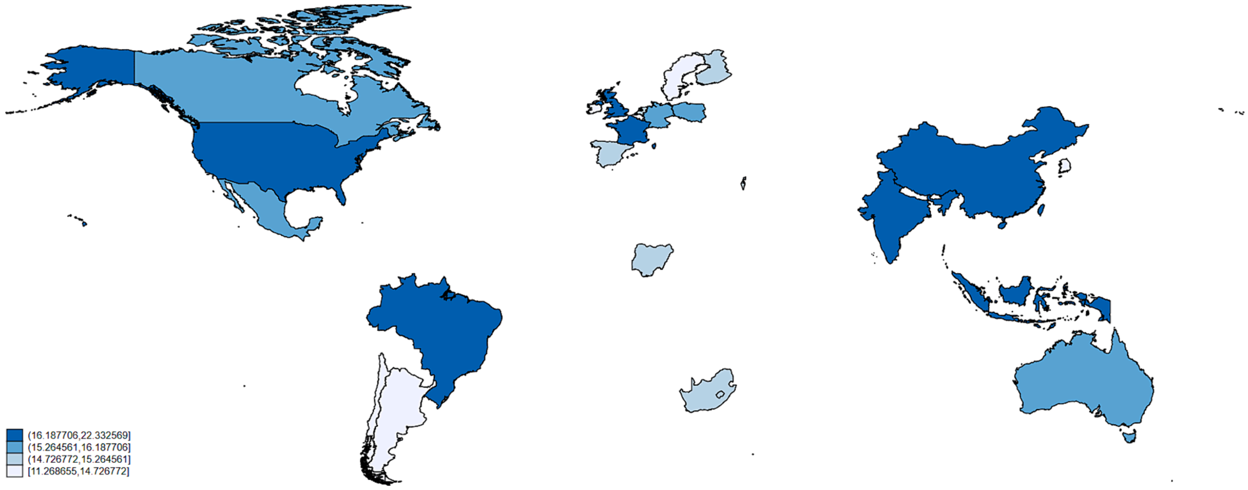

Fig. 1. Spatial distribution of Aggregate Fintech-enabled Financing (AFF) (Average of 2013–2020). *Note:* The Aggregate Fintech-enabled Financing (AFF) is measured as the aggregated Fintech financing volume of each country adjusted by GDP per capita and then taking the natural logarithm. The list of 25 countries included are: Argentina, Australia, Belgium, Brazil, Chile, China, Canada, Finland, France, Germany, India, Indonesia, Ireland, Israel, Mexico, Netherlands, Nigeria, Poland, Singapore, South Africa, South Korea, Spain, Sweden, United Kingdom, and United States.

Therefore, the CCAF data provides a reliable global coverage of Fintech-enabled financing volume and is currently the largest global database of alternative finance transactions. For our 25 sample countries, we summarise in Table 1 the number of Fintech financing platforms included by CCAF for our sample period 2013–2019. In 2020 for instance, data of the Fintech-enabled financing volume for these 25 countries are based on 1398 platforms, nearly 80 % out of 1771 platforms globally. Fig. 1 further demonstrates the sound geographic inclusion of these 25 countries, covering key economies in Asia, Africa, North America, South America, Europe, and Australia.

Annual surveys are conducted where individual Fintech financing platforms provide information on volumes of Fintech transactions. The surveys focus specifically on online crowdfunding and P2P transactions. Data is gathered on platforms that are open to the public even if it is partial. Private transactions that target non-public or specialised groups which are not widely accessible to the public are excluded from the sampling. Platforms that operate solely as mobile and online payment platforms or online platforms that operate traditionally as financial intermediaries are also excluded. Therefore, compared with previous studies mentioned above (e.g., Fung et al., 2020; Daud et al., 2022; Franco et al., 2020; Li et al., 2020), the CCAF dataset provides a more direct and comparable measure of Fintech by capturing the actual size of financing enabled by Fintech.

Fintech transactions of CCAF are classified as debt-based, equity-based and non-financial. Debt-based Fintech transactions are the most popular and encompass fixed asset lending, corporate loans, secured and unsecured lending. Depending on their features (e.g., the parties transacting, the source and purpose for the funding), these are categorised under key subheadings including balance sheet lending, P2P/marketplace lending, debenture (debt-based securities), mini-bonds and invoice trading. The size of the latter three debt financing classifications is negligible compared to the balanced sheet and P2P lending which dominate the debt-based Fintech transactions. Moving to the equity-based Fintech financing, it is majorly composed of the equity-based crowdfunding and real estate crowdfunding. It represents the provision of funds by investors in exchange for equity stakes or shares of profits of the projects, firms and real estates that secure funding. Finally, the non-financial Fintech transactions run return models which allow investors with altruistic and philanthropic motivations to fund projects that strongly align with their social agenda. Investors support such projects and companies for non-monetary rewards and satisfaction. Non-financial models comprise of reward-based and donation-based crowdfunding.[3]

We include all above-mentioned Fintech platforms-enabled financial activities to measure Fintech. A number of studies have shown that Fintech credit is more likely to thrive in more developed countries with higher GDP per capita coupled with an effective judicial system, favourable climate for doing business, relaxed regulations and highly advanced bond and stock markets (e.g., Claessens et al., 2018; Frost, 2020; Cornelli et al., 2020). Therefore, for better comparability among countries at different stage of economic development, the CCAF alternative finance data of each country is scaled by GDP per capita. After taking the natural logarithm, the series is referred to as the Aggregate Fintech-enabled Financing (AFF) henceforth.

Apart from our paper, some other studies have adopted the CCAF alternative finance database since its inception. The focus of these extant studies ranges from data analysis and attempts of establishing causality effects between Fintech and specific aspects of the financial system. For instance, Baeck et al. (2014), Zhang et al. (2017), Rau et al. (2020) and Ziegler et al. (2021) conduct in-depth

[3] See Rau (2020) for a more extensive description on the data and sampling methodology of the CCAF Database.

analyses on the database to report on the global development of Fintech lending markets across developed and emerging markets. Additionally, Havrylchyk (2018) and Peng et al. (2023) employ the database to understand the influences of regulatory frameworks on the growth of Fintech lending at country-level. Claessens et al. (2018) and Wang et al. (2023) broadly investigate the drivers of global Fintech credit markets for period 2013–2016 and year 2020, respectively. Cornelli et al. (2020) adopt the CCAF database to examine the rate of expansion of Fintech credit and the adoption drivers across 79 countries from 2013 to 2020. Bazarbash and Beaton (2020) also employ the database to assess whether Fintech helps to fill credit gaps in the consumer and business loan markets at country-level during 2015–2017. Le et al. (2021) explore the relationship between Fintech credit and bank efficiency for 80 countries from 2013 to 2017 while Ioannou and Wójcik (2022) examines the relationship between Fintech and financial development for Latin America from 2014 to 2018. In the area of financial inclusion, Oh and Rosenkranz (2022) study the effects of Fintech on financial development and literacy using this set of data while Kim et al. (2021) examine the role of Fintech for trade finance in the Central Asian economic region.

While previous studies have employed the CCAF database, our research distinguishes itself as the first to use this dataset for the explicit examination of its relationship with financial stability (as discussed in the second contribution in Section 2.3). Additionally, unlike the extant studies, we take a keen interest in understanding the influence of the various components of the Fintech market by decomposing the data into its three largest transactional segments, namely crowdfunding, business lending and consumer lending. Through this approach, we further contribute to the literature by demonstrating the unique interactions of financial stability with the different aspects of the Fintech lending market.

3.2. Three main components of the aggregate Fintech-enabled financing

We further include the three main components of AFF, namely crowdfunding (CF), business lending (BL) and consumer lending (CL). CF is made up of equity-based, real estate, revenue-sharing, donation-based and reward-based crowdfunding. Equity-based crowdfunding involves transactions related to the sale of registered or unregistered shares often by private firms in their early stages to investors. Real estate crowdfunding involves the pooling of funds by a crowd of investors to finance a real estate project. The project is usually managed by a professional real estate developer who manages all aspects of the project, including the acquisition of the property, marketing, and selling of the units. The funding may be structured as either equity or debt. Equity investors receive part ownership in the financed property while debt investors receive interest on the funds provided. Revenue-sharing crowdfunding ties the repayment of investor funds to future profits expected to yield to the borrowing firm. The dependency of repayments on firm performance generally results in variable repayments and investment horizons across the lifetime of the investment. Donation-based and reward-based crowdfunding fund projects and companies in exchange for non-financial returns or to support philanthropic projects with no expectations for financial rewards in return. BL consists of balance sheet business and P2P business lending while CL includes balance sheet consumer lending and P2P consumer lending. Balance sheet financing involves loans financed with the balance sheet of the platform. This means the platform contributes its own funds in the lending processes. Funds used are usually raised by the platform from individual investors to enable the Fintech platform to offer loans directly to borrowers. P2P or marketplace lending on the other hand involves the direct loan transactions between the investor and the borrower. While BL involves loans that are provided by individuals and institutions to small and medium sized enterprises (SMEs) and businesses, CL tends to be predominantly unsecured loans to individuals and consumer-based borrowers (Rau, 2018; 2020).

In addition to the noticeable difference in the process, motivation and destination, these three sub-groups of Fintech financing also have markedly different default rates. Crowdfunding has the highest project success rates among all Fintech models due to its rigorous fundraising process run by skilled investor groups, institutional investors and venture capitalists (Wang et al., 2019) and strict screening process (Pierrakis and Collins, 2013). After crowdfunding, Fintech business lending has appreciable success rates compared to Fintech consumer lending (Chishti, 2016; Mollick and Robb, 2016; Schwartz, 2018), for the latter is often used as a lender of last resort to most households and small-scale borrowers after they have exhausted all other means of borrowing (Walthoff-Borm et al., 2018) which leads to its highest recorded default rates across all Fintech models (Chishti, 2016; Mollick and Robb, 2016; Schwartz, 2018).

Given the distinctions among CF, BL and CL discussed above, we expect them to have varied impact on financial stability. Similar to AFF, we adjust CF, BL and CL by GDP per capita to take into account the different level of economic development before taking the natural logarithm.

3.3. Aggregate financial stability index

We construct the AFSI to capture financial stability for each of our 25 countries. Following Albulescu (2009), Morris (2010), Karanovic and Karanovic (2015) and Gustiana (2021), the AFSI includes the Financial Development Index (FDI), the Financial Vulnerability Index (FVI), the Financial Soundness index (FSI) and the World Economic Climate Index (WECI) to assess the development of the financial system, the ability of the financial system to respond to potential shocks, the solvency and liquidity of the credit institutions and macroeconomic conditions of the world, respectively. In total, 18 sub-indicators are included for these four sub-indices. While Albulescu (2009), Morris (2010), Karanovic and Karanovic (2015) and Gustiana (2021) employ equal weights, we employ the principal component analysis (PCA) method to determine the weights of these sub-indicators. Information of each of the four indices and their sub-indicators is summarised in Appendix C.

All variables are normalised using min–max normalisation method which gives the range of values between 0 and 1 to enable comparability across variables and to mitigate the problems of outliers (Morris, 2010). Equation (1) below is employed:

$$nI_{it} = \frac{I_{it} - min(I_i)}{max(I_i) - min(I_i)} \tag{1}$$

where i and t refer to country and time, respectively, I denotes the variable of interest (i.e., the 18 sub-indicators summarised in Appendix C), nI represents the normalised variable, nI_{it} denotes the normalised variable I for country i at time t, and $max(I_i)$ and $min(I_i)$ represent the respective highest and lowest values of the variable. The normalisation is followed by the assigning of weights to each sub-index per its influence on financial stability. Assigning equal weighting treats all variables equally, failing to recognise their different level of contribution to financial stability (Illing and Liu, 2003; Morris, 2010). To overcome this, we assign the weights using the PCA method and obtain *AFSI* as:

$$AFSI_{it} = \phi_1 FDI_{it} + \phi_2 FVI_{it} + \phi_3 FSI_{it} + \phi_4 WECI_{it} + \varepsilon_{it} \tag{2}$$

Where ϕ denotes the assigned weights for each sub-index and ε is the error term. A higher (lower) value of AFSI suggests an improvement (deterioration) in financial stability. As discussed in Section 2, it covers a much broader dimension of the financial market compared with the Z-scores and does not suffer from the down-side risk bias as the VaR type models.

AFSI provides a single yet comprehensive quantitative measure for easy monitoring of stability (Gadanecz and Jayaram, 2008) and is effective in its ability to detect financial crisis compared with Z-score or other partial composite measures like the banking stability index and the market liquidity index (Illing and Liu (2003) and Van den End (2006)). To further demonstrate the effectiveness of AFSI, we compared AFSI with the Z-score of our sample countries (where natural logarithm of one plus Z-score (ln(1 + Z-score)) was employed following Daud et al. (2022)). When plotted side by side, it is observed that the Z-score measure produces a smoother curve with much less visible peaks and troughs relative to the AFSI. The figure is not presented here to save space and is available upon request. We also calculated the standard deviation of AFSI for the 25 countries over our sample period 2013–2020 (i.e., 1.18) which was also larger than that of the ln(1 + Z-score) (i.e., 0.437). It confirms that AFSI is more effective and in capturing (and hence more sensitive to) any changes in various aspects of financial stability as it considers a wide range of 18 indicators under the four sub-indices reflecting financial development, financial vulnerability, financial soundness and the world economic climate.

3.4. Control variables

To control for the financial and economic environment of each country, we capture the financial conditions of sovereign risks, market uncertainties and contagion risk using public debt to GDP ratio (*PD*), the Economic Policy Uncertainty (*EPU*) index and cross-border currency exposure to total assets ratio (*CBE*), respectively. GDP growth rate (*GDPG*), inflation (*INFL*) and interest rate (*IR*) are adopted to measure economic growth, price instability and interest rate environment, respectively, to reflect the economic conditions. They are summarised in Appendix B.

Sovereign risk communicates the debt levels of an economy and the capacity of the economy to service these debts (Broner et al., 2010). Excess public debt heightens sovereign risk in the financial system, increases financial markets volatility and raises the risk of default, which progressively jeopardises the financial stability (Ondo, 2017). Rising market uncertainty disrupts information flow (Mishkin, 1999), adversely affects investment by causing financial distortions (changes in credit spreads) (Gilchrist et al., 2014), and distorts asset prices and trade (Segal et al., 2015). Employing the EPU index as an indicator of aggregate uncertainty, Phan et al. (2021) find that it strongly deteriorates financial stability regardless the use of country- or bank-level data. Integrated financial markets provide opportunities for expansion and improved risk sharing, but also pose threats of contagion risk through cross-border exposures (Degryse et al., 2010; Tonzer, 2015). Degryse et al. (2010) employ cross-border exposure to reflect contagion risk and demonstrate that it poses serious threat to financial stability. High GDP growth rate is often associated with less overall insolvency risk and less loan risk (Yin, 2019) and enhances financial stability (Creel et al., 2015), whilst interest rate hikes increase the cost of capital and worsen investors' ability to service their debts (Louzis, et al., 2010). The inclusion of interest rate as a control variable will also provide insights on the view that the "low-for-long" scenario after the 2008 global financial crisis might affect financial stability (BIS, 2018). Price instability introduced by high inflation rate decreases borrowers' real income and raises the likelihood of defaults (Mpofu and Nikolaidou, 2018) which hinders the financial stability.

3.5. A brief overview of the data

The descriptive statistics and correlation matrix are presented in Table 2 and 3, respectively. Given the sample period 2013–2020 for 25 countries, there are a total of 200 observations for each variable except for CL which has 186 observations due to some missing datapoints for Ireland and Belgium. The Aggregate Fintech-enabled Financing, its three main components (all scaled by GDP per capita as discussed in section 3.1) and the economic policy uncertainty series (all in natural logarithm) are respectively denoted as *AFF*, *CF*, *BL*, *CL* and *EPU*. The aggregate financial stability, *AFSI*, is in an index form. All other variables are in percentages.

Table 3 shows that *AFF* and its three main components (*CF*, *BL*, *CL*) have relatively low standard deviation at 2.54 %, 2.1 %, 3.48 %, and 4.7 % respectively, suggesting that datapoints are mostly clustered around the mean point. Fig. 2 further illustrates *AFF* for each country and Fig. 3 depicts *CF*, *BL* and *CL*. Fig. 2 shows that China, the United States (US) and the United Kingdom (UK) are countries with highest average *AFF* during 2013–2020 while Singapore, Ireland and Belgium record the lowest. Fig. 3 demonstrates that China's consumer lending has been the most preferred form of Fintech credit followed by business lending and then crowdfunding. China recorded the highest *AFF* in 2017. However, it declined in 2020 largely attributed to a noticeable drop in business lending. In 2020, the

Table 2
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
AFSI	200	0.129	1.18	−2.984	3.953
AFF	200	15.747	2.543	10.074	24.381
CF	200	13.831	2.097	8.452	19.606
BL	200	14.212	3.481	−2.768	23.188
CL	186	13.701	4.711	−2.57	24.019
CBE	200	0.995	0.056	0.786	1.122
IR	200	3.183	4.128	−11.601	16.656
INFL	200	2.432	2.763	−0.874	16.524
PD	200	85.303	24.605	30.5	157.047
GDPG	200	1.939	3.681	−10.823	25.16
EPU	200	5.024	0.508	3.296	6.297

Note: AFSI: Aggregate Financial Stability Index; AFF: aggregate Fintech-enabled financing; CF: crowdfunding, BL: business lending; CL: consumer lending; CBE: cross border exposure; IR: interest rate; INFL: inflation rate; PD: public debt; GDP: growth rate of the Gross Domestic Product; EPU: Economic Policy Uncertainty Index.

Table 3
Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) AFF	1.000									
(2) CF	0.741	1.000								
(3) BL	0.701	0.398	1.000							
(4) CL	0.662	0.394	0.684	1.000						
(5) CBE	−0.054	0.067	0.062	0.023	1.000					
(6) IR	−0.036	0.112	0.100	0.152	0.087	1.000				
(7) INFL	−0.165	0.066	0.071	−0.025	0.004	0.736	1.000			
(8) PD	0.143	0.080	−0.043	0.090	−0.060	−0.183	−0.103	1.000		
(9) GDPG	−0.008	0.134	0.245	0.127	0.030	0.160	0.100	−0.182	1.000	
(10) EPU	0.149	−0.061	−0.023	0.083	−0.055	−0.087	−0.073	0.226	−0.341	1.000

Note: AFF: aggregate Fintech-enabled financing; CF: crowdfunding, BL: business lending; CL: consumer lending; CBE: cross border exposure; IR: interest rate; INFL: inflation rate; PD: public debt; GDP: growth rate of the Gross Domestic Product; EPU: Economic Policy Uncertainty Index. The correlations between AFF and its three main components (CF, BL, CL) are shown but is of no practical relevance as AFF does not enter the same estimation with any of its components.

US recorded the highest *AFF* which was largely contributed by high growth in consumer lending that year. The highest *AFF* in the UK is also recorded in 2020. Unlike China and the US, crowdfunding is more popular in the UK and contributed most to the Fintech credit.

The AFSI takes both positive and negative values. Positive AFSI values communicate a healthy financial system while negative values indicate dwindling financial stability. Table 1 shows that *AFSI* ranged between −2.98 and 3.95 with a mean of 0.129. Fig. 4 further depict *AFSI* for all 25 countries from 2013 to 2020. Most countries, especially Germany and France, have experienced rising financial stability. In contrast, Nigeria and Argentina have seen declines in *AFSI*. Countries such as China, India and Spain had declining indices in some years followed by rising in other periods.

The correlation matrix is illustrated in Table 3. The highest correlation occurs between *CBP* and *INFL* (73.6 %). As a precautionary measure, we replace *IR* and *INFL* by the real interest rate which is the difference between *IR* and *INFL* and our empirical findings remain unchanged. Hence there is generally no concern arising for the existence of multicollinearity among independent variables. Fully aware of the impact the Covid 19 pandemic may have on financial and economic indicators, we analysed the percentage changes of all variables in 2020 and compared them to that in the preceding three years. We did not observe dramatic spikes or drops in the 2020 data. Nonetheless, as a robustness check, we exclude year 2020 from the sample and our results remain largely unchanged (see Sections 5.3 and 6.3).

4. Methodology

The standard Ordinary Least Squares (OLS) model expects the dependent variable of unit i to be explained by the explanatory variables of the same unit and that any unexplained variations should be considered unobserved. Spatial models, however, 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 financial stability, an endogenous interaction effect is observed when a change in financial stability in a country causes changes in financial stability in neighbouring countries, i.e., there is a spatial dependence in financial stability across countries. Exogenous interaction effects refer to when the explanatory variables of financial stability in one country influences the financial stability in other countries. Correlated effects are related to unobserved and similar environmental factors across countries that affect financial stability in a similar way but are not observed, i.e., the errors are correlated across space. Incorporating all three spatial interaction effects gives:

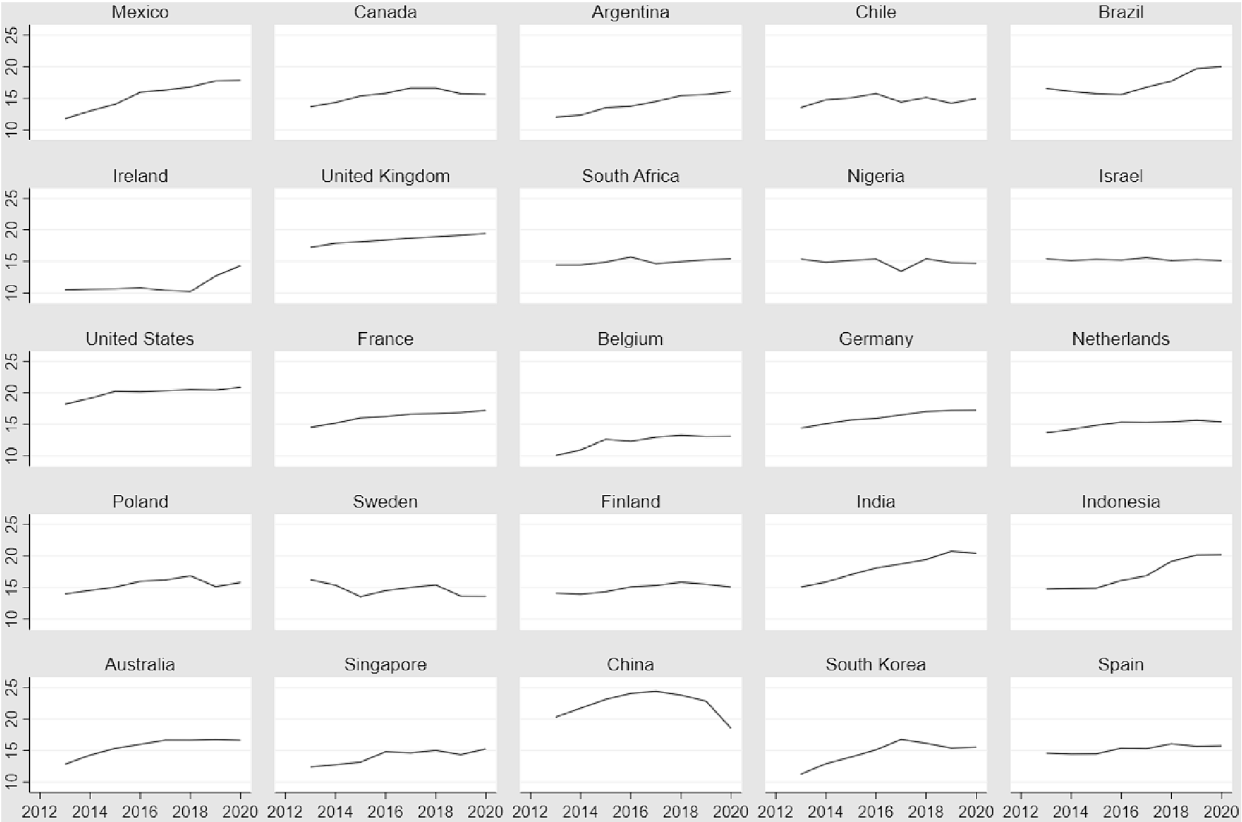

Fig. 2. Aggregate Fintech-enabled Financing (AFF) (2013–2020). *Note:* The Aggregate Fintech-enabled Financing (AFF) is measured as the aggregated Fintech financing volume of each country adjusted by GDP per capita and then taking the natural logarithm.

$$y_{it} = \rho W y_{jt} + X_{it}\beta + WX_{jt}\theta + \mu_i + \delta_t + u_{it}, i, j = 1, \cdots.., N, \tag{3}$$

$$u_{it} = \lambda W u_{jt} + \varepsilon_{it}, \tag{4}$$

$$-1 \leq \rho \leq 1 - 1 \leq \lambda \leq 1, \tag{5}$$

where subscripts i and t denote spatial units (countries) and time, respectively. y_{it} and y_{jt} refers to financial stability in country i and j $(i \neq j)$ at time t, ρ measures endogenous interaction effects, or the impact of financial stability in countries other than country i on financial stability in country i. W is an $N \times N$ non-negative matrix specifying the spatial arrangement of countries. X_{it} includes our main variable of interest, namely the Fintech variable (*AFF* and then *CF*, *BL* and *CL*) and the control variables (*PD*, *EPU*, *CBE*, *GDPG*, *INFL* and *IR*) in country i at time t (see Section 3 for discussion on data). β represents the coefficients of Fintech and the control variables. θ includes parameter estimates of the exogenous interaction effects (i.e., Fintech and control variables), or how financial stability of country i responds to changes in explanatory variables of country j. μ_i and δ_t represent country- and time-fixed effects, respectively. λ measures the correlated interaction effects (Wu) and ε_{it} denotes the error term.

Although it is technically possible to estimate Equation (3), it is problematic to interpret the result if all three spatial interaction effects are considered together (Elhorst, 2010). The Spatial Autoregressive Regression (SAR) model considers spatial dependence in the dependent variable (i.e., first item in Equation (3)) only and the Spatial Error Model (SEM) allows only the correlated effects (i.e., $\lambda W u_{jt}$). The Spatial Auto Combined (SAC) model excludes spatially lagged independent variables in estimations but includes ρ and λ, and the Spatial Durbin Model (SDM) leaves out the correlated effects but captures the endogenous and exogenous interaction effects (i.e., first and third term in Equation (3), respectively).[4] 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

[4] In all specifications, we tested for both time- and country- fixed effects (δ_t and μ_i) following Lee and Yu (2010) and Belotti et al. (2017) in our empirical analysis. However, the time-fixed effect δ_t was insignificant whilst the country-fixed effect μ_i was highly significant (at 1% significance level) throughout. Therefore, we incorporated country-fixed effect μ_i in our estimations in Tables 4-9.

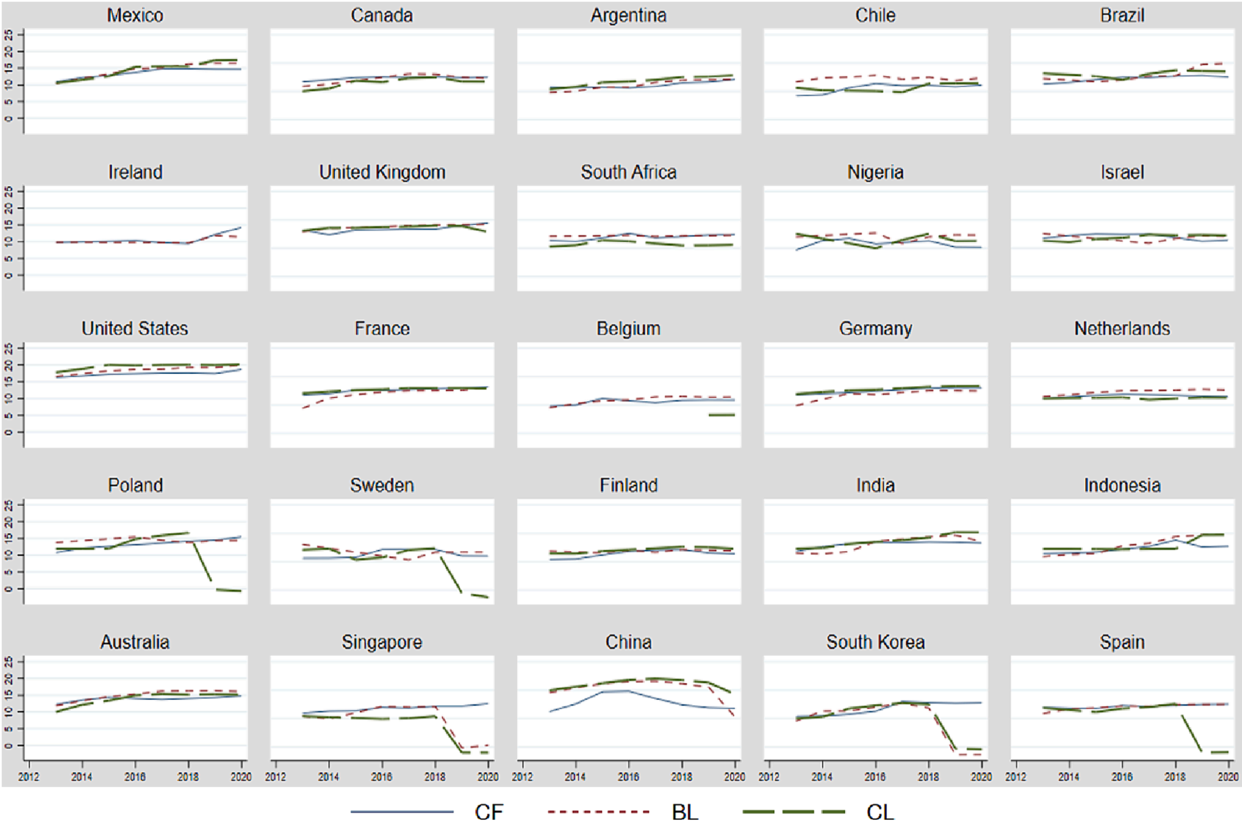

Fig. 3. Decomposition of AFF (2013–2020). *Note:* CF, BL and CL denote crowdfunding, business lending and consumer lending, respectively.

relatively less concern. This clearly points to the SDM from alternative candidates of spatial models. On the same account, Elhorst (2012) further indicates that the SDM yields unbiased coefficient estimates even if the true data generation process is an SEM, SAC or SAR.

Equation (3) can be rewrite as follows by dropping the subscripts:

$$y = (I - \rho W)^{-1}(X\beta + WX\theta) + (I - \rho W)^{-1}\varepsilon \tag{6}$$

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

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

A spatial weight matrix is required to express the spatial dependence structure. It can take many forms including contiguity, nearest neighbour and inverse distance weight matrices (Qu and Lee, 2015). The contiguity matrix requires spatial entities to share boundaries which is not applicable in our case as many countries do not share borders. Also, it captures only local spillover which arises from immediate neighbours. The nearest neighbour matrix considers certain closest neighbours to an entity and hence captures local spatial interactions only (Getis and Aldstadt, 2004). The inverse distance matrix regards all units as interdependent and are constructed based on the linear distance (d_{ij}) where weights are equal to $1/d_{ij}$. It concerns the global spatial interaction effects that cumulate across all units in the sample. To allow for non-linear distance relationships, the distance decay (or the inverse squared distance) matrix builds on $1/d_{ij}^2$ and assumes that strength of spatial relationships decays at a faster rate proportional to distance. Therefore, the distance decay matrix captures both global and local effects (Kopczewska et al., 2017; Lu and Wong, 2008). As such, we employ the distance decay matrix for our main analysis, and we adopt the 5-nearest neighbour and inverse distance matrices for supplementary information on

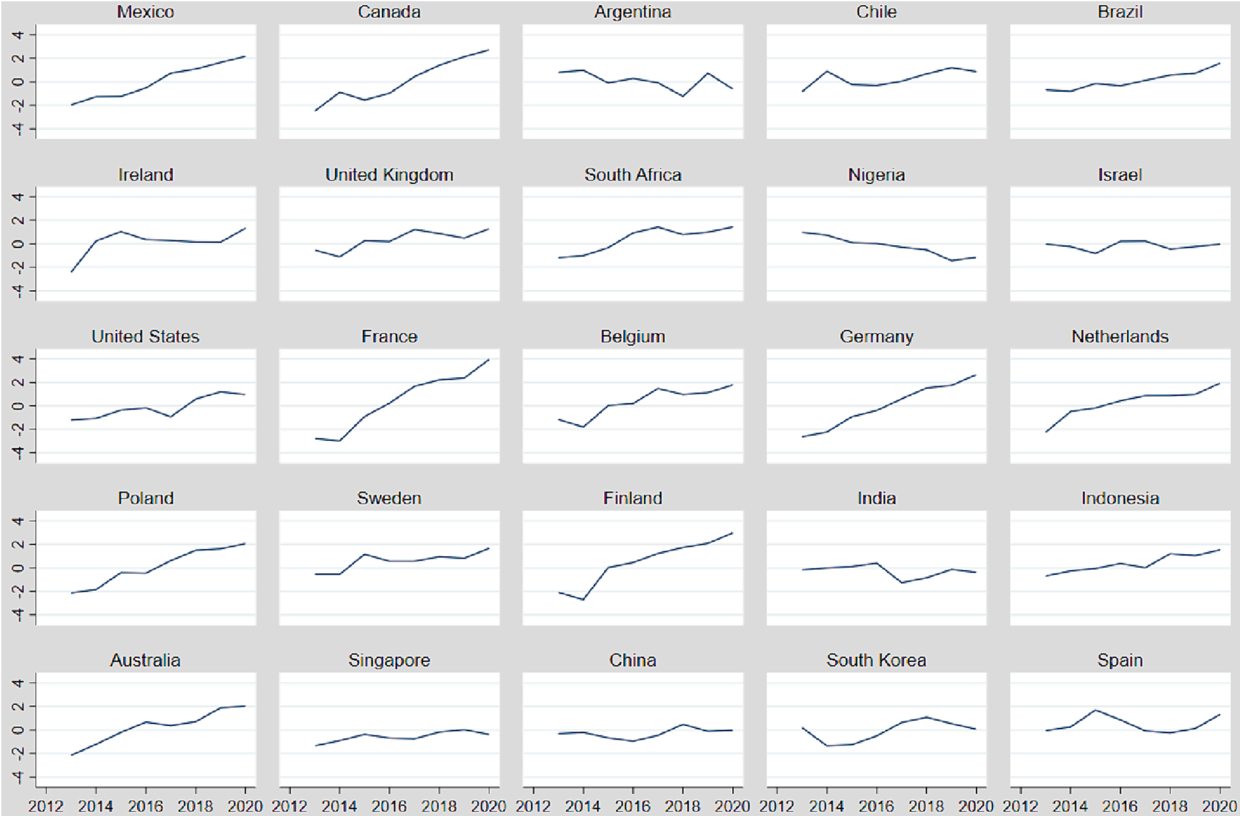

Fig. 4. Aggregate Financial Stability Index (AFSI) (2013–2020). *Note:* The Aggregate Financial Stability Index (AFSI) is constructed based on 4 sub-indicators encompassing 18 indicators.

global and local effects, respectively.

5. The main empirical results

5.1. Spatial model choice

We first conduct a spatial autocorrelation test for the *AFSI* using the Moran's I test in Fig. 5. It shows a positive value of 0.321 at 1 % significance level. This indicates similarities among countries and provides evidence of spatial dependence among countries. Fig. 6 further illustrates that countries with similar level of financial stability are spatially clustered together, confirming that financial stability is positively spatially correlated among countries. It corroborates with evidence of transmission of financial volatility and financial contagion (e.g., Degryse et al., 2010; MacDonald et al., 2018) discussed in Section 2 and strongly underscores the necessity of considering spatial spillover effect in financial stability.

Next, we estimate the SDM, SAR, SEM and SAC models to identify the most suitable specification.[5] The estimation results of Equation (6) using all four spatial models and the OLS are presented in Table 4. Columns (2)-(5) employ the distance decay matrix which considers both global and local spillover effects. Columns (6)-(9) and (10)-(13) adopt the inverse distance and 5-nearest neighbour matrices for supplementary information on global and local spillover effects, respectively, as discussed in Section 4. Diagnostic test results along with AIC scores are reported at the bottom of the table. Note that we employ robust spatial Hausman test, and the results suggest fixed effect at 1 % significance level for all specifications in Table 4.

In Columns (2)-(5) where the distance decay matrix is used, the spatial dependence denoted by ρ is positive and significant at 1 % level for SDM, SAR and SAC (Column (2), (3) and (5) respectively), suggesting that financial stability in a given country tends to move in the same direction as that of other countries. SEM estimates the spatial error (λ) which is also significant at 1 % level (Column (4)).

[5] Following Anselin et al. (1996), we employ the Lagrange Multiplier (LM) test for the choice between spatial lag model (using the LM-lag test) and spatial error model (using the LM-Error test). However, LM-Lag, LM-Error and the robust version of both tests are significant. Therefore, following the advice of Anselin et al. (1996), we carry out further investigation to find the most appropriate model analysing the SDM, SAR, SEM and SAC models.

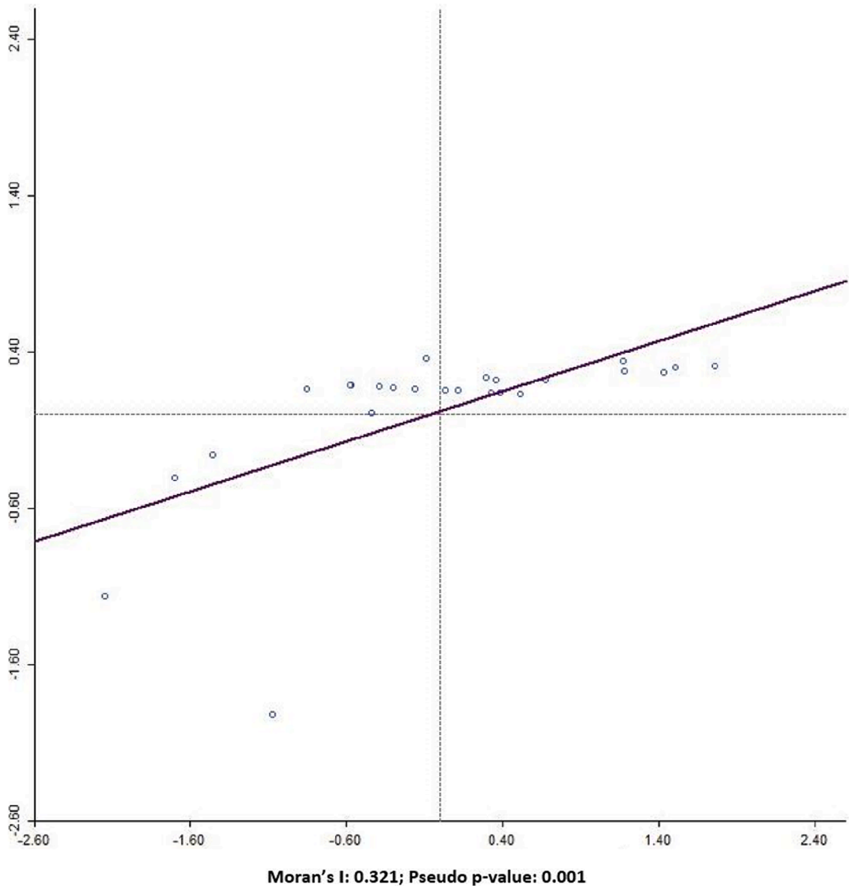

Fig. 5. Moran's I test for Aggregate Financial Stability Index (AFSI). *Note:* Each dot represents the period average value of AFSI of one of the 25 sample countries. The list of 25 countries included are: Argentina, Australia, Belgium, Brazil, Chile, China, Canada, Finland, France, Germany, India, Indonesia, Ireland, Israel, Mexico, Netherlands, Nigeria, Poland, Singapore, South Africa, South Korea, Spain, Sweden, United Kingdom, and United States.

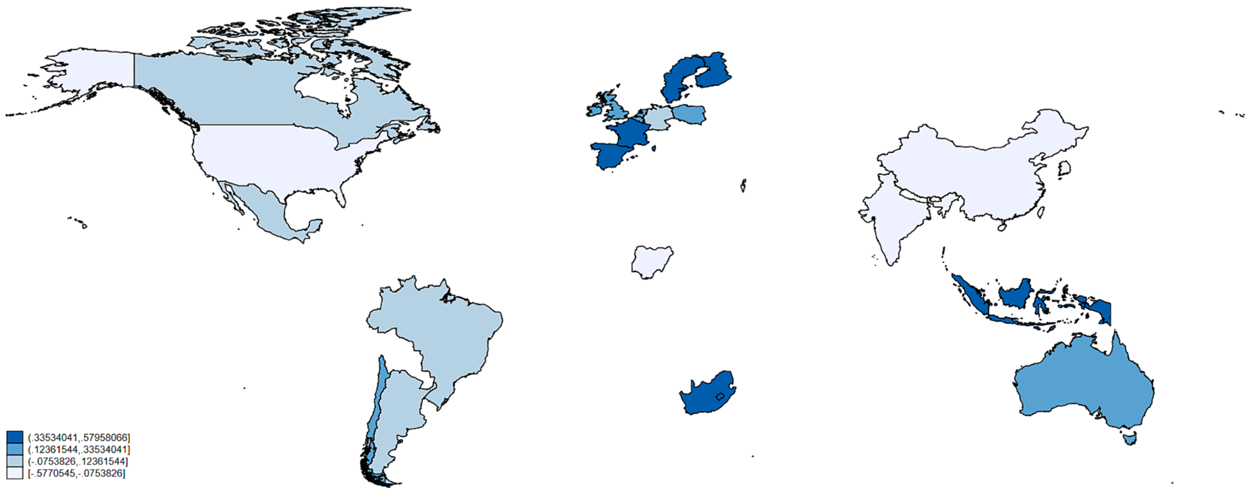

Fig. 6. Spatial distribution of Aggregate Financial Stability Index (AFSI) (Average of 2013–2020). *Note:* The list of 25 countries included are: Argentina, Australia, Belgium, Brazil, Chile, China, Canada, Finland, France, Germany, India, Indonesia, Ireland, Israel, Mexico, Netherlands, Nigeria, Poland, Singapore, South Africa, South Korea, Spain, Sweden, United Kingdom, and United States.

Table 4
Model selection using alternative weight matrix: Full sample.

Dependent Variable: *AFSI*		Distance decay weight matrix				Inverse distance weight matrix				Nearest neighbour weight matrix			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	OLS	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC
AFF	.385***	.174***	.228***	.21***	.206***	.14**	.16***	.145**	.172***	.174**	.224***	.211***	.17***
	(.066)	(.064)	(.057)	(.068)	(.058)	(.066)	(.059)	(.067)	(.063)	(.068)	(.059)	(.072)	(.049)
GDPG	.002	.08***	.037	.052*	.033	.095***	.051**	.09***	.064*	.093***	.037	.054*	.03
	(.029)	(.031)	(.023)	(.03)	(.022)	(.032)	(.023)	(.031)	(.033)	(.032)	(.024)	(.032)	(.019)
PD	−.007	.003	0	.001	.001	.005	.003	.005	.003	.005	.003	.004	.004
	(.007)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.005)
CBE	.708	.251	.19	.135	.162	.106	.028	−.012	.047	−.229	−.217	−.458	−.01
	(1.397)	(1.133)	(1.12)	(1.152)	(1.055)	(1.142)	(1.106)	(1.138)	(1.143)	(1.19)	(1.146)	(1.234)	(.933)
INFL	−.046	−.049	−.067	−.095*	−.05	−.023	−.047	−.048	−.056	−.016	−.082	−.101*	−.029
	(.067)	(.056)	(.054)	(.057)	(.054)	(.056)	(.053)	(.055)	(.056)	(.058)	(.055)	(.058)	(.051)
EPU	1.054***	.342	.699***	.733***	.594**	.26	.558**	.458*	.596**	.185	.591**	.543**	.505**
	(.284)	(.256)	(.233)	(.256)	(.241)	(.259)	(.232)	(.258)	(.242)	(.261)	(.241)	(.277)	(.206)
IR	.019	−.006	−.008	−.024	−.001	−.02	−.013	−.03	−.02	−.024	−.006	−.013	.002
	(.036)	(.029)	(.029)	(.028)	(.028)	(.029)	(.029)	(.028)	(.03)	(.03)	(.029)	(.03)	(.027)
cons	−11.252***												
	(2.312)												
Wx													
Wx:AFF		.171*				.143				.256**			
		(.099)				(.151)				(.101)			
Wx:GDPG		−.115***				−.190***				−.131***			
		(.041)				(.058)				(.049)			
Wx:PD		−.010				−.042*				−.016			
		(.012)				(.024)				(.015)			
Wx:CBE		1.033				3.194				2.795			
		(1.769)				(2.973)				(2.103)			
Wx:INFL		.222*				.184				.209			
		(.12)				(.171)				(.128)			
Wx:EPU		−.062				−.437				.289			
		(.416)				(.611)				(.537)			
Wx:IR		.056				.086				.077			
		(.043)				(.091)				(.076)			
ρ (rho)		.382***	.480***		.574***	.408***	.643***		.528**	.262***	.481***		.675***
		(.079)	(.066)		(.093)	(.135)	(.076)		(.249)	(.099)	(.069)		(.067)
λ (lambda)				.55***	−.200			.741***	.309			.546***	−.597***
				(.072)	(.176)			(.059)	(.440)			(.075)	(.208)
N	200	200	200	200	200	200	200	200	200	200	200	200	200
R^2	.308	.132	.112	.042	.131	.21	.128	.009	.078	.142	.114	.035	.173
Between R^2	.049	.387	.074	.019	.11	.29	.056	.044	.046	.22	.065	.027	.133
Within R^2	.308	.438	.338	.238	.351	.485	.311	.078	.26	.474	.328	.21	.356
Log likelihood	−273.583	−243.997	−252.633	−255.492	−252.078	−240.848	−248.732	−248.071	−248.335	−244.048	−253.873	−257.738	−250.61
AIC	563.166	547.993	551.266	528.984	552.157	541.696	543.464	514.143	544.67	548.096	553.747	533.475	549.219
Hausman test	44.51***	107.9***	69.26***	28.21***		97.35***	62.15***	33.18***		78.47***	46.74***	44.86***	
Waldtest $\theta = 0$		17.27**				15.77**				19.65***			
Waldtest $\theta + \beta\rho = 0$		22.99***				14.45**				27.38***			
Lrtest $\theta = 0$		125.87***				91.81***				153.43***			

Note: AFSI: Aggregate Financial Stability Index; AFF: aggregate Fintech-enabled financing; CBE: cross border exposure; IR: interest rate; INFL: inflation rate; PD: public debt; GDP: growth rate of the Gross Domestic Product; EPU: Economic Policy Uncertainty Index. t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively. The nearest neighbours weight matrix includes 5 nearest neighbouring countries. Fixed effect is adopted in all case based on Hausman test statistics (see fourth last row).

Table 5
Direct, indirect and total marginal effects using alternative weight matrix: Full-sample.

	Distance decay weight matrix Based on the SDM model Table 4 Column (2)			Inverse distance weight matrix Based on the SDM model Table 4 Column (6)			Nearest neighbour weight matrix Based on the SDM model Table 4 Column (10)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
AFF	.198***	.430***	.628***	.160**	.159*	.319**	.192***	.374***	.566***
	(.063)	(.113)	(.116)	(.063)	(.09)	(.132)	(.067)	(.11)	(.108)
GDPG	.069**	−.091*	−.021	.092***	−.207**	−.115	.086***	−.102*	−.016
	(.027)	(.049)	(.049)	(.029)	(.082)	(.082)	(.029)	(.054)	(.051)
PD	.002	.002	.004	.002	−.088**	−.085**	.004	.003	.007
	(.006)	(.004)	(.01)	(.005)	(.039)	(.04)	(.006)	(.004)	(.01)
CBE	.184	.11	.293	.247	.133	.38	−.306	−.216	−.522
	(1.119)	(.729)	(1.831)	(1.116)	(1.444)	(2.458)	(1.132)	(.793)	(1.904)
INFL	−.035	.353**	.318*	−.025	−.028	−.053	−.024	−.018	−.042
	(.056)	(.17)	(.187)	(.057)	(.072)	(.124)	(.059)	(.044)	(.102)
EPU	.396	.246	.643	.329	.34	.669	.353	.232	.584
	(.257)	(.175)	(.418)	(.249)	(.327)	(.549)	(.255)	(.181)	(.425)
IR	−.005	−.004	−.009	−.029	−.031	−.06	−.023	−.017	−.039
	(.031)	(.021)	(.051)	(.03)	(.037)	(.064)	(.031)	(.023)	(.053)

Note: AFF: aggregate Fintech-enabled financing; CBE: cross border exposure; IR: interest rate; INFL: inflation rate; PD: public debt; GDP: growth rate of the Gross Domestic Product; EPU: Economic Policy Uncertainty Index. t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively. The nearest neighbours weight matrix includes 5 nearest neighbouring countries. Fixed effect is adopted in all case based on Hausman test statistics. ρ (rho) for all three SDM specifications is positive and significant at 1% level.

As the SAR and SEM are nested models of the SDM, we conduct the LR and Wald tests where the SDM can be simplified into SAR model if the null that the spatially lagged independent variables are jointly insignificant ($\theta = 0$) is not rejected, and the SDM can be simplified into SEM if the null of $\theta + \rho\beta = 0$ is not rejected. As both null of $\theta = 0$ and $\theta + \rho\beta = 0$ are rejected at least at 5 % significance level (Column (2)), neither SAR nor SEM is the appropriate model. Between SAC and SDM, AIC is used as the former is not nested in the latter. Again, the SDM is chosen based on lower AIC value than the SAC model. As such, the SDM is the most appropriate model under the distance decay matrix.

In Columns (6)-(9) and (10)-(13), we adopt two alternative weight structure of the inverse distance and the nearest neighbour matrices, respectively. They show positive and highly significant ρ (when estimated). The null of $\theta = 0$ and $\theta + \rho\beta = 0$ are rejected at least at 5 % significance level under both alternative weight matrices (Columns (6) and (10)), and SDM has lower AIC than SAC in both cases. Therefore, Columns (6)-(13) in Table 4 confirm that SDM is the most suitable model regardless of the choice of weight matrices.

Given above, we focus our attention on the SDM model (Columns (2), (6) and (10)). In Column (2) where distance decay weight matrix is employed, ρ is positive (0.383) and highly significant (at 1 % level), suggesting spatial dependence in the independent variable financial stability. Both *AFF* and its spatially lagged *WAFF* have positive coefficients (0.174 and 0.171 at 1 % and 10 % significance level, respectively). It indicates that enhancement in financial stability in location *i* instigated by an increase in Fintech in location *i* is augmented by growth in Fintech in surrounding countries. Control variables that are significant include *GDPG* and *INFL*. While *GDPG* has a positive sign, its spatial lag (*WGDPG*) shows negative impact. Although higher GDP growth contributes to a more local stable financial system, high economic growth elsewhere may extract local economic and financial resources and deteriorate local financial stability. The spatial lag of inflation (*WINFL*) has a positive sign. High domestic inflation often causes capital outflows. But if capital outflows from country *j* flow into country *i*, it may provide investment and benefit economic development and financial stability for country *i*. Overall, the statistically significant spatially lagged dependent and independent variables in SDM clearly shows that ignoring spatial effects causes bias in the fixed effects estimates in OLS (Column (1)).

In Columns (6) and (10) where the inverse distance and nearest neighbour matrices are employed, *AFF* remains positive and significant at 5 % level. Its spatial lag *WAFF* is positive and significant at 5 % in Column (10) but is insignificant in Column (6). As the nearest neighbour matrix reflects local spatial interaction effects and the inverse distance matrix reflects the global effects, it suggests that the impact of country *j*'s Fintech financing on country *i*'s financial stability is stronger locally than globally. In other words, the geographical proximity plays a role here.

It is important to emphasise that ρ has consistently been positive and highly significant in all specifications in Table 4. It provides spatial evidence confirming suggestions made by earlier studies that financial stability of an economy is under the influence of that of other economies (Tonzer, 2015; Engel, 2016; Agénor and Pereira da Silva, 2018). Ignoring the spatial dependence of financial stability could lead to biased estimates, which highlights the necessity of using spatial models to account for such dependence as done in our study.

5.2. Direct, indirect and total effects

As the SDM is found to be the most suitable model, we then estimate the direct, indirect and total effects employing the SDM with fixed effect. The results are summarised in Table 5, where Columns (1)-(3), (4)-(6) and (7)-(9) are estimates based on the respective Columns (2), (6) and (10) in Table 4. Following Kopczewska et al. (2017), we exclude insignificant spatially lagged independent variables and re-estimate with the significant ones in the SDM in Table 5 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.

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, a change in an explanatory variable in a country influences not only financial stability in this country but also financial stability in other economies. The former is termed as the direct effect while the latter is defined as the indirect effect. Furthermore, impacts brought by a change in an explanatory variable in one country pass through 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. Total effects are the summation of the direct and indirect effects.

In Columns (1)-(3) in Table 5, *AFF* has positive direct and indirect effects on *AFSI* at 1 % significance level, implying that an increase in Fintech financing in an economy not only positively affects financial stability domestically but also spills over and enhance financial stability in neighbouring countries. Many studies have argued that the development of Fintech could enhance financial stability as Fintech promotes diversification and decentralisation of financial products and services (FSB, 2017), improves capital allocation efficiency (Carney, 2017), facilitates services in remote and less served jurisdictions (Feyen et al., 2021) and reduces information asymmetry to maintain a stable and transparent economy (Philippon, 2016; Omarova, 2018). The positive direct effect of *AFF* on *AFSI* provide empirical evidence substantiating these arguments. Furthermore, the positive indirect effect of *AFF* on *AFSI* lends support to one of the advantages of Fintech activities that they could increase cross-border competition in financial services over time (Frost, 2020), which raises efficiency in financial services and contributes to financial stability beyond borders (Ntwiga, 2020; Wu et al., 2023). In addition, cross-border expansion of Fintech firms could support greater diversification and risk-sharing across economies, leading to greater financial stability both home and abroad (Frost, 2020). This works through technological and knowledge spillover conditions that reduce information asymmetry for efficient resource allocation (Ngyuyen et al., 2020; Huang, 2021). Finally, the size of the indirect effects (0.430) is noticeably bigger than that of direct effects (0.198). It shows that Fintech financing has far reaching impact on neighbouring jurisdictions improving their financial stability. This is attributable to the economic uniqueness that exists across countries (Kowalewski and Pisany, 2023). For instance, Fintech adoption and development rate tend to be greater in countries with higher loan cost, weaker market competition and unmet credit demands (Hasan et al., 2021; Frost, 2020; Kowalewski and Pisany, 2023). Hence, spillover to such countries would generate far greater impact on financial stability relative to other jurisdictions (Kowalewski et al., 2021). Overall, the total effects of Fintech are positive (0.628) and highly significant at 1 % level. The results provide firm evidence that Fintech-enabled financing significantly improves financial stability.

Results using the two alternative weight matrices strongly corroborate with that of the distance decay matrix. Specifically, results using the inverse distance matrix (Columns (4)-(6)) show positive direct (0.160), indirect (0.159) and total effects (0.319) of *AFF* on *AFSI* at 5 %, 10 % and 5 % significance level, respectively. Results based on the nearest neighbour matrix (Columns (7)-(9)) also show positive direct (0.192), indirect (0.374) and total effects (0.566) of *AFF* on *AFSI*, all at 1 % significance level. Furthermore, the estimates using the nearest neighbour matrix have larger and statistically more significant values than that using inverse distance matrix. It implies that the positive spatial spillover of Fintech financing in country *j* to financial stability in country *i* is stronger for neighbours which are geographically closer. Geographic proximity has long been considered as a key determinant of the economic behaviour of individuals or entities due to the existence of information asymmetry and agency conflicts (Wu et al., 2022). Many studies confirm that the cost of information acquisition and supervision diminishes as the geographical distance between investors and firms decreases (El Ghoul et al., 2013; Opie et al., 2019: Hu et al., 2021). Furthermore, interactions and similarities in culture, religion, language and values are in general more prevalent across countries that are geographically closer (García-Gavilanes et al., 2014; Kowalewski et al., 2021). Therefore, owing to diminished information asymmetry and a congruent cultural milieu, the cross-border spread of Fintech lending is likely to be stronger in geographically closer neighbouring countries, leading to its more noticeable positive spillover effects on financial stability in these closely situated countries.

For the control variables, as expected, *GDPG* has positive and significant direct effect on *AFSI* in Columns (1), (4) and (7). However, its indirect effect is negative in Columns (2), (5) and (8) and significant at least at 10 % level. Chandra and Thompson (2000) show that highway investments raise the level of economic activity in the counties that the highways pass directly through but draw activity away from adjacent counties. Al-Rjoub (2021) confirms this as they find GDP to contribute negatively to the stability of neighbours. In a similar vein, high GDP growth in one country may draw economic and financial resource away from other countries which imposes an adverse impact on their financial stability. Due to the opposite signs of the direct and indirect effects, the total effect of *GDPG* on *AFSI* is insignificant in Columns (3), (6) and (9). *PD* has positive but insignificant effects on *AFSI* across Columns (1)-(9) except that under the inverse distance matrix only, *PD* exhibits a significant indirect (−0.088 in Column (5)) and total effect (−0.085 in Column (6)) on *AFSI*. High public debt raises interest rates due to the heightened risk of insolvency associated with debt levels (Dorrucci et al., 2009; İlgün, 2016). Such higher interest rate flows to other jurisdictions through international integration and trade flows (Alper and Forni, 2011). The negative spillover effect of country *j*'s *PD* to country *i*'s *AFSI* indicates high *PD* in one country increases the cost of borrowing on the global market, exposing other countries to high cost of fund acquisition which has significant consequences to financial stability. *INFL* has negative but insignificant effects on *AFSI* across Columns (1)-(9), with the exception of positive and significant indirect (0.353 in Column (2)) and total effect (0.318 in Column (3)) under the distance decay matrix. High inflation in a country poses a potential threat to investors and can cause capital outflow to other countries (Liu et al., 2023). Neighbouring countries receiving these capital inflows could see these capital inflows benefit their real economic outcomes, financial development and subsequently financial stability (BIS, 2021). *IR* remains insignificant throughout, implying the post-2008 crisis low interest environment does not seem to be linked to financial stability.

Our empirical analysis so far firmly validates the consideration of spatial dependence across countries when examining the impact of Fintech development on financial stability. Our findings show strong positive direct, indirect and total contribution of the former towards the latter. Results using alternative weight matrices reveals that the positive spatial spillover of Fintech financing is stronger for neighbours with closer geographical proximity.

5.3. Robustness checks

In this section, we provide three sets of robustness check. First, we exclude the three leading players of Fintech financing, namely China, US and UK (see Fig. 2 and discussion in Section 3), to observe whether their presence exerts dominance on the whole sample. Second, we exclude year 2020 from our sample to filter any distortion that might arise from the Covid 19 pandemic. Finally, we exclude both China, US, UK and year 2020 to remove the leading countries and Covid 19 impact.

Given that China, US and UK are economies with the highest average AFF, prior to conducting the robustness checks, we examined the number of Fintech platforms and volume of Fintech lending for the remaining 22 countries. For the number of Fintech platforms, based on Table 1, the average ratio of the combined number of platforms in the 22 countries to that of the top three economies was greater than one (i.e., 117 %) for the whole sample period 2013–2020. It implies that over half of the platforms remained in the sample when China, US and UK were removed. More specifically, during 2013–2015, the 22 countries had a similar sum of platforms compared to that of China, US and UK; in period 2016–2020, the combined number of platforms of the former surpassed that of the latter. For instance, there were 825 Fintech platforms in the 22 countries in 2020, compared to 573 in China, US and UK. Concerning the volume of Fintech lending, based on CCAF data, the average ratio of the sum of the 22 nations was 1.06-fold of the three leading

Table 6
Model selection: Sub-samples.

	Excluding China, US and UK				Excluding year 2020				Excluding China, US, UK and year 2020			
Dependent Variable: *AFSI*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC
AFF	.195**	.267***	.261***	.252***	.244***	.306***	.302***	.287***	.26***	.337***	.325***	.321***
	(.076)	(.066)	(.079)	(.066)	(.075)	(.063)	(.078)	(.066)	(.081)	(.068)	(.084)	(.068)
GDPG	.091***	.047*	.06*	.043*	.148***	.157***	.146***	.153***	.153***	.162***	.158***	.157***
	(.034)	(.026)	(.033)	(.025)	(.036)	(.036)	(.035)	(.036)	(.038)	(.037)	(.038)	(.037)
PD	.002	−.001	0	0	.004	−.002	0	−.002	0	−.005	−.003	−.005
	(.007)	(.006)	(.007)	(.006)	(.007)	(.006)	(.007)	(.006)	(.007)	(.007)	(.008)	(.007)
CBE	−.211	−.24	−.396	−.19	−.012	−.187	.038	−.243	−.531	−.721	−.521	−.724
	(1.25)	(1.249)	(1.281)	(1.2)	(1.068)	(1.051)	(1.087)	(1.011)	(1.179)	(1.162)	(1.199)	(1.107)
INFL	−.038	−.062	−.09	−.049	.017	.038	.008	.046	.021	.04	.013	.049
	(.06)	(.058)	(.06)	(.059)	(.057)	(.056)	(.059)	(.054)	(.059)	(.059)	(.062)	(.057)
EPU	.373	.751***	.87***	.668**	.522**	.619***	.762***	.54**	.531*	.654**	.864***	.538*
	(.289)	(.264)	(.282)	(.279)	(.261)	(.238)	(.256)	(.25)	(.285)	(.266)	(.279)	(.281)
IR	−.013	−.016	−.026	−.012	−.046	−.06**	−.072**	−.051	−.055*	−.071**	−.078**	−.061*
	(.031)	(.031)	(.03)	(.03)	(.031)	(.03)	(.029)	(.032)	(.032)	(.032)	(.031)	(.033)
Wx												
Wx:AFF	.246**				.182				.292**			
	(.116)				(.113)				(.126)			
Wx:GDPG	−.133***				−.008				−.016			
	(.051)				(.066)				(.097)			
Wx:PD	−.01				−.021				−.015			
	(.014)				(.014)				(.017)			
Wx:CBE	1.286				.565				.715			
	(1.865)				(1.686)				(1.797)			
Wx:INFL	.238*				.236**				.239*			
	(.133)				(.119)				(.132)			
Wx:EPU	−.276				−.38				−.603			
	(.468)				(.411)				(.452)			
Wx:IR	.02				.047				.018			
	(.046)				(.045)				(.048)			
ρ (rho)	.351***	.454***		.525***	.291***	.419***		.49***	.253***	.401***		.482***
	(.083)	(.07)		(.105)	(.092)	(.072)		(.108)	(.097)	(.076)		(.102)
λ (lambda)			.505***	−.146			.486***	−.151			.455***	−.183
			(.078)	(.192)			(.082)	(.195)			(.088)	(.195)
N	176	176	176	176	175	175	175	175	154	154	154	154
R^2	.235	.2	.109	.217	.07	.068	.038	.075	.178	.168	.109	.181
Between R^2	.298	.003	0	.01	.341	.165	.083	.185	.347	.099	.063	.113
Within R^2	.443	.344	.27	.354	.477	.394	.326	.405	.493	.412	.342	.428
Log likelihood	−221.554	−229.442	−231.973	−229.184	−196.575	−203.496	−206.211	−203.226	−176.905	−183.74	−186.606	−183.353
AIC	503.109	504.884	481.947	506.367	453.151	452.993	430.422	454.451	413.81	413.481	391.213	414.705
Hausman test	54.13***	29.80***	19.83**		67.74***	35.26***	24.15***		44.31***	21.19***	19.53**	
Waldtest $\theta = 0$	15.77**				13.84*				13.67*			
Waldtest $\theta + \beta\rho = 0$	20.84***				19.27***				19.40***			
Lrtest $\theta = 0$	121.59***				156.71***				161.00***			

Note: AFSI: Aggregate Financial Stability Index; AFF: aggregate Fintech-enabled financing; CBE: cross border exposure; IR: interest rate; INFL: inflation rate; PD: public debt; GDP: growth rate of the Gross Domestic Product; EPU: Economic Policy Uncertainty Index. t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively. All models use distance decay weight matrix. When alternative (inverse distance and 5-nearest neighbour) weight matrices are employed, again the SDM is the chosen specification and hence we do not present these results to save space (they are available upon request). Fixed effect is adopted in all case based on Hausman test statistics (see fourth last row).

Table 7
Direct, indirect and total effects: Sub-samples.

	Excluding China, US and UK Based on the SDM model Table 6 Column (1)			Excluding year 2020 Based on the SDM model Table 6 Column (5)			Excluding China, US, UK and year 2020 Based on the SDM model Table 6 Column (9)		
	(1) Direct effects	(2) Indirect effects	(3) Total effects	(4) Direct effects	(5) Indirect effects	(6) Total effects	(7) Direct effects	(8) Indirect effects	(9) Total effects
AFF	.216***	.49***	.705***	.332***	.209***	.541***	.136**	.403***	.539***
	(.072)	(.124)	(.123)	(.064)	(.054)	(.096)	(.058)	(.116)	(.147)
GDPG	.086***	−.102*	−.016	.163***	.105***	.268***	.082*	.051	.132*
	(.031)	(.056)	(.053)	(.036)	(.038)	(.066)	(.043)	(.032)	(.071)
PD	.003	.002	.004	0	0	.001	.001	0	.001
	(.006)	(.004)	(.01)	(.006)	(.005)	(.011)	(.003)	(.002)	(.006)
CBE	−.111	−.069	−.18	−.184	−.12	−.304	.214	.107	.321
	(1.239)	(.706)	(1.924)	(1.064)	(.71)	(1.76)	(1.301)	(.892)	(2.163)
INFL	−.013	.342**	.329*	.04	.367**	.406**	.022	−.065	−.043
	(.061)	(.172)	(.192)	(.056)	(.159)	(.173)	(.04)	(.139)	(.157)
EPU	.382	.206	.588	.641***	.408**	1.049***	.153	.088	.24
	(.29)	(.172)	(.449)	(.241)	(.183)	(.399)	(.184)	(.118)	(.296)
IR	−.016	−.01	−.025	−.054*	−.035	−.089	−.043	−.027	−.069
	(.032)	(.02)	(.051)	(.032)	(.024)	(.054)	(.029)	(.021)	(.048)

Note: AFF: aggregate Fintech-enabled financing; CBE: cross border exposure; IR: interest rate; INFL: inflation rate; PD: public debt; GDP: growth rate of the Gross Domestic Product; EPU: Economic Policy Uncertainty Index. t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively. All models use distance decay weight matrix. Fixed effect is adopted in all case based on Hausman test statistics. ρ (rho) for all three SDM specifications is positive and significant at 1% level.

countries during 2013–2020, suggesting that the combined Fintech lending volume of the 22 economies had been bigger than that of China, US and UK. Further, in every year during 2013–2020, the combined volume of the 22 nations consistently equalled or exceeded that of the three prominent countries. Therefore, notwithstanding the prominence of China, US and UK as primary Fintech lenders, the information pertaining to the remaining 22 countries maintains a sound and robust level of representativeness.[6]

Table 6 presents the model selection results and Table 7 summarises the corresponding direct, indirect and total effects. Unlike Section 5.2, in this section we show the distance decay matrix results only as it accounts for both local and global effect and to save space. Results using the inverse distance and nearest neighbour matrices substantiate our findings and are available upon request. The same applies to Section 6.

In Table 6, ρ is positive and significant at 1 % level in all cases when estimated, suggesting that financial stability in one country tends to move in the same direction with its neighbours. λ in SEM is also significant at 1 % level. We then take similar steps as explained in Section 5.1 and check the hypothesis $\theta = 0$. It is rejected at 5 %, 10 % and 10 % significance level in Column (2), (6) and (10), respectively. The null of $\theta + \rho\beta = 0$ is rejected and 1 % significance level in Columns (3), (7) and (11). The AIC statistics are lower in SDM in Column (1), (5) and (8) than SAC model in (4), (8) and (12), respectively. Therefore, results in Table 5 suggest that the SDM is the most appropriate model.

Table 7 summarises the direct, indirect and total effect estimates based on the SDM in Columns (1), (5) and (9) in Table 6. Similar to Section 5.2, following Kopczewska et al. (2017), only significant spatially lagged independent variables were included in the re-estimation of SDM. In Columns (1)-(3) when China, US and UK are excluded, the results are very similar to ones using the full sample in Columns (1)-(3) in Table 5: *AFF* has positive and highly significant (at 1 % level) direct, indirect and total effects on *AFSI*. Thus, our main results remain robust regardless of whether these three Fintech financing leaders are included. Indeed, although it is hard to dispute the global systemic importance of China, US and UK, some recent studies have shown exponential growth in Fintech markets in countries elsewhere such as Canada and France (Cumming and Schwienbacher, 2018) and India and South America (Lee and Shin, 2018; Muthukannan et al., 2020). Therefore, although remained relative smaller compared to China, US and UK, Fintech development in other countries is encouraging and its positive impact on financial stability should not be overlooked. Furthermore, the size of the direct, indirect and total effects in this sub-sample (0.216, 0.490, 0.705 in Columns (1)-(3) in Table 7) are consistently larger than that in the full sample (0.198, 0.430, 0.628 in Columns (1)-(3) in Table 5). It implies that for countries with smaller size of Fintech-enabled financing, the growth of Fintech would have a more noticeable positive impact on financial stability. This could be a likely indication that countries with smaller Fintech sizes are in an initial growth phase of Fintech development, and they have potential for greater growth (Vaganova et al., 2021; Shin and Choi, 2019). Additionally, the diminishing marginal trend in the Fintech growth cycle ensures that countries with a smaller size of Fintech lending recoup higher utility benefits, whilst countries with a larger magnitude of Fintech lending enjoy lower utility as they are approaching a stable/maturity phase (Moro-Visconti, 2021; Bu et al., 2023). For control

[6] In addition, as shown in the rest of this section, comparing to the full sample results in Tables 4 and 5, the exclusion of China, US and UK has not caused any fundamental changes in the results (Tables 6 and 7). Specifically, in Table 6 the statistics continued to suggest SDM to be the most suitable model; in Table 7 the signs of key variable of interest (i.e., *AFF*) and most control variables remained unchanged although there were changes in the size of the coefficients which were expected (and also explained in the case of the key finding of the increased coefficients on *AFF* after the removal of China, US and UK).

Table 8
Model selection: Three main components of aggregate Fintech financing–crowdfunding, business lending and consumer lending.

	Full sample				Excluding China, US and UK				Excluding year 2020				Excluding China, US, UK and year 2020			
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AFSI	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC
CF	.272***	.207***	.239***	.215***	.442***	.315***	.414***	.417***	.255***	.235***	.249***	.23***	.401***	.363***	.416***	.414***
	(.061)	(.057)	(.061)	(.062)	(.08)	(.067)	(.074)	(.075)	(.065)	(.06)	(.063)	(.074)	(.083)	(.07)	(.074)	(.074)
BL	.033	.044	.044	.042	.058*	.066*	.069**	.07**	.019	.034	.042	.039	.023	.038	.051	.05
	(.031)	(.031)	(.032)	(.031)	(.034)	(.034)	(.034)	(.033)	(.038)	(.037)	(.037)	(.037)	(.039)	(.037)	(.037)	(.038)
CL	.014	.014	.035	.036	.012	.01	.033	.033	.022	.019	.033	.034	.018	.019	.032	.032
	(.025)	(.024)	(.025)	(.023)	(.025)	(.026)	(.026)	(.025)	(.029)	(.028)	(.028)	(.028)	(.029)	(.028)	(.029)	(.029)
GDPG	.095**	.013	.036	.058	.086*	.02	.046	.051	.173***	.175***	.173***	.17***	.178***	.192***	.189***	.191***
	(.042)	(.026)	(.038)	(.043)	(.044)	(.029)	(.038)	(.04)	(.06)	(.059)	(.059)	(.057)	(.062)	(.061)	(.06)	(.061)
PD	.008	.001	.003	.005	.007	0	0	.001	.007	−.001	.003	.004	.002	−.006	−.004	−.004
	(.006)	(.006)	(.007)	(.006)	(.007)	(.007)	(.007)	(.007)	(.008)	(.007)	(.008)	(.008)	(.009)	(.008)	(.008)	(.008)
CBE	.42	.379	.49	.304	−.479	−.286	−.456	−.506	.55	−.09	.228	.227	−.293	−.869	−.762	−.781
	(1.139)	(1.16)	(1.168)	(1.107)	(1.225)	(1.268)	(1.256)	(1.229)	(1.123)	(1.112)	(1.117)	(1.083)	(1.209)	(1.205)	(1.208)	(1.217)
INFL	−.023	−.088*	−.105*	−.086	−.014	−.083	−.102*	−.098*	.017	−.009	−.017	−.014	.032	−.002	−.011	−.01
	(.056)	(.054)	(.055)	(.056)	(.058)	(.056)	(.056)	(.057)	(.058)	(.055)	(.058)	(.057)	(.06)	(.057)	(.059)	(.06)
EPU	.493*	.815***	.94***	.792***	.713**	.937***	1.232***	1.224***	.516*	.723***	.837***	.777***	.593*	.788***	1.034***	1.02***
	(.265)	(.246)	(.259)	(.281)	(.307)	(.276)	(.274)	(.278)	(.274)	(.253)	(.264)	(.293)	(.31)	(.275)	(.278)	(.286)
IR	−.016	−.017	−.032	−.028	−.017	−.021	−.032	−.029	−.044	−.039	−.053*	−.05*	−.051	−.046	−.053*	−.054*
	(.03)	(.031)	(.03)	(.028)	(.031)	(.032)	(.03)	(.029)	(.033)	(.033)	(.03)	(.03)	(.034)	(.033)	(.031)	(.032)
Wx																
Wx:CF	.112				.023				.151				.162			
	(.11)				(.135)				(.12)				(.144)			
Wx:BL	.057				.03				−.005				−.021			
	(.062)				(.064)				(.074)				(.072)			
Wx:CL	−.164***				−.17***				−.115**				−.131**			
	(.048)				(.046)				(.055)				(.052)			
Wx:GDPG	−.109**				−.114**				−.109				−.071			
	(.055)				(.057)				(.1)				(.101)			
Wx:PD	.001				−.003				−.021				−.018			
	(.016)				(.017)				(.019)				(.021)			
Wx:CBE	.868				1.996				.953				1.502			

(*continued on next page*)

Table 8 (*continued*)

	Full sample				Excluding China, US and UK				Excluding year 2020				Excluding China, US, UK and year 2020			
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AFSI	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC	SDM	SAR	SEM	SAC
	(1.775)				(1.857)				(1.731)				(1.816)			
Wx:INFL	.272**				.288**				.18				.185			
	(.119)				(.126)				(.122)				(.131)			
Wx:EPU	−.419				−1.008**				−.359				−.751*			
	(.421)				(.453)				(.416)				(.452)			
Wx:IR	.045				.03				.056				.039			
	(.041)				(.04)				(.043)				(.042)			
ρ (rho)	.348***	.431***		−.27	.322***	.368***		−.125	.331***	.406***		−.165	.259***	.326***		.047
	(.084)	(.07)		(.197)	(.087)	(.075)		(.182)	(.093)	(.073)		(.297)	(.098)	(.079)		(.201)
λ (lambda)			.533***	.691***			.497***	.575***			.496***	.606***			.418***	.379**
			(.074)	(.098)			(.077)	(.124)			(.077)	(.18)			(.086)	(.192)
N	184	184	184	184	160	160	160	160	161	161	161	161	140	140	140	140
R^2	.186	.156	.068	.038	.214	.228	.149	.131	.084	.081	.048	.038	.119	.142	.116	.12
Between R^2	.093	.003	0	.004	.078	.02	.006	.003	.232	.16	.082	.07	.321	.17	.12	.124
Within R^2	.5	.332	.273	.211	.549	.38	.361	.354	.47	.34	.307	.284	.528	.414	.407	.409
Log likelihood	−215.947	−230.405	−228.957	−228.39	−240.848	−248.732	−248.071	−248.335	−180.826	−188.849	−187.867	−187.766	−156.372	−164.637	−163.25	−163.223
AIC	507.894	518.81	479.914	516.779	541.696	543.464	514.143	544.67	437.653	435.698	397.735	435.533	388.744	387.274	348.499	386.445
Hausman test	83.38***	77.58***	45.61***		46364.56***	94.14***	79.15***		84.95***	70.76***	61.24***		9259.08***	115.65***	73.22***	
Waldtest $\theta = 0$	28.92***				31.27***				16.05*				16.53*			
Waldtest $\theta + \beta\rho = 0$	26.02***				23.38***				14.08				13.75			
Lrtest $\theta = 0$	78.99***				219.02***				150.18***				186.99***			

Note: AFSI: Aggregate Financial Stability Index; CF: crowdfunding, BL: business lending; CL: consumer lending; CBE: cross border exposure; IR: interest rate; INFL: inflation rate; PD: public debt; GDP: growth rate of the Gross Domestic Product; EPU: Economic Policy Uncertainty Index. t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively. All models use distance decay weight matrix. When alternative (inverse distance and 5-nearest neighbour) weight matrices are employed, again the SDM is the chosen specification and hence we do not present these results to save space (they are available upon request). Fixed effect is adopted in all case based on Hausman test statistics (see fourth last row).

variables, similar to the full sample, *GDPG* has positive direct, negative indirect and no significant total effect, and *INFL* has no direct but positive indirect and total effects.

When excluding year 2020 (i.e., Columns (4)-(6) in Table 7), *AFF* continues to have positive and highly significant (at 1 % level) effects on *AFSI*. For control variables, compared to the full sample results in Columns (1)-(3) in Table 5, the indirect effect of *GDPG* turned positive, leading to a positive total effect on *AFSI*. In 2020 when there lacked economic growth in most parts of the world, any GDP growth would serve as an extremely powerful magnet attracting economic and financial resources from neighbouring countries and adversely affect the financial stability in these countries (Kohlscheen et al., 2020; Asare and Barfi, 2021). The exclusion of year 2020 may have significantly reduced such negative spillover effect and we now find positive influence of country *j*'s *GDPG* on country *i*'s *AFSI* during 2013–2019. This implies that during periods of economic stability, regional endeavours aimed at fostering economic growth have facilitated a fair allocation of financial resources among countries (Gómez-Zaldívar et al., 2020; Anousheh et al., 2020). The presence of commonly shared economic objectives and policy instruments has ensured that economic growth in one jurisdiction stimulates similar growth in neighbouring regions and thereby promote their financial stability (Sverko et al., 2020). *EPU* has turned from insignificant in the full sample results in Columns (1)-(3) in Table 5 to remaining positive but highly significant in Columns (4)-(6) in Tables 7 when 2020 is removed. Ashraf and Shen (2019) demonstrate that EPU contributes positively to interest rates spread in the syndicated loan market. Kim (2019) confirms this and explains that rise in credit spreads encourages investment activities among lenders due to the incentive of passing on the premium for uncertainty to borrowers. Borrowers with net present value projects greater than the cost of premiums are willing to take such loans. This cycle keeps the financial system of a country in equilibrium through the loan market. The positive direct effect of *EPU* on *AFSI* may reflect such rebalancing of the financial system in phases of economic uncertainty. For the positive indirect effects, Balcilar et al. (2017) document that the welfare benefits of portfolio diversification during uncertain periods in the US produces significant positive spillover for the global capital market helping investors gain favourable returns on investment. Brogaard and Detzel (2015) echo this as forecasted excess market returns increased with EPU. Hoek et al. (2022) also observe that economic policy shocks associated with Federal Open Market Committee announcements anticipated to promote employment and growth in the US have generally send positive spillovers in emerging markets.

In the last three columns in Table 7 (Columns (7)-(9)) when both China, US, UK and year 2020 are excluded, *AFF* remains to have positive and highly significant (at 1 % level) effects on *AFSI*. *GDPG* has positive total effect on *AFSI* due to positive direct effect.

Therefore, the three sets of estimates in Table 8 show that our main findings in Section 5.2 are robust to the exclusion of the three Fintech financing leaders (China, US and UK), year 2020, and both. *AFF* has consistently positive and highly significant (at 1 % level) direct, indirect and total effects on *AFSI*. We also find that such positive impacts are stronger in countries with relatively smaller size of Fintech financing.

6. Further analysis – Three main components of the aggregate Fintech-enabled financing

Given the differences in the funding process and default rates among Fintech crowdfunding, business lending and consumer lending (see discussion in Section 3.2), this section further examines the impact of these three main components of Fintech financing on financial stability. The main results and three sets of robustness checks are summarised in Tables 8 and 9.

Table 9
Direct, indirect and total effects: Fintech crowdfunding, business lending and consumer lending.

	Full sample Based on SDM model Table 8 Column (1)			Excluding China, US and UK Based on SDM model Table 8 Column (5)			Excluding year 2020 Based on SDM model Table 8 Column (9)			Excluding China, US, UK and year 2020 Based on SDM model Table 8 Column (13)		
	(1) Direct effects	(2) Indirect effects	(3) Total effects	(4) Direct effects	(5) Indirect effects	(6) Total effects	(7) Direct effects	(8) Indirect effects	(9) Total effects	(10) Direct effects	(11) Indirect effects	(12) Total effects
CF	.305***	.182***	.488***	.474***	.235***	.709***	.292***	.181***	.473***	.449***	.204***	.653***
	(.06)	(.053)	(.097)	(.07)	(.07)	(.112)	(.065)	(.056)	(.105)	(.074)	(.068)	(.108)
BL	.046	.027	.073	.067**	.033*	.099**	.026	.015	.042	.033	.014	.047
	(.03)	(.019)	(.048)	(.032)	(.018)	(.048)	(.037)	(.024)	(.06)	(.037)	(.018)	(.053)
CL	.003	-.17***	-.167**	-.008	-.209***	-.217***	.017	-.14*	-.123	.013	-.155**	-.142*
	(.023)	(.063)	(.074)	(.023)	(.057)	(.067)	(.027)	(.072)	(.084)	(.027)	(.061)	(.072)
GDPG	.097***	-.103*	-.006	.076*	-.117*	-.041	.186***	.117**	.303***	.193***	.089**	.282***
	(.038)	(.062)	(.053)	(.04)	(.062)	(.056)	(.059)	(.05)	(.102)	(.06)	(.043)	(.095)
PD	.006	.004	.01	.006	.003	.009	.004	.003	.007	-.001	0	-.002
	(.006)	(.004)	(.011)	(.007)	(.004)	(.011)	(.008)	(.005)	(.013)	(.008)	(.004)	(.012)
CBE	.512	.308	.82	-.22	-.141	-.361	.175	.082	.257	-.669	-.313	-.982
	(1.136)	(.709)	(1.827)	(1.197)	(.648)	(1.825)	(1.145)	(.727)	(1.855)	(1.202)	(.619)	(1.788)
INFL	-.012	.351**	.339*	.001	.382**	.383**	.017	.01	.027	.033	.014	.046
	(.06)	(.174)	(.194)	(.061)	(.168)	(.189)	(.062)	(.041)	(.102)	(.063)	(.031)	(.092)
EPU	.588**	.35**	.938**	.719***	-1.156*	-.437	.679***	.42**	1.099***	.731***	-.462	.269
	(.238)	(.158)	(.375)	(.263)	(.616)	(.71)	(.243)	(.182)	(.4)	(.263)	(.58)	(.664)
IR	-.014	-.009	-.023	-.021	-.011	-.032	-.042	-.027	-.069	-.049	-.023	-.072
	(.031)	(.02)	(.05)	(.031)	(.017)	(.047)	(.033)	(.024)	(.056)	(.033)	(.019)	(.05)

Note: CF: crowdfunding, BL: business lending; CL: consumer lending; CBE: cross border exposure; IR: interest rate; INFL: inflation rate; PD: public debt; GDP: growth rate of the Gross Domestic Product; EPU: Economic Policy Uncertainty Index. t-statistics are in parentheses; ***, ** and * indicate statistical significance at 1, 5 and 10% level, respectively. All models use distance decay weight matrix. Fixed effect is adopted in all case based on Hausman test statistics. ρ (rho) for all three SDM specifications is positive and significant at 1% level.

6.1. Spatial model choice

First, we investigate the full sample results presented in Column (1)-(4) in Table 8. ρ is positive and significant at 1 % level in SDM and SAR but insignificant in the SAC model. λ in SEM is significant at 1 % level. $\theta = 0$ and $\theta + \rho\beta = 0$ are rejected and 1 % significance level in Column (2) and (3), respectively. The AIC statistic is lower in SDM in Column (1) than SAC model in (4). Therefore, SDM is the most appropriate model.

6.2. Direct, indirect and total effects

Columns (1)-(3) in Table 9 summarise the direct, indirect and total effects estimates based on the SDM specification in Column (1) in Table 8. *CF* is observed to have a positive direct (0.305), indirect (0.182) and total effects (0.488) on *AFSI* at 1 % significance level. This implies that an increase in crowdfunding in country *i* positively affects financial stability not only in country *i* but also in neighbouring countries. On the other hand, *BL* has no significant direct, indirect and total effects on *AFSI*. In the case of *CL*, there is no significant direct effect but negative indirect (−0.170) and total effects (−0.167) on *AFSI* at 1 % and 5 % significance level, respectively. It suggests Fintech-enabled consumer lending in country *i* has negative spillover effect on financial stability in its neighbouring countries.

Several key channels may be understood to facilitate the dominating positive impact of *CF* on *AFSI*. First, as discussed in Section 3.2, crowdfunding accounts for the highest project success rates among all Fintech models due to its rigorous fundraising process which ensures that projects are accurately valuated to match the target funds. The considerable presence of highly skilled investor groups, institutional investors and venture capitalists on crowdfunding platforms is a credit to the broad expertise and in-depth financial knowledge that are crucial in identifying worthwhile projects (Wang et al., 2019; Gallucci et al., 2023). It is worth noting that, much of the screening process involves the use of big data and machine learning tools such as random forest, decision trees and support vector machines to predict with accuracy the expected success rate (Nguyen et al., 2023). Through this effort, Wang et al. (2020) and Qu et al. (2022) show that there is 90 % − 92.3 % prediction accuracy of fundraising outcomes and precision in matching crowdfunding projects to the most appropriate backers. This translates to fewer project failures with limited adverse economic impact to the financial system.

Secondly, the 'all or nothing model' applied by most crowdfunding platforms ensures a strict screening process where only viable projects showing serious commitments from investors are allowed to proceed. In this feature, crowdfunding platforms exert the right to return funds to investors when the target amount is not reached while also ensuring that no more than the target amount is raised. This process helps the platform gauge the level of investors' faith and loyalty to a given project while also avoiding the problem of resource overallocation (Pierrakis and Collins, 2013; Li et al., 2023) to keep the financial system efficient. In line with this finding, Cordova et al. (2015) demonstrate a strong positive relationship between project success and the amount of per day dollar amounts received from investors.

Lastly, unlike business and consumer lending, crowdfunding is the only channel that provides an avenue for funding social initiatives which are essential for economic stability. Through crowdfunding, capital is allowed to flow to the needed sectors even if they are not financially rewarding. Reward and donation-based crowdfunding aids social entrepreneurship efforts in the area of education, health, agriculture, technology and climate. Through such initiatives, the financial system benefits from the growth in human capital, innovation and technology to drive economic growth and stability (Campanella et al., 2023). Nega and Schneider (2014) compare the impact of social entrepreneurship to that of microfinancing and allude to the capacity of social entrepreneurship to act as a microeconomic strategic tool to development. They reveal that social enterprises drive the economy closer to efficiency through its ability to pursue capitalist ventures with positive externalities while seeking the shared prosperity of the society. Hence, via financing social entrepreneurship, donation-based crowdfunding help promote stability levels through its goal of facilitating capital allocation at grassroots to marginalised groups. Amofah (2021) confirms this showing that skills impacted through social initiatives have encouraged small-scale business start-ups among household groups in Africa and stimulated improved quality of life and poverty alleviation. Kang et al. (2017) further show that the forcefulness of crowdfunding in promoting innovation is key to the wide promotion of knowledge spillover into new regions. The use of online tools ensures that the spillover is not only local but also global, which encourages various jurisdictions to channel resources into further development of innovations for efficient capital allocation, diversification and decentralisation of financial products and services in remote and less served countries.

In contrast to the positive effects of *CF*, *CL* shows no positive direct effect and negative indirect and total effects on financial stability. Walthoff-Borm et al. (2018) reveal that Fintech consumer lending platform, especially P2P platforms, appear to operate as a lender of last resort to most households and small-scale borrowers when all personal funds and avenues are exhausted. Fintech consumer lending often thrive in less institutionalised systems (Claessens et al., 2018; Haddad and Hornuf, 2019; Tello-Gamarra et al., 2022). Furthermore, the lack of transparency and trust are also concerning issues of consumer lending. Suryono et al. (2021) analyse the development of P2P consumer lending in Indonesia and find high level of distrust among market participants on the lending platforms due to concerns over fraud. Chorzempa and Huang (2022) and Rao (2021) make similar discoveries on the Chinese market. Both studies point to the lapse in regulatory mechanisms to effectively monitor Chinese consumer lending platforms as the facilitator of widespread fraudulent and illegal lending practices which ultimately triggered a P2P bubble burst in 2018. Braggion et al. (2018) shows P2P lending undermines regulation in the credit market and may potentially lead to excessive household debt. These undesirable properties of consumer lending may have offset any direct benefit it could bring to financial stability. Moreso, the negative indirect effect indicates that Fintech consumer lending has a negative spillover effect to neighbours. Increased adoption of consumer lending spread lending misconducts and excess credit supply to neighbouring countries which could stimulate massive levels of defaults, propagate procyclicality and asset price bubbles which jeopardises financial stability not only locally but also across border.

Gemayel and Preda (2018) find evidence of this on the SocialEX and TradEX social trading platforms.

In terms of *BL*, its impact on financial stability is absent. The lack of direct effect may be due to the fact that differences in banking structures and support schemes for SMEs in various countries determine how relevant Fintech business lending operations affect financial stability (Gopal and Schnabl, 2022). Likewise, the relatively smaller size and consequently lower penetration level of Fintech business lending compared to that of crowdfunding and consumer lending may limit its impact on the financial system (Ziegler et al., 2021). For the spillover effect, it is possible that when the increase of Fintech business lending is transmitted to neighbouring countries, the benefit for financial stability is offset by the uniqueness of each country's financial structure and policy towards SMEs.

For the control variables, *GDPG*, *INFL* and *EPU* are variables showing significant impact on *AFSI*. The results of *GDPG* and *INFL* are very similar to that under *AFF* in Columns (1)-(3) in Table 5 in Section 4.2. *EPU* shows positive and significant direct, indirect and total effects on *AFSI*. The positive effects of *EPU* are explained in Section 5.3 and hence are not repeated here.

Thus, using the three main components of aggregate Fintech financing (*CF*, *BL* and *CL*), our empirical results again underline the importance of considering spatial dependence across countries. Furthermore, our findings show the positive contribution of crowdfunding towards financial stability and the destabilising effect of Fintech consumer lending. Combining these with the main results in Section 5, it indicates that crowdfunding is the main driver of the positive effect that aggregate Fintech financing has on financial stability.

6.3. Robustness checks

Similar to Section 5.3, we present three sets of robustness checks excluding first the three leading players of Fintech financing (i.e., China, US and UK), then year 2020, and finally both. The results are reported in Columns (5)-(12) in Table 8 and Columns (4)-(12) in Table 9. ρ is positive and significant at 1 % level in all cases when shown except in SAC model. The λ in SEM is also significant at 1 % level. The hypothesis $\theta = 0$ is rejected for SAR model in Columns (6), (10) and (14) and $\theta + \rho\beta = 0$ is rejected for SEM model in Column (7). Although $\theta + \rho\beta = 0$ is not rejected for SEM model in Columns (11) and (15), as SDM yields unbiased coefficient estimates even if the true data generation process is a SEM or SAR (Elhorst, 2012), we adopt SDM in these two cases for consistence. The AIC statistics are lower in SDM in Column (5), (9) and (13) than SAC model in (8), (12) and (16), respectively. Therefore, SDM remains to be our chosen model.

Column (4)-(12) in Table 9 summarise the direct, indirect and total effects estimates based on the SDM specification in Columns (5), (9) and (13) in Table 8. Looking at results across the three sub-samples in Columns (4)-(12) in Table 9, a noticeable feature is that *CF* has consistently positive and highly significant (at 1 % level) direct, indirect and total effects on *AFSI*. It corroborates with the full-sample finding (Column (1)-(3) in Table 9) and confirms crowdfunding's strong positive impact on financial stability regardless of whether using full- or various sub-samples. Furthermore, in our first sub-sample (without China, US and UK), the direct, indirect and total effects of *CF* (i.e., 0.474, 0.235 and 0.709 in Columns (4)-(6), respectively) are consistently larger than that of the full sample (i.e., 0.305, 0.182 and 0.709 in Columns (1)-(3), respectively). It implies that the positive effect of crowdfunding on financial stability is greater in nations where crowdfunding is less developed. In accordance with Chen et al. (2020), this occurs due to the diminishing marginal effects of crowdfunding along its developmental stages. In their study, Chen et al. (2020) explain that at the initial growth stage, crowdfunding exhibits a positive albeit declining rate of impact on firm performance, and this eventually changes into a progressively negative rate of impact as crowdfunding grows into stable and maturity phases. This is also very similar to the corresponding results under the aggregate Fintech financing in Section 5.3.

Across the three sub-samples, *CL* shows very similar results as the full sample with no direct effect and negative indirect and total effects on financial stability. The only exception is its total effect when year 2020 is excluded (Column (9)) which remains negative but turns insignificant. Under the influence of Covid pandemic in 2020, the default rate in Fintech consumer lending, which was already higher than crowdfunding and business lending, had grown noticeably (World Bank and World Economic Forum, 2020; Jagtiani et al., 2023), exacerbating its adverse impact on financial stability. As such, the exclusion of year 2020 may have removed its strong negative spillover in that year and led to overall insignificant total effect on financial stability.

For *BL*, it remains insignificant in the second and third sub-samples (Columns (7)-(12)), which is consistent with the full sample results (Columns (1)-(3)). However, it has significant positive direct, indirect and total effect on financial stability in the first sub-sample when China, US and UK are excluded (Columns (4)-(6)). As discussed earlier, compared to Fintech consumer lending which has the highest recorded default rates across all Fintech models, Fintech business lending has promising levels of success rates after crowdfunding (Chishti, 2016; Mollick and Robb, 2016; Schwartz, 2018). The willingness of governments to promote SMEs growth and the huge credit gap that exists for small business loans propels the increased dependence on Fintech-enabled business lending to facilitate SMEs growth (Thakor, 2020). Compared to China, US and UK, the sub-samples are countries with smaller sized Fintech business lending, and it is in high demand. For instance, Schindler (2017) and Ioannou and Wójcik (2022) show strong demand for Fintech business financing among emerging countries to support business ventures. Thus, the positive effect of *BL* on *AFSI* when excluding the three leading countries implies that when Fintech business lending is relatively low in a country, its positive impact on effective resource allocation and financial stability is more profound, and it sends positive spillover to neighbouring jurisdictions.

For control variables, the first sub-sample (without China, US and UK in Columns (4)-(6)) show very similar results as the full sample (Columns (1)-(3)) except that *EPU* has negative indirect effect. Nevertheless, *EPU* has no significant total effect on financial stability due to the opposite signs of direct and indirect effect. Its indirect and total effects become insignificant in the last sub-sample. In the latter two sub-samples, *GDPG*'s indirect and total effects turn positive, which is similar to the *AFF* results in Columns (4)-(6) in Table 7. *INFL* no longer has any significant impact in the latter two sub-samples.

Therefore, the three sets of robustness checks confirm crowdfunding's consistently positive direct, indirect and total effects on financial stability. Such positive impact is more profound in countries with smaller size of crowdfunding. Fintech consumer lending remains negative indirect and total effects except total effect turning insignificant when year 2020 is removed. Fintech business lending remains ineffective except showing positive direct, indirect and total effects on financial stability when China, US and UK are excluded.

7. Conclusions and policy implications

This study examines the impact of Fintech on financial stability in 25 countries from 2013 to 2020. We account for spatial dependence in financial stability across borders by employing several alternative spatial models. We adopt a novel measure for Fintech using the aggregate Fintech-enabled financing volumes from the Cambridge Centre for Alternative Finance. It also offers information on Fintech financing at disaggregated level, namely crowdfunding, business lending and consumer lending, which have different funding processes and default rates.

Our findings can be summarised as follows. First, our spatial model analysis strongly validates the consideration of spatial dependence in financial stability across countries. The SDM specification is found to be the most appropriate spatial model for our data. Second, analysis employing the aggregate Fintech financing demonstrates that Fintech financing has strong positive direct, indirect and total effects in enhancing financial stability. Investigation using alternative weight matrices further reveals that the positive spatial spillover of Fintech financing is stronger for neighbours with closer geographical proximity. The positive impact of Fintech on financial stability is robust regardless of three set of sub-samples excluding the three Fintech leaders (i.e., China, US and UK), year 2020, and both. Such positive impact is more profound in countries with smaller sizes of Fintech financing. Third, using the three main components of aggregate Fintech financing, we find positive direct, indirect and total effects of crowdfunding on financial stability and the conversely destabilising effect of consumer lending. This finding remains robust across all three sub-samples. Similar to aggregate Fintech financing, crowdfunding has a stronger positive impact on financial stability in countries where its size is relatively smaller. Fintech business lending shows a positive effect on financial stability only when China, US and UK are excluded.

Our analysis has important policy implications. We find consistent evidence that Fintech improves financial stability domestically and in neighbouring countries, and such positive influence is stronger in countries with smaller Fintech credit volume. It calls for adequate (rather than excessive or inadequate) financial structure and regulatory framework to support and guide healthy growth of Fintech credit (Rau, 2018; Claessens et al., 2018) to fully release its benefit on financial stability. Furthermore, in some jurisdictions, certain classes of investors are restricted from investing in Fintech products based on their levels of income and wealth brackets, and foreign-based crowdfunding companies are sometimes barred from trading in certain aspects of the Fintech industry such as securities (Dushnitsky et al., 2016; Alhammad et al., 2021; Yasar, 2021). Therefore, sound, country-specific financial structure and regulation are needed to create an equal playing field for Fintech companies. Given the strong spillover effect of Fintech financing, cooperation between global regulators is vital due to differences in regulation across different markets and the potential for regulatory arbitrage during the expansion of cross-border Fintech activities (Frost, 2020).[7]

Also, our study demonstrates that underneath the aggregate Fintech financing, crowdfunding promotes financial stability whilst the opposite is true for consumer lending. Therefore, while creating an advocating financial and regulatory environment for Fintech activities discussed above could support crowdfunding, given that consumer lending has high default (Chishti, 2016; Mollick and Robb, 2016; Schwartz, 2018) and fraud rate (Suryono et al., 2021), the supervision and monitoring of consumer lending should focus on these areas to restrict its adverse influence on financial stability. However, the balance between the regulatory stringency to protect consumers and investors and the flexibility to not stifling financial innovation that responsibly and sustainably benefits the public needs to be delicately kept (Lagarde, 2018). Given the dependence of SMEs on Fintech business lending (Thakor, 2020) and the credit gap SMEs face globally (World Bank, 2022), relevant support schemes are required to facilitate Fintech business lending to reach SMEs more effectively. This could bring more efficient capital allocation and may subsequently release potential positive impact of Fintech business lending on financial stability.

CRediT authorship contribution statement

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

Data availability

Data will be made available on request.

[7] In the event of an external emergence events such as the 2008 financial crisis, as traditional financial institutions have become more intertwined with alternative markets like Fintech start-up, issues such as third-party reliance (when several highly important financial institutions depend on the same third-party supplier for services) can lead to adverse consequence to the stability of the financial system (Clemons and Madhani, 2010). Therefore, despite the positive impact of Fintech development on financial stability observed in our study, a ring-fencing network (as proposed by Lai and Van Order (2017)) is essential to separate Fintech financing from the broad banking sector, mitigating contagion from Fintech activities to banks and *vice versa*.

Appendix A. List of countries

The set of 25 countries included in this study are: Argentina, Australia, Belgium, Brazil, Chile, China, Canada, Finland, France, Germany, India, Indonesia, Ireland, Israel, Mexico, Netherlands, Nigeria, Poland, Singapore, South Africa, South Korea, Spain, Sweden, United Kingdom, and United States.

Appendix B. Variable measurement and data source

Variable Name	Measurement and Data Source
Aggregate Financial Stability Index (AFSI)	See Appendix C
Aggregate Fintech-enabled Financing (AFF)	Aggregated Fintech financing volume of each country adjusted by GDP per capita. We then take the natural logarithm of the series. Aggregated Fintech financing volume is collected from Cambridge Centre of Alternative Finance (CCAF); GDP per capita data is from the World Bank.
Crowdfunding (CF)	It includes equity-based, real estate, revenue-sharing, donation-based and reward-based crowdfunding (adjusted by GDP per capita and then taken natural logarithm). Data source: same as AFF.
Business Lending (BL)	It includes balance sheet business and P2P/ marketplace business lending (adjusted by GDP per capita and then taken natural logarithm). Data source: same as AFF.
Consumer Lending (CL)	It includes balance sheet consumer lending and P2P/ marketplace consumer lending (adjusted by GDP per capita and then taken natural logarithm). Data source: same as AFF.
Public debt (PD)	It measures the sovereign risk and is the public sector debt as a percentage of GDP (%). Data are collected from DataStream, International Monetary Fund (IMF) and the World Bank.
GDP growth rate (GDPG)	Real Gross Domestic Product growth rate (%). Data are collected from the World Bank.
Cross-border exposure (CBE)	Cross-border currency exposure as a percentage of total assets (%). Data are collected from DataStream and the IMF.
Economic Policy Uncertainty (EPU)	Economic Policy Uncertainty Index in natural logarithm. Data are collected from DataStream and the Federal Reserve Economic Data.
Inflation (INFL)	Year on year percentage change in Consumer Price Index (%). Data are collected from the World Bank.

Note: *AFF*, *CF*, *BL*, *CL* and *EPU* are in natural logarithm. The aggregate financial stability is in an index form. All other variables are in percentages.

Appendix C. . Aggregate financial stability Index (AFSI)

Indicators		Impact	Sub-indices	Data Source
Market capitalisation / GDP	I_{d1}	+	Financial Development Index (FDI)	World Bank
Total credit / GDP	I_{d2}	+		
Interest spread	I_{d3}	−		
Herfindahl-Hirschman Index (HHI)	I_{d4}	+		
Inflation rate	I_{v1}	−	Financial Vulnerability Index (FVI)	World Bank
General budget deficit /surplus (% GDP)	I_{v2}	+		
Current account deficit / surplus (% GDP)	I_{v3}	+		
REER excessive depreciation or appreciation	I_{v4}	−		
Non-government credit / Total credit	I_{v5}	+		
Deposits / M2 (variation %)	I_{v6}	+		
(Reserves / Deposits) / (Notes & coins / M2)	I_{v7}	+		
Non-performing loans / Total loans	I_{s1}	−	Financial Soundness Index (FSI)	IMF
Regulatory capital / Risk weighted assets	I_{s2}	+		
Liquidity ratio	I_{s3}	+		
General risk ratio	I_{s4}	+		
World Economic Climate Index − CESifo	I_{w1}	+	World Economic Climate Index (WECI)	IMF
World Inflation rate	I_{w2}	−		
World Economic Growth	I_{w3}	+		

Note: Studies that used similar approach (but not for the group of countries analysed in our study) include Albulescu (2009), Morris (2010), Karanovic and Karanovic (2015) and Gustiana (2021).

Appendix D. . List of abbreviations

AIC	Akaike Information Criteria	INFL	Inflation rate
AFF	Aggregate Fintech-enabled Financing	IR	Interest rate
AFSI	Aggregate Financial Stability Index	LM	Lagrange Multiplier Test
BIS	Bank of International Settlement	ML	Maximum Likelihood Test
BL	Business Lending	OLS	Ordinary Least Squares
CBE	Cross-border Exposure	OECD	Organization for Economic Co-operation and Development
CF	Crowdfunding	OIC	Organization of Islamic Cooperation

(*continued on next page*)

(*continued*)

AIC	Akaike Information Criteria	INFL	Inflation rate
CL	Consumer Lending	PCA	Principal Component Analysis
CCAF	Cambridge Centre for Alternative Finance	PD	Public Debt
CoVaR	Conditional Value at Risk	P2P	Peer-to-peer lending
EPU	Economic Policy Uncertainty	SAC	Spatial Auto Combined
Fintech	Financial Technology	SAR	Spatial Autoregressive Regression
FDI	Financial Development Index	SEM	Spatial Error Model
FSB	Financial Stability Board	SDM	Spatial Durbin Model
FSI	Financial Soundness Index	SRISK	Conditional Capital Shortfall
FVI	Financial Vulnerability Index	UK	United Kingdom
GDP	Gross Domestic Product	US	United States
GDPG	GDP growth rate	VaR	Value at Risk
IMF	International Monetary Fund	WECI	World Economic Climate Index

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