The Impact of FinTech Credit on Financial Stability: An Empirical Study.

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Declaration

I declare that this thesis contains no material that has been accepted for the award of any other degree or diploma in any institution or university. This thesis is based on my original work except for quotations and citations, which have been acknowledged accordingly. I also declare that this thesis has not been previously or simultaneously submitted, either partially or wholly, for any other qualification at any university or institution.

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Dedication

I specially dedicate this craftwork to my dear husband, Khaufelo, and our three lovely kids for their unwavering support throughout this journey. Without their constant support and prayers, achieving this goal would have been impossible-thank you, fam!

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This has indeed been an incredibly long journey—a path filled with lots of memories of challenges, turbulences, and success stories. I want to take this moment to appreciate and thank several people who have contributed to the successful completion of this study. Special thanks are extended to my University Supervisory Team, Dr Khurshid Djalilov, and Professor Hassan Yazdifar for guiding me and ensuring that I reach the final phase of this journey. A special mention to my Sponsor, the Bank of Botswana, for believing in me and investing in my career and studies. Special thanks to my family and friends for their support, encouragement and prayers during difficult times. Words alone are not enough to express my utmost gratitude! Above all, I give glory to God Almighty for His grace, sustenance and strength to carry on through the storms and waves! Indeed, "I can do all things through Christ who strengthens me" Philippians 4:13 (New King James Version Bible)

Abstract

The advent of FinTech credit, a new technological-financial innovation engaged in bank-like activities, has created new dimensions in nonbank credit intermediation, with potential implications for financial stability. However, existing literature and policy debates provide mixed views about the impact of FinTech credit on financial stability. Moreover, the expansion of nonbank credit confronts the role of macroprudential policy in safeguarding financial stability beyond banking. This study aims to investigate whether FinTech credit disrupts or enhances overall financial stability and whether it impacts bank risk-taking. Additionally, the study explores the impact of macroprudential policies on the growth of FinTech credit.

This study utilises cross-country unbalanced panel data from 25 economies over the period 2005Q1 to 2019Q4. A weighted sum approach is employed to construct the aggregate financial stability index used to measure financial stability. To measure bank risk-taking, five bank risk-taking measures, namely: credit, liquidity, portfolio, leverage, and insolvency risks, are used. Furthermore, the integrated macroprudential policy (iMaPP) dataset developed by Alam et al. (2019) is used to construct macroprudential policy variables. Several econometric models are employed for baseline estimations and robustness analysis.

The main findings reveal significant evidence of a non-linear (inverted U-shaped) relationship between FinTech credit and overall financial stability and bank risk-taking. These findings suggest that FinTech credit may enhance overall financial stability to a certain threshold, after which a further increase in FinTech credit may disrupt financial stability. Similarly, the expansion of FinTech credit may initially increase bank risk-taking but later lessen it. The results also show that macroprudential policies promote the growth of FinTech credit, which may undermine its effectiveness and contribute to financial stability risks. The results remain stable based on the extensive and robust analysis performed. The study provides important policy implications and contributes to existing and emerging theories such as nonbank credit intermediation and financial innovations.

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List of abbreviations and acronyms

AI	Artificial Intelligence
APIs	Application Programming Interfaces
BFCI	Bloomberg Financial Conditions Index
BigTech	Big Technology
BIS	Bank for International Settlement
BOE	Bank of England
CBOE	Chicago Board Options Exchange
CCAF	Cambridge Centre for Alternative Finance
DLT	Distributed Ledger Technology
ECB	European Central Bank
EMDEs	Emerging Market and Developing Economies
ESRB	European Systemic Risk Board
EU	Europe Union
FE	Fixed Effect
FGLS	Feasible Generalised Least Squares
FinTech	Financial Technology
FSB	Financial Stability Board
FSI	Financial Stability Index
GFC	Global Financial Crisis
GFDD	Global Financial Development Database
GMM	Generalised Method of Moments
GMPI	Global Macroprudential Policy Instrument
iMaPP	Integrated Macroprudential Policy
IMF	International Monetary Policy
IOSCO	International Organization of Securities Commissions
LAC	Latin America and the Caribbean
MaPP	Macroprudential Policy
MENA	Middle East and North Africa
MSMEs	Micro, Small and Medium-Sized Enterprises
NBFIs	Non-bank Financial Intermediaries
NBFI	Non-bank Financial Intermediation
OECD	Organisation for Economic Co-operation and Development
OFR	Office of Financial Research
P2P	Peer to Peer
PwC	Price Waterhouse Cooper
RE	Random Effect
ROA	Return on Assets
SDGs	Sustainable Development Goals
SYS-GMM	System generalized moment estimation
SSA	Sub-Saharan African
S&P GMI	Standard and Poor Global Market Intelligence
UK	United Kingdom
US	United States
VIX	Volatility Index
WBG	World Bank Group
WEF	World Economic Forum
WLS	Weighted Least Squares
IFC	Irving Fisher Committee

CHAPTER 1: INTRODUCTION AND BACKGROUND

1.1. Introduction

Prior to the 2007-2009 global financial crisis (GFC) and subsequent recessions, the financial sector's share of overall economic activity recorded significant growth. This was partly due to the proliferation of credit and other financial assets resulting from increased leverage in the banking sector and the subsequent expansion of the non-bank sector (Constâncio et al. 2019). These structural changes have since altered the dynamics in certain financial markets, coupled with the increasing growth of financial intermediation undertaken by non-deposit-taking contenders, often lightly regulated (Thakor 2020; Organisation for Economic Cooperation and Development (OECD) 2020). Underpinning these structural transformations in financial intermediation was a rising of a complex and decentralised technologically enabled innovation in financial services and their potential increasing participation in the broader financial system (Marqués et al. 2021). Increased credit intermediation involving entities outside the traditional banking system, especially when it involves the build-up of leverage, liquidity, maturity and credit transformation, also accentuated the potential build-up of vulnerability in the financial system (OECD 2020).

These developments have since sparked global debates, raising concerns for financial stability within the policy and academic circles (Braggion et al. 2021; Fung et al. 2020; Li et al. 2020a).[1] This has further incited a global call for prudential monitoring to stretch beyond the banking sector and incorporate other sections of the financial system (Buch 2020; Boh et al. 2019; Constâncio et al. 2019). The recent developments have become even more relevant as the financial services industry evolves, presented by a revolution of a new digital era, this time in the form of "FinTech" – an established key player at the heart of the fourth industrial revolution (Abbasi et al. 2021; Machkour and Abriane 2020; Chang et al. 2020). FinTech typically integrates finance and technology (Chang et al. 2020; Lee and Shin 2018) and is broadly depicted as an application of technological innovations in financial services (Wójcik 2021; Haddad and Hornuf 2019; International Organization of Securities Commissions (IOSCO) 2017). For the purpose of this study, a

[1] The possible implications of such FinTech activities also extends to several main functions performed by central banks, such as the implementation and transmission of monetary policies, and the regulation and oversight of financial markets infrastructures (Marqués et al. 2021)

widely used FinTech definition by the Financial Stability Board (FSB) is adopted' thereby broadly defined as a "technologically enabled financial innovation that could result in new business models, applications, processes, products, or services with an associated material effect on financial markets and institutions and the provision of financial services" (FSB 2017, p.7).

FinTech typically appears as a multifaceted ecosystem that is particularly active in the provision of various bank-related activities that encapsulate some prudentially essential economic functions.[2] One of these activities is categorically termed "FinTech credit", which refers to "financial products and services that are developing outside the traditional regulated banking and capital market sectors via innovative and predominately online channels, instruments and systems" (World Bank Group (WBG) and Cambridge Centre for Alternative (CCAF) 2019 p.13). This study exclusively focuses on such FinTech credit activities associated with digital or online lending platforms that directly match lenders (i.e., individuals, investors) with borrowers (i.e., households and businesses) without the intermediation of traditional financial institutions such as banks (Bertsch and Rosenvinge 2019).

FinTech credit explores the forces that shape new dynamics in the functions of finance and accentuates fundamental transformation that shifts some parts of traditional banking's core functions in a manner that redefines the financial sector's technological-innovative approach. It thereby creates new financial intermediation dimensions beyond the traditionally regulated spectrum (WBG and CCAF 2019; Wardrop et al. 2015). It typically leverages technology and innovation, delivered via online channels by bypassing traditional financial institutions, (thereby "disintermediates" (Ehrentraud et al. 2020b; Nicoletti 2017; Minto et al. 2017), re-intermediates (Wójcik 2021; Langley and Leyshon 2020) and reshapes the way credit is provided and accessed (Gomber et al. 2018).

Moreover, the FinTech innovation tends to concentrate on specific segments of the value chain, thereby having the potential to unbundle or disaggregate core banking functions previously originated and sold by the banking sector (González-Páramo 2017). The

[2] Currently, FinTech activities are classified into five broad areas namely: (i) credit, deposits, and capital-raising services; (ii) payments, clearing and settlement (including digital currencies); (iii) insurance; (iv) investment management; and (v) market support (Parenti 2020; Navaretti et al. 2018; FSB 2017).

decentralisation of financial services thus eliminates or reduces the core function of one or more traditional financial intermediaries involved in providing financial services; in some instances, it diverts risks emanating from traditional intermediaries to the nonbank sector (FSB 2019b). More specifically, the FinTech lending aspect is even close in nature to such banking functions linked to credit intermediation activities such as credit, liquidity, maturity transformations and the creation and credit risk transfer (FSB 2017).

The increased scrutiny of financial intermediation by the nonbank sector following the GFC motivates the investigation of the potential implications of FinTech credit on financial stability. In particular, the emergence of FinTech credit appears to have sparked lively debates regarding its potential to materially enhance, transform and disrupt business models, applications, frameworks, processes, or products in various areas of the financial services sector (Gray and Leibrock 2017). A held general consensus is that FinTech credit may significantly alter and disrupt existing financial intermediation structures, such as regulatory frameworks, processes, and services, through new business models backed by sophisticated technologies (Vives 2019b; Tarullo 2019; Demertzis et al. 2018). While lending activity remains one of the critical functions of traditional banks, new nonbank credit intermediation also poses threats to traditional banks, with potential implications for overall financial stability. Although the traditional banking system remains the of any financial system, its existence is being scrutinised owing to increased market competition and regulatory pressure, contributing to the decline in bank market share relative to non-banks market share.

Non-banks, also referred to as non-bank financial intermediaries (NBFIs), continue to secure a significant portion of the market share while migrating some of the credit activities and financial risks outside the regulated banking system (Buch 2020; Quarles 2020; FSB 2020b; 2019b). While this may appear as a risk diversification incentive, recent studies reveal that the rapid expansion of FinTech credit may pose prudential regulatory concerns, if sustained over long periods, becomes unstable or grow to a significant share of nonbank credit (Bertsch and Rosenvinge 2019; Boh et al. 2017; FSB 2017). Such rapid credit expansion may further outpace economic fundamentals and output, potentially posing risks to financial stability (Koong et al. 2017). As such, FinTech credit could become a source of instability, a potential channel for regulatory arbitrage and even generate new vulnerabilities and risks (Forbes 2021; Braggion et al. 2021; Buch

2020; FSB 2020a; 2020b). Furthermore, emerging studies suggest that nonbank credit could circumvent the efficacy of existing regulatory frameworks such as macroprudential policies (MaPP) (Braggion et al. 2021; Claessens et al. 2021; Cizel et al. 2019). As previously demonstrated by the United States (US) post-subprime crisis, where tightened regulatory framework steered the rapid expansion of shadow banking, the risk that increased regulatory pressure may boost a rise in non-bank activities has become apparent.

Presently, debates on the impact of FinTech credit on financial stability have aroused the attention of policymakers and the academic community. However, roundtable discussions, debates and action research have mainly focused on the theoretical guidance of FinTech credit and case analysis of the impact of FinTech credit on the general banking and financial system. Notwithstanding the underlying factors that explain these observations, the time series trends raise probing questions about the link between the conceptual fundamentals for the existence of FinTech as a financial intermediary and how it co-exists with the real economy. In this light, this study seeks to explore the implications of FinTech credit on financial stability from three components that constitute an aspect of economic research that still lacks theoretical underpinning and empirical evidence. First, the study examines the relationship between FinTech credit and overall or aggregate financial stability. Second, the study further narrows the analysis to the banking sector, specifically examining the association between FinTech credit and bank risk-taking. Last, the study examines the link between FinTech credit and MaPP.

1.2. Research objectives and questions

1.2.1. Research objectives

The overarching objective of this study is to evaluate the implication of FinTech credit on financial stability. Specifically, the study explores how FinTech credit impacts the overall stability of the financial system and the risk-taking behaviour of traditional banks. Also, the study investigates the effect of MaPP on the growth of FinTech credit. Therefore, the specific objectives of this study are to empirically:

1. *Investigate whether FinTech credit enhances or disrupts the overall financial stability*;

2. *Examine the effect of FinTech credit on bank risk-taking, and*
3. *Assess the impact of macroprudential policies on FinTech credit growth*.

1.2.2. Research questions

To achieve the research objective of this study, the research questions on the impact of FinTech credit on financial stability are drawn in three standalone empirical chapters. Although crafted individually, the empirical chapters align with the central objective. The study, therefore, attempts to answer the following questions in line with the objectives of this study.

1. *Does FinTech credit enhance or disrupt the overall financial stability*?
2. *Does FinTech credit increase or decrease bank risk-taking*?
3. *Do macroprudential policies influence FinTech credit growth*?

1.3. Rationale and scope of the study

This study considers and deliberates on the association between FinTech credit and three broad themes: (i) overall financial instability, (ii) bank risk-taking, and (iii) macroprudential policy. To keep the analysis of this study focused, the coverage of this study is restricted to "FinTech credit", a Fintech lending segment that encompasses credit (loans) facilitated by digital or online lending platforms not operated by commercial banks or lending companies (Claessens et al. 2018; Bank for International Settlement (BIS) and FSB 2017).[3] The study adopts a macro approach due to its interest in examining the overall implication of FinTech credit to financial stability. The interest in this study is thus motivated by several factors. First, this study follows the recent evolving academic and policy debates that suggest that FinTech credit may have important implications for banking and financial stability. In particular, credit activities undertaken by NBFI entities are of outmost relevance to financial stability (FSB 2021).

Lately, the FSB report has categorically placed FinTech credit on areas of non-banks that may pose bank-like financial stability risks (see., FSB 2020a; 2019b) and one of the supervisory and regulatory issues that merit the attention of regulatory authorities (FSB

[3] Other recent studies provide a broader overview and focus on the FinTech market (see., Berg et al. 2022; Agarwal and Zhang 2020; Thakor 2020; Vives 2019)

2017).[4] According to FSB (2021), due to reliance on new digital processes, credit and operational risks are the major risks observed in FinTech credit. Moreover, several jurisdictions have reported credit intermediation whose activities are supported by new technologies, such as machine learning, enabling near-instant credit risk assessment and heterogenous products and services (FSB 2021). According to the researcher's knowledge, this study provides the first empirical study investigating the link between nonbank credit and financial stability.

Second, the study is motivated by the unprecedented rise in NBFI activities (especially after the GFC), which now make up a much bigger market share of the financial system. This standpoint has been motivated by increasing attention to the growing role of NBFIs (e.g., FSB 2020; 2019c), particularly emerging FinTech innovation. Based on data availability of FinTech credit (a subset of NBFIs), the current study focuses on economies that have experienced considerable growth in FinTech credit. It thus employs cross-country panel data comprising advanced and emerging markets and developing economies (EMDEs) from 2005 to 2019. The primary reason behind the selected period of study is to provide coverage on the growth and size of FinTech credit from its (official) inception, thus incorporating the period before, during, and after the GFC.

Overall, despite the challenges with the availability of FinTech credit data (as with many other previous studies), the econometric analysis of this study in the three empirical chapters is undertaken over a relatively longer time period from 2005Q1 to 2019Q4, which is relatively the lifespan of FinTech credit since it was officially recorded. The duration of the study includes the periods before, during, and after the 2008 financial crisis, as well as includes higher frequency (quarterly) panel data than the regular use of low frequency (annual) data. To date, the most available comparable and comprehensive data on this type of activity has been compiled by the CCAF and its collaborating academic and industry partners (see., Cornelli et al. 2021; 2020; Rau 2021; 2020; Ziegler et al. 2021; 2020). While this database has a significantly wider coverage, they are limited to annual data spanning from 2013 to 2018.

[4] Twenty-two (22) out of twenty-five (25) jurisdictions identified FinTech (lending) credit as the most common and recent innovation in the NBFI sector (FSB 2020a; 2019b).

Third, while the standard financial sector indicators tend to focus on the aggregate measures of overall bank lending to the private sector (Beck et al. 2012), little attention is given to private sector lending from the nonbank sector. This study, therefore, uses FinTech credit as a nonbank credit indicator. The study thus explores different measures of FinTech credit as estimated by a share of FinTech credit to total domestic credit (Frost et al. (2019), a percentage of GDP (Bazarbash et al. 2020) and FinTech credit per capita (Cornelli et al. 2021; 2020; Rau 2020; Frost et al. 2019). Previous empirical consistency justifies the emphasis on a credit aggregate as the target for this study. It holds that strong credit growth is directly associated with boom-bust financial cycles and tends to precede crises (Kim and Mehrotra 2018; Alessi and Detken 2018). Moreover, domestic credit growth is widely identified as one of the most robust and significant predictors of banking and financial crises (Röhn et al. 2015; Aikman et al. 2014), the root cause of systemic banking crises (Alessi and Detken 2018) and financial instability, particularly during periods of economic downturns (Kim and Mehrotra 2018).

In contrast, most studies tend to exclude issues stemming from the involvement of the FinTech industry in the activities that can be associated with the NBFI sector (Trapanese 2021). For example, Claessens et al. (2021) categorically measure NBFI as a share of NBFI assets to total domestic financial assets.[5] Other literature uses the "number of FinTech firms (Phan et al. 2021) and "internet finance" constructed as an index based on "text mining" or search engines such as "Baidu's search index" as a proxy for FinTech development (Wang et al. 2021; Dong et al. 2020; Guo and Shen 2019).[6]

Fourth, the potential impact of FinTech credit on the traditional banking sector has also become an area of great interest to policymakers, regulators, and academia. While this attention has produced a vast body of research linking FinTech credit and bank credit (Cornelli et al. 2021; Hornuf et al. 2021; Ali et al. 2019; Zhang et al. 2019; Tang 2019), little attention has been paid to how FinTech credit impacts on banks' risk-taking. However, emerging studies that attempted to explore this relationship largely focused on a general taxonomy or measure of FinTech, such as the "internet finance" index (see. Dong et al. 2020; Guo and Shen 2019). These measures are based on a broader measure

[5] The NBFIs measure used is based on a broader nonbank market comprising of segments such as insurance corporations, pension funds, other financial intermediaries.
[6] The taxonomy of internet finance comprises six major models: third-party payment, peer to peer (P2P) loan platforms, big data finance, crowdfunding and wealth management (Deng 2015).

of FinTech development and do not explicitly capture credit information from the FinTech credit market. The analysis of this study is narrowed to bank stability level to examine the impact of FinTech credit on bank risk-taking. This provides a different perspective to the first analysis by highlighting how FinTech credit affects the banking system from a risk perspective.

Fifth, a focus on the association between FinTech credit and financial stability cannot overlook the interaction of MaPP and the processes of nonbank financial intermediation. However, the current MaPP framework focuses primarily on the banking sector; meanwhile, the framework for the non-bank financial sector largely lacks a macroprudential perspective (de Guindos 2021). There is also limited inclusion of NBFI components in MaPP and financial stability measures. This means that there may be fewer safeguards in the non-bank space, leaving risks to grow unchecked, but as market conditions deteriorate, increases the risk of non-banks amplifying shocks (de Guindos 2021). This may also undermine the effectiveness of MaPP (Braggion et al. 2021; Claessens et al. 2021; Cizel et al. 2019). This study draws on the impact and or limitations of MaPP on nonbank credit, providing a basis for this study.

Sixth, the FinTech revolution has created data gaps that impact several of central banks' main functions, academic research, and central bank statistics. The potential data gaps arising from increased FinTech activity in the financial system and the lack of official data present more significant challenges for financial authorities and academic research (Marqués et al. 2021). The paucity of data on new forms of credit also conflicts with the macroeconomic relevance of credit markets (Cornelli et al. 2020), thus reflecting that some nonbanks engaged in credit intermediation are not systematically assigned to the financial sector (Godoy et al. 2020). This also hampers the ability of policymakers and researchers to measure and monitor the scope of the nonbank credit market and develop an accurate picture of emerging nonbank activities and potential risks arising from therein.

As FinTech credit becomes more economically relevant, it is becoming ever more important to have adequate data on the flow and stock of loans and other credit characteristics for regulatory and research on credit and digital innovation (Cornelli et al. 2020). More importantly, it becomes difficult to have a clear view of total indebtedness in the economy to make accurate assessments of financial risks such as credit and liquidity and credit risks, which could threaten their capacity to ensure financial stability (Marqués et al. 2021). Against this background, it is necessary to broaden empirical research on the implication of FinTech credit on financial stability in order to address new and evolving risks emerging from FinTech. The current study thereby attempts to address the objectives of this study by employing data collected from FinTech credit platforms, thus contributing to research.

Seventh, the expansion of FinTech activity could also generate larger transmission channels, causing risks stemming from the FinTech sector to spread to the wider financial system. This may become more pronounced, particularly if traditional financial intermediaries have indirect or direct exposures to FinTech entities through their linkages with the wider financial sector (Durdu and Zhong 2022; Marqués et al. 2021; FSB 2020b). New micro and macro-financial risks may be introduced or even amplify existing ones (Marqués et al. 2021; Parenti 2020) in addition to the traditional risks inherent to the financial sector. Since the crisis, there has been an increasing need to raise awareness regarding the potential risks that FinTech credit could pose to financial stability, notwithstanding that FinTech credit activity could also benefit and enhance financial stability (BIS and FSB 2017). Moreover, while NBFIs can contribute to a more diversified and efficient financial system, they could also become a source of instability to the financial system (Carstens 2021). This study, therefore, attempts to demonstrate whether such entities like FinTech credit may become a source of risks to banking and financial stability and even circumvent existing regulatory policies. This is because maturity and or liquidity transformation, leverage and imperfect credit transfer can give rise to vulnerabilities in the financial system that could amplify or transmit shocks (FSB 2021).

Last, thinking in hindsight about the early indicators of the GFC, the resilience of the financial system was undermined, leaving it more vulnerable to financial shocks. What is even clearer is that excessive household leverage, market inefficiencies in short-term liquidity, and the externalities associated with financial intermediaries' activities may result in a systemic risk (Kenç 2016). The financial crisis reminds us that there can be many risks to the financial sector and that existing institutions are not only susceptible to risks, but new entrants may also usher in new risks or even escalate existing ones (Mnohoghitnei et al. 2019; Gray and Leibrock 2017). Any emerging market development, such as FinTech innovation, has the potential to generate additional interconnections to the financial system.

1.4. Research originality and contribution of the study

This study makes several contributions to the academic literature. A detailed summary of the research originality and contribution of the study is discussed in the last chapter of this study.

1. This study complements and contributes to emerging and existing literature, policy and other industry players in several ways. It also bears important policy implications.
2. To the best of the researcher's knowledge, this study provides the first attempt to empirically investigate the link between FinTech credit and three concepts: financial stability, bank risk-taking and MaPP.
3. This study is among the first to utilise a rich panel dataset to measure FinTech credit as a nonbank credit aggregate, a variable that is believed to carry significant information about risks and a good indicator of systemic banking and financial crises (Alessi and Detken 2018; Kim and Mehrotra 2018; Röhn et al. 2015).
4. The study uses high-frequency (quarterly country-level) data over a 15-year period rather than low-frequency (annual) data used in most existing studies.[7] The high-frequency data offers a few data advantages, thereby allowing for a more comprehensive measure of FinTech credit intermediation.
5. The consideration of an extended period of study is significant as it allows this study to incorporate the periods from FinTech credit inception, including pre, during, and post-2008 financial crisis, thus, shedding much-needed insight on the effect of the GFC on FinTech credit growth.
6. While several existing literature mainly focuses on various aspects of FinTech using micro or individual country data (e.g., Jagtiani and Lemieux 2018; Zhang et al. 2017), this study broadens the existing research by providing global empirical evidence using cross-country data of 25 economies (both advanced and EMDEs).

[7] The most comprehensive database available is by Cornelli et al. (2020) who provide the first comprehensive annual country panel database for total FinTech credit for 79 countries from 2013 to 2019 (see., Cornelli et al. 2021; 2020; Rau 2021; 2020; Ziegler et al. 2021)
.

7. The study employs comprehensive measures of financial stability, bank risk-taking and MaPP instead of using single-dimensional indicators such as Z-scores and single regulatory indicators.
8. Given the mixed views regarding the relationship between FinTech credit and both financial stability and bank risk-taking, the study brings into consideration a possible nonlinear relationship, unlike previous studies that normally assume a linear relationship.
9. The study also provides the first empirical investigation of the association between FinTech credit and MaPP and reveals the varying effects of MaPP on different forms of credit.

1.5. The structure of the study

The structure of this study is presented in eight main parts. The current chapter (Chapter 1) introduces and motivates the research problems. It also presents the research objectives and research questions and an outline of the study contributions. The remainder of the study is structured as follows. Chapter 2 presents an overview of the growth and developments of the FinTech credit market. Chapter 3 presents a literature review that supports this study and develops the hypothesis. Chapter 4 discusses the research methods and data. This includes the specifics of the methodology used in the study, data sources and the empirical strategies for all three primary research objectives.

Chapters 5, 6 and 7 are empirical chapters that specifically address the three primary research objectives of the study. Chapter 5 (the first empirical chapter) seeks to answer the first research question: *Does FinTech credit enhance or disrupt the overall financial stability?* Chapter 6 (the second empirical chapter) answers the second research question: *Does FinTech credit increase or decrease bank risk-taking?* The third empirical chapter (Chapter 7) addresses the third research question: *Do macroprudential policies influence FinTech credit growth*? In answering these questions, in each empirical chapter, the study provides a detailed presentation of the findings, discussions and summary of the study. Last, Chapter 8 presents conclusions, policy implications, contributions, limitations and future research.

CHAPTER 2: GLOBAL OVERVIEW OF THE FINTECH CREDIT INDUSTRY

2.1. Introduction

This chapter discusses the overview of current FinTech credit developments. It provides a brief description and definitions of FinTech credit. It also provides an insight into the recent developments in the FinTech credit market and highlights the growth patterns of FinTech credit so far, as well as how FinTech lending works. It also describes and provides details regarding the FinTech credit platforms through which the data of this study was obtained. The study begins by defining what FinTech and Fintech credit are as well as how FinTech credit lenders differ from other nonbank lending institutions or NBFIs. Additionally, the current section provides insight into the scope and size of FinTech credit.

2.2. Definition and classifications of FinTech

FinTech has become quite an obscure term that tends to be described differently by various people. Defining FinTech enables the identification and clarification of key areas of focus in this study. It also enables a better understanding of the changing dynamics between FinTech segments. Notwithstanding the lack of an official definition of FinTech, this study looks at various descriptions of FinTech. FinTech is generally viewed as a web of specialised distributive financial channels, financial institutions and markets, processes, financial instruments, technologies, and assets emerging outside the traditional financial system (Dabrowski 2017; Wardrop et al. 2015). A remarkably similar definition derived from the Bali FinTech Agenda (2018) defines FinTech as "advances in technology that have the potential to transform the provision of financial services spurring the development of new business models, applications, processes, and products" (IMF-WBG 2019). Consistent with the definition adopted by the IMF and WBG in their joint Bali FinTech Agenda (2018) and prior CCAF and the World Economic Forum (WEF) publications, FinTech encompasses advancements in technology and modifications in business models that can potentially transform the provision of financial services through the development of innovative instruments, channels and systems (CCAF, WBG and WEF 2020). An overview of different FinTech definitions is annexed in *Table 2.1.*

Table 2.1: Overview of different FinTech definitions

Author	**Definitions of FinTech**	**Views on the FinTech ecosystem**	**Focus**
WEF (2015)	"..defined as the use of technology and innovative business models in financial services".	FinTech embodies a new set of products tailored to the needs of small businesses. These include marketplace("peer-to-peer") lending, merchant and e-commerce finance, invoice finance, online supply chain finance, and online trade finance.	Technology-oriented and function-oriented focus
FSB (2017)	"FinTech is defined as technology-enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on the provision of financial services."	FinTech activities can be organized into five categories: (i) payments, clearing, and settlement; (ii) deposits, lending, and capital raising; (iii) insurance; (iv) investment management; and (v) market support.	Technology-oriented and function-oriented focus
Schindler (2017)	Schindler (2017) has adopted FSB working definition	"By my own estimation, items that would be considered FinTech according to this definition include (...): online marketplace lending (called peer-to-peer lending by some), equity crowdfunding, robo-advice, financial applications of distributed ledger technology, and financial applications of machine learning."	Technology-oriented and function-oriented focus
Philippon (2019)	"FinTech covers digital innovations and technology-enabled business model innovations in the financial sector."		Technology-oriented focus
BIS (2018)	The BIS has adopted the FSB working definition.	The BIS categorises FinTech as "(i) credit, deposit, and capital-raising services, (ii) payments, clearing and settlement services, (iii) investment management service"	Technology-oriented and functionally oriented focus
IMF-WBG (2018)	FinTech is "the advances in technology that have the potential to transform the provision of financial services spurring the development of new business models, applications, processes, and products."		Technology-oriented focus

OECD (2018)	"FinTech involves not only the application of new digital technologies to financial services but also the development of business models and products which rely on these technologies and more generally on digital platforms and processes."	FinTech areas are "payments, planning, lending and funding, trading and investment, insurance, cybersecurity, operations, and communication."	Technology-oriented and function-oriented focus
Thakor (2020)	"...FinTech is the use of technology to provide new and improved financial services."	"The areas that FinTech covers can be broadly described as (i) credit, deposits, and capital-raising services; (ii) payments, clearing, and settlement services, including digital currencies; (iii) investment management services (including trading); and (iv) insurance."	Technology-oriented and function-oriented focus
Ehrentraud et al (2020b)	"...we adopt the FSB's working definition for FinTech." "To characterize the FinTech environment, we distinguish three categories: FinTech activities, enabling technologies and policy enablers."	FinTech activities can be found in the following financial services categories: (i) deposits and lending; (ii) capital-raising and alternative sources of funding; (iii) asset management, trading, and related services; (iv) payments, clearing, and settlement services; (v) insurance; and (vi) crypto assets.	Technology-oriented and function-oriented focus
Mirchandani et al. (2020).		"FinTech can be broken down into several different areas within the financial sector..." (i) asset management, (ii) cryptocurrency, (iii) crowdfunding, (iv) investment management, (v) marketplace lending	Functional focus
ECB (2020)	FinTech is a term used throughout the response to refer to financial technology - in the ECB's view, an umbrella term for any kind of technological innovation used to support or provide financial services that could result in changes to business models, applications, processes, or product		Technology-oriented focus
Chemmanur et al. (2020)	"FinTech (...) refers to the use of the latest technology in solving problems in financial services (...)."	"The FinTech Ecosystem can broadly be divided into following eight industry segments: (i) payments and money transfer, (ii) digital banking, (iii) digital wealth management (...), (iv) capital markets innovations, (v) FinTech lending (...), (vi) equity crowdfunding, (vii) InsureTech (...) and (viii) PropTech (...)."	Technology-oriented and function-oriented focus

Beck (2020)	"On the one hand, FinTech can refer to the integration of technology into product and service offerings by financial service providers to improve their use and delivery to consumers. On the other hand, it can also be understood as new technology-driven players that aim to compete with traditional financial institutions in the delivery of financial services."		Technology-oriented focus
Goo and Heo (2020)	"FinTech (...) revolves around providing traditional financial services in new forms using technology."	"Different areas of the FinTech industry range from payment, billing, lending, wealth management, money transfer, mortgage, and real estate to insurance, personal finance, capital market, blockchain, and cryptocurrency personal finance, capital market, blockchain, and cryptocurrency."	Technology-oriented and function-oriented focus

Source: (Treu 2022) and author's compilation

Due to different views of existing definitions of FinTech, there is great heterogeneity in the literature which divides the definition of Fintech between the technology-oriented and function-oriented focus (Treu 2022). For instance, according to Muthukannan et al. (2021), the FinTech ecosystem is characterised by a heterogeneous, dynamic and evolving network of organisations and the innovative mechanisms by which the scalability of financial services could be enhanced. However, a common consensus regarding the "FinTech" term is the composition of the key words "financial" and "technology" (Hikida and Perry 2020; Mirchandani et al. 2020; Chemmanur et al. 2020). Some existing literature explicitly identifies both emerging technologies and new business models and processes but does not recognise the linkages between the two (Treu 2022).

This study follows both the technology-oriented and function-oriented approaches. For the purpose of this study, the study follows an established FinTech taxonomy developed by the CCAF, a research centre at the University of Cambridge. The working taxonomy brings together a coherent conceptualisation of FinTech activities whilst appreciating the sector's diversity and differentiated business models. Furthermore, it is equally important to underscore that for the purposes of this study, the scope of FinTech is narrowed to *(i)* a set of activities (which could either be regulated or unregulated depending on the jurisdiction) that contributes to the provision of financial services, predominately facilitated by *(ii)* those entities operating outside the traditional finance system (CCAF, WBG and WEF 2020).

The FinTech phenomenon is not entirely a new concept in financial services. The current FinTech market segment typically embodies several financial services segments such as (i) credit issuance and capital-raising services; (ii) payments, clearing and settlement (including digital currencies); (iii) insurance; (iv) investment management; and (v) market support (Parenti 2020; Navaretti et al. 2018; FSB 2017). A more recent CCFA (2022) include FinTech (digital) lending; FinTech capital raising; FinTech payments; enterprise tech provisioning; crypto-asset exchange; wealthtech; insurtech; regtech; FinTech banks; digital custody; digital identity; alternative credit analytics; FinTech savings and consensus services. This FinTech taxonomy currently includes discrete primary FinTech verticals and sub-verticals that are further classified into two overarching groups – *retail facing* (i.e., the provision of financial products and services focused on consumers, households and MSMEs, and more likely to be (business to consumer (B2C)) and *market provisioning* (i.e., enables or supports the infrastructure or key functionalities of FinTech sector) (CCAF, WBG and WEF 2020). *Table 2.2* below summarises the taxonomy system of the FinTech ecosystem. An elaborate overview of each of the primary FinTech verticals and associated sub-verticals can be found in *Appendix A.*

Table 2.2:The CCFA FinTech taxonomy and classification system

Category	FinTech Vertical (Business Model)	Sub-verticals/(Business models included in each vertical)
Retail Facing (Consumers, Households & MSMEs)	Digital Lending	Peer to peer (P2P)/Marketplace (Consumer, Business, and Property Lending), Balance Sheet Consumer Lending, Balance Sheet Business Lending, Balance Sheet Property Lending, Debt-based Securities, Invoice Trading, Crowd-led Microfinance, Consumer Purchase Financing/Customer Cash-advance, Digital Merchant- cash Advance Solutions
	Digital Capital Raising	Equity-based Crowdfunding, Real Estate Crowdfunding, Revenue/Profit Share Crowdfunding, Reward-based Crowdfunding, Donation-based Crowdfunding
	Digital Banking	Fully Digitally Native Bank (Retail), Fully Digitally Native Bank (MSME), Marketplace Bank (Retail), Marketplace Bank (MSME), Banking as a Service (BaaS), Agent Banking (Cash-in/ Cash-out)
	Digital Savings	Digital Money Market/Fund, Digital Micro Saving Solutions, Digital Savings Collective/Pool, Savings-as-a-service (SaaS)
	Digital Payments	Digital Remittances (Domestic and Cross Border-P2P), Money transfer (P2P, P2B, B2P, B2B), eMoney Issuers, Mobile Money, Acquiring services providers for merchants, Points of access (PoS, mPoS, on-line PoS), Bulk Payment Solutions - Payroll, Grants, etc., Top-ups and refill, Payment gateways, Payment aggregators, API Hubs for Payments, Settlement and clearing services providers
	Digital Asset Exchange	Order-book, DEX relayer, Single dealer platform/OTC trading, Trading bots, HFT services, Advanced trading services, Brokerage services, Aggregation, Bitcoin Teller Machines (BTM), P2P marketplaces, Clearing
	Digital Custody	Software Wallet (Mobile Wallet/Tablet Wallet/Desktop Wallet), Web Wallet (eMoney Wallet), Vault services, Key management services, Hardware Wallet
	InsurTech	Usage-based, Parametric-based, On-Demand Insurance, Peer-to-Peer Insurance, Technical Service Provider, Digital Brokers or Agents, Comparison Portal, Customer Management, Claims & Risk Management Solutions, IoT (including telematics)
	WealthTech	Digital Wealth Management, Social Trading, Robo-Advisors, Robo Retirement/Pension Planning, Personal Financial Management /Planning, Financial Comparison Sites
Market Provisioning	RegTech	Profiling and due diligence, Blockchain forensics, Risk Analytics, Dynamic Compliance, Regulatory Reporting, Market Monitoring
	Alternative Credit & Data Analytics	Alternative Credit Rating Agency, Credit Scoring, Psychometric Analytics, Sociometric Analytics, Biometric Analytics
	Digital Identity	Security & Biometrics, KYC Solutions, Fraud Prevention & Risk Management
	Enterprise Technology Provisioning	API Management, Cloud Computing, AI/ML/NLP, Enterprise Blockchain, Financial Management and Business Intelligence, Digital Accounting, Electronic Invoicing

Source CCAF, WBG and WEF (2022)

FinTech (digital) lending is a subset or one of the FinTech business models that form the focus of the study. Specifically, this study is aimed at the FinTech in the lending segment shown in the developed taxonomy of FinTechs' intermediating functions. Within the digital lending segment, the study exclusively focuses on consumer lending, business lending, real estate and invoice trading[8]. However, the data excludes some securities lending and lending in the emerging field of cryptocurrency markets. This study uses FinTech credit data from balance sheet lending, P2P/marketplace lending and invoice trading.[9] FinTech credit activity varies significantly across and within jurisdictions due to heterogeneity in the business models of the online credit platforms (BIS and FSB 2017).

The developed taxonomy of FinTechs' intermediating functions and classification system that describes the FinTech credit activity used in this study is presented in *Table 2.3*.[10] The FinTech credit segment incorporates different sub-segments that include balance sheet lending, P2P/marketplace lending, debt-based securities, and others. The FinTech credit marketplace networks and heterogeneous digital platform entities, individuals and/or institutional that encompass a variety of innovative business models to provide loans (secured or unsecured) to consumers, households and business borrowers or MSMEs (e.g., Lending Club, Prosper, Zopa, Funding Circle). In the case of balance sheet lending by large institutions (e.g., OnDeck Capital, SoFi, Kabbage), credit is offered exclusively to businesses and the property market and, in some cases, consumers. *Figure 2.1* depicts the FinTech credit architecture that illustrates its network topology.

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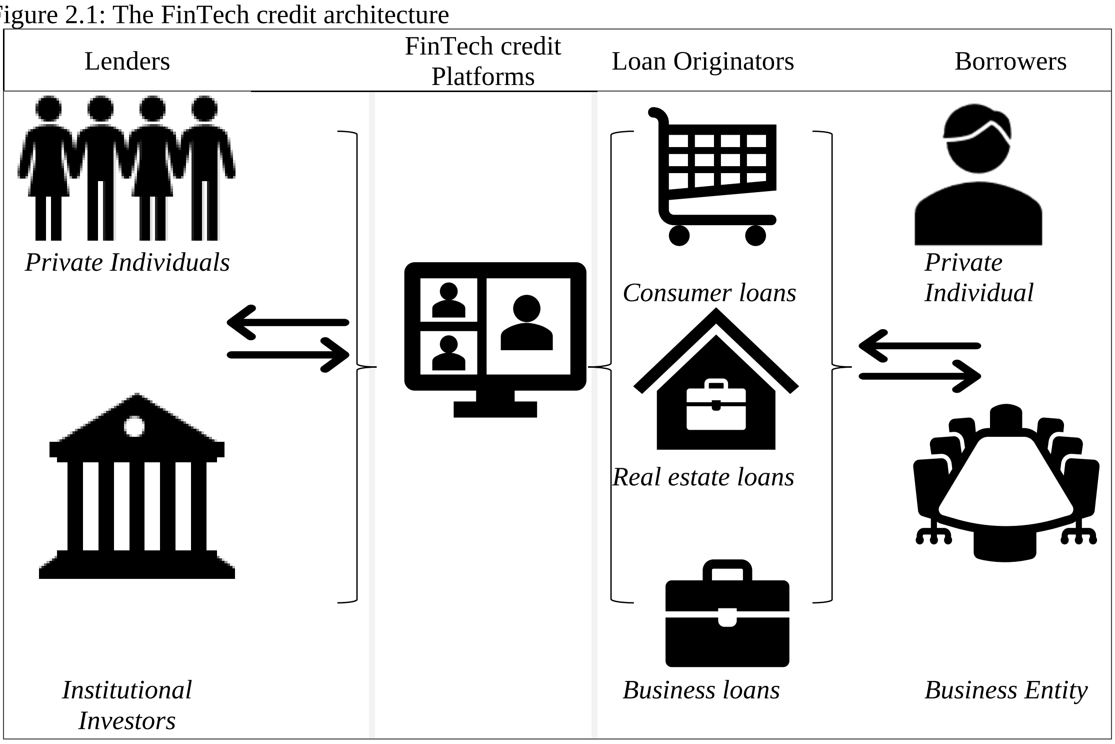
[8] Data includes a small number of debt securities for some countries.
[9] Other debt-based securities, mini-bonds, crowd-led microfinance, customer cash-advance, and merchant cash-advance were not captured at the time of data collection.
[10] Alternative credit excludes digital capital raising such as investment-based crowdfunding and non-investment-based crowdfunding

Table 2.3: A taxonomy of FinTech (digital) credit business models

FinTech Segment	**Sub-Segment**	**Business Model**	**Definitions**
FinTech (Digital) Lending	Balance Sheet Lending	Business Lending	Platform entity that provides unsecured or secured loans directly to a business
		Property Lending	Platform entity provides loans, secured against a property, directly to a consumer or business
		Consumer Lending	Platform entity provides unsecured or secured loan directly to a consumer
	P2P / Marketplace Lending	Business Lending	Individuals and/or institutional funders provide a loan to a business
		Property Lending	Individuals and/or institutional funders provide a loan, secured against a property, to a consumer or business borrower
		Consumer Lending	Individuals and/or institutional funders provide a loan to a consumer borrower
	Debt-Based Securities	Debt-Based Securities	Individuals and/or institutional funders purchase debt-based securities, typically a bond or debenture, at a fixed interest rate
		Mini-Bonds	Individuals or institutions purchase securities from companies in the form of an unsecured bond which is 'mini' because the issue size is much smaller than the minimum issue amount needed for a bond issued in institutional capital markets.
		Invoice Trading	Individuals and/or institutional funders purchase invoices or receivables from a business at a discount
		Crowd-Led Microfinance	Interests and/or other profits are re-invested (forgoing the interest by donating) or provide microcredit at lower rates.
		Customer Cash-Advance	A buy now/pay later payment facilitator or Store Credit solution, typically interest bearing
		Merchant Cash-Advance	A merchant cash advance provided via an electronic platform, typically with a retail and/or institutional investor counterpart receiving fixed payments or future payments based on sales.

Source: CCFA (2022) Cambridge Fintech Ecosystem Atlas (ccaf.io)

Figure 2.1: The FinTech credit architecture



Source: Author's illustration

2.3. How FinTech lending works

The FinTech lending process is comprised of a series of procedures conducted by FinTech platforms to issue loans online. While FinTech and traditional lenders tend to provide some similar functions, i.e., lending to both individuals and businesses, their processes, tools, and customer experience are somewhat different. FinTech lenders operate by using digital technology tools to help lenders issue loans online. They have transformed the lending process through the introduction of alternative lending models, offered faster approvals and funding processes, and made use of data from several different alternative sources to quickly determine how likely a borrower is to pay back the loan. There are several sub-sections and business models within FinTech (digital) lending, including balance sheet lending, P2P/marketplace lending, debt-based securities, invoice trading and others (see *Table 2.3*).

FinTech lending platforms make loans/credit by typically following one of two business models—originate-to-distribute or balance sheet lending (Ben-David et al. 2022). This model is common in consumer lending and is used as well for small business lending. The first business model is common in consumer lending and small business lending. It is a "simple" or "traditional" P2P lending or 'segregated account' model, under which loans are issued directly from the investors (lenders) to the borrowers without the FinTech platform being engaged in risk transformation. Individual loan contracts are thus established between borrowers and creditors, and funds and contractual loan repayments are segregated from the platform's own account (Beck et al. 2022). This typically allows online FinTech platforms to provide a low-cost, standardised loan application process and act as operators or intermediaries directly matching borrowers and lenders that directly enter into loan agreements without assuming any credit risk (Claessens et al. 2018).[11] However, the operations of various platforms may vary. For instance, a platform may only conduct functions such as a pre-screening of projects or, in some instances, undertakes a more in-depth credit risk assessment/scoring of creditors (Beck et al. 2022). FinTech lending platforms that originate to distribute tend to earn a fee for the screening and origination of the loan (Ben-David et al. 2022). They principally generate revenue from fees levied on the transacting parties, such as fees for account setup, loan origination

[11] The investor in this case takes on the risks immediately (Claessens et al. 2018).

and ongoing loan repayment. (Beck et al. 2022). Investments and loans under this model are usually duration-matched; hence the risk of liquidity mismatch is eliminated.

Over time, some platforms have migrated from traditional P2P lending to institutional lending. This is through marketplace lending, through which platforms engage with credit institutions or other lenders to originate the loans and conclude the loan agreement with the borrower. This form of institutionalised lending typically resells the repayment claims arising from the loan agreements in the form of partial claims to individual investors. These partial claims are often publicly offered to institutional investors, i.e., credit institutions/lenders – directly or through an intermediary in the form of an online lending platform. The institutional investors may thus obtain fees as a fixed percentage of the loan amount and or fees from the borrower's monthly repayments. This type of model is gaining more traction and creating some concerns expressed on the possible creation of a secondary market for loans. According to Claessens et al. (2018), some P2P platforms may assist this process by providing a secondary market where investor sales can take place or through the transfer of credit rights.

Within these two key lending models, some hybrid models have evolved, leading to balance sheep lending where platforms use their own balance sheet to retain some part of credit risks. Balance sheet lenders are economically similar to traditional banks in that their profits come from the spread between the cost of funds and the interest and fees paid by borrowers' net losses (Ben-David et al. 2022). They originate and retain loans on their own balance sheet, akin to the usual business model of a non-bank lender (Beck et al. 2022). However, balance sheet lenders do not fund their loans with deposits as banks do. Instead, they use debt facilities that often are collateralised with loans. Other models include "invoice trading" platforms whereby investors purchase discounted claims on a firm's invoices (receivables). Another emerging trend gaining traction in the consumer lending segment is called the "buy-now-pay-later" (BNPL) business model for services that some FinTech firms facilitate for retail customers (Berg et al. 2022; Beck et al. 2022).

2.4. Developments in the FinTech credit market

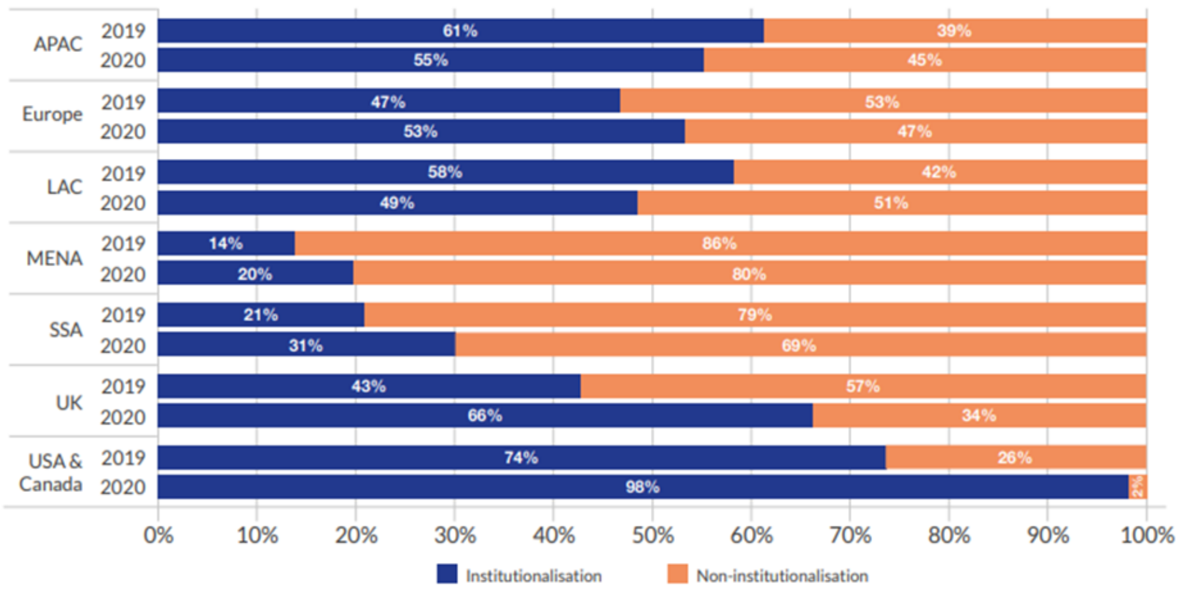
Over the past decades, financial regulators and authorities have cooperated and undertaken initiatives in collaboration with multilateral international bodies such as the FSB, IMF, G20, and the World Bank, with the aim to stimulate competitive innovation and boost economic growth. According to the 2019 UN Secretary-General's Task report, FinTech presents significant opportunities to transform the financial sector in alignment with Sustainable Development Goals (SDGs), particularly SDG goal 9 (*industry, innovation, and infrastructure*) (UN, 2019). However, the FinTech phenomenon is not entirely a new concept in financial services. However, the past decade has witnessed a tremendous transformation in the FinTech market, particularly through the emergence of nonbank financial intermediation by FinTech lending platforms. FinTech credit, in its current form, has been in existence for almost two decades. The world's early FinTech credit or lending pioneers were the UK Zopa, founded in 2005, followed by the US Prosper Marketplace and Lending Club in 2006 and 2007, respectively, and Paipaidai in China in 2007. FinTech credit has since become a key public policy priority and a possible vehicle for sustainable development and stability in digital financing.

The FinTech credit market has experienced various stages of development, transforming from basic P2P lending models to more sophisticated "marketplace lending". The marketplace lending – which has been widely researched in the academic, has since evolved over time from a P2P business model to heavy institutional funding of established retail and institutional investors (e.g., asset managers, investment banks, hedge funds, private equity firms and banks), direct or balance sheet lending and securitisation market (Jagtiani and Lemieux 2018; FSB 2017; Akkizidis and Stagars 2015). The majority of FinTech credit has reduced from marketplace lending to a balance sheet lending model, expanding annual business lending by 43% and estimated at USD 31bn in 2020 (Ziegler et al. 2021).

The active participation of corporate and institutional investors has significantly contributed to the growing FinTech credit. Wei (2015) estimated a contribution of these funding to up to two-thirds of all FinTech credit platforms. Cortese (2014) also estimates more than 80% of the funding is estimated to dominate the US platforms. Furthermore, the growing demand for securities backed by FinTech credit emphasises the growing role of institutional funding in boosting loan growth (see., *Figure 2.2*). To capture this, according to Ziegler et al. (2021), in 2019, institutional investors provided approximately $28.5 billion, which is 16% of the entire alternative finance global volume for that year. A further estimate of $43.6 billion was provisioned by institutional investors, which is 42% of the entire global volume for 2020 (Ziegler et al. (2021). In 2018, approximately

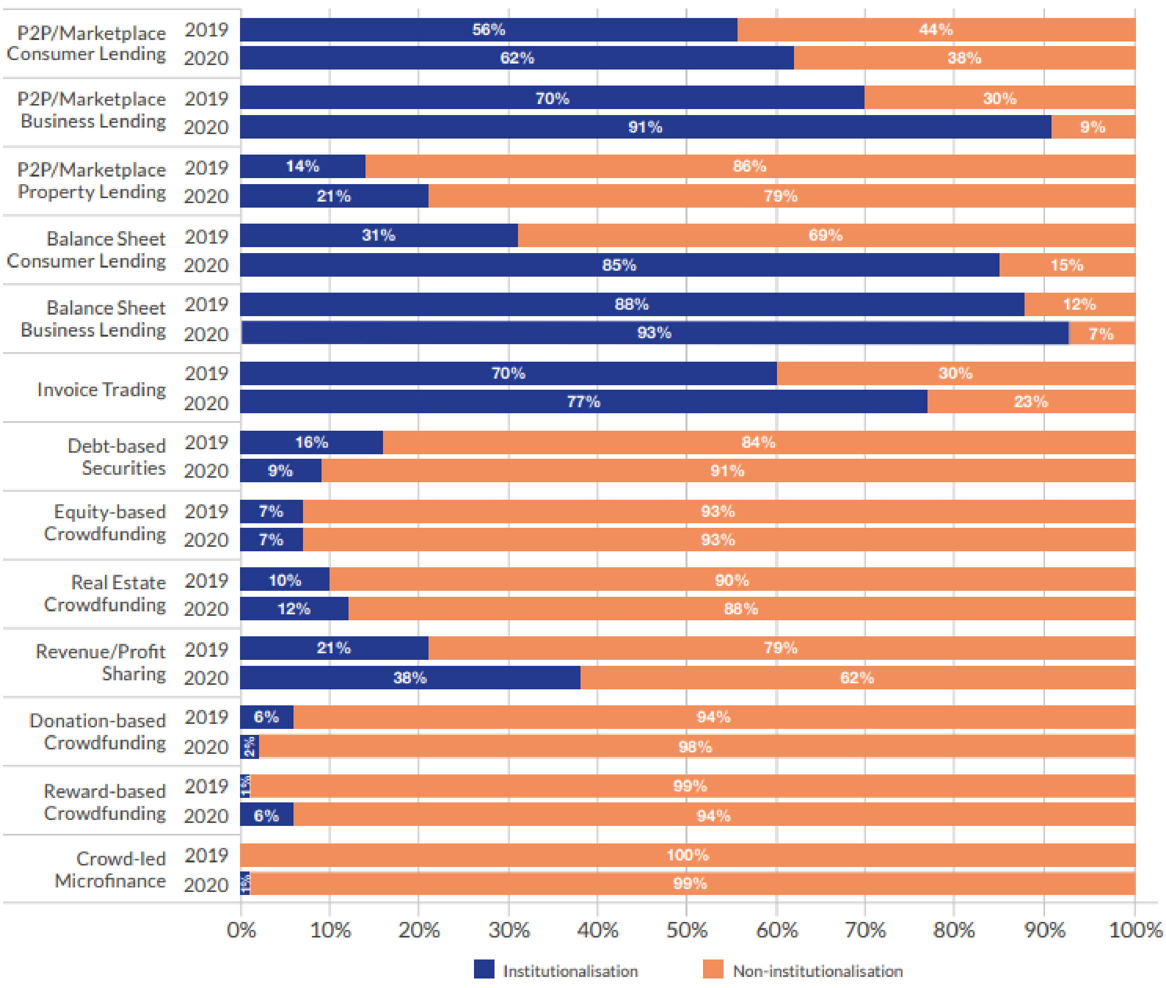
$162 billion of FinTech credit volumes directly stemmed from funding provided by institutional investors (Ziegler et al. 2020). *Figure 2.3* show that debt-based FinTech credit models make up the highest proportion of institutionally led funding, approximately more than two-thirds of their total volume provided by these investors. Debt-based models are usually divided into balance-sheet lending and P2P/marketplace lending (CCAF, WBG and WEF 2022)

Figure 2.2: Proportion of institutionalisation by region, 2019-2020



Source: Zieglar (2021)

Figure 2.3: Proportion of institutionalisation by model, 2019-2020



Source: Zieglar (2021).

The unprecedented growth and the disruptive potential of emerging technological developments in finance challenge the existing institutional and regulatory arrangements in the financial sector (Parenti 2020). According to Ehrentraud et al. (2020a), only a few jurisdictions have developed regulatory frameworks designed to target specific FinTech activities such as loan crowdfunding or FinTech credit. However, the authors assert that the new regulatory categories for FinTech innovations do not always aim to control the specific risks they pose but instead seek to enhance competition or financial inclusion by imposing (temporarily) lighter requirements. Moreover, while the regulatory frameworks have been broadened in some jurisdictions to include nonbanks, some important policy gaps remain in several countries. Some activities, such as FinTech credit, are still excluded from national credit statistics. Also, according to the (ESRB) 2016, the scope of loan-to-value (LTV) limits exclude nonbanks in some European countries.

2.5. The growth and market size of FinTech credit

This study provides a brief overview of the global market size of global alternative finance, in this case, FinTech lending. Global alternative finance, in this case, represents flows of new digital loan origination issued via an online FinTech credit platform for consumers and businesses. However, estimating the size of the FinTech lending market remains a challenge due to the lack of official FinTech credit data and data on the stock of FinTech lending is also difficult to collect (Ziegler et al. 2021). This makes it difficult to estimate the growth of global Fintech credit. To date, the most available global comparable and comprehensive data on this type of activity has been compiled by the BIS and CCAF and its collaborating academic and industry partners (see., Cornelli et al. 2021; 2020; Rau 2021; 2020; Ziegler et al. 2021; 2020). Currently, cross-country data studies provide a comprehensive overview of FinTech credit volumes and other alternative forms of lending globally (Ziegler et al. 2021; Cornelli et al. 2020; Frost et al. 2019; Claessens et al. 2018). For instance, a new BIS database estimate by Cornelli et al. (2020) provide a comprehensive annual country panel database for total alternative credit volumes (FinTech credit and Big-Technology (BigTech) credit) for 79 countries from 2013 to 2019. "BigTechs" are typically large companies whose primary activity is technology (Berg et al. 2022) or digital services rather than financial services (Frost et al. 2019). These established networks, such as Amazon, Apple, PayPal, and Google, are making a significant mark in alternative finance (Cornelli et al. 2020; Frost et al. 2019; FSB 2019a).

The current global trends indicate that FinTech credit activities display potential growth over different regions at varying depths, scopes and sizes. According to Anagnostopoulos (2018), the financial system passed through a "financial crisis and regulation-enabled growth" during the period between 2008 and 2013, where investment in financial technology solutions experienced a fourfold increase in growth compared to venture capital. FinTech credit was the second-largest segment by transaction values after digital payments, accounting for 20% of transaction values versus 63% of digital payments in 2020 (CCAF, WBG and WEF 2022). In contrast with the payments segment, FinTech credit activities remain largely concentrated in advanced economies, with most of the activity and growth spurred by digital platforms, while at a global level, the activities of FinTech credit platforms in EMDEs have decreased (CCAF, WBG and WEF 2022).

Globally, FinTech credit currently constitutes a relatively smaller share of overall lending compared to traditional bank credit, but its growth rates outpace traditional lending growth rates (Berg et al. 2022). For instance, beyond 2013, the global market size of FinTech lending skyrocketed. A number of published data reveal a significant increase in global alternative finance volume (both FinTech credit and BigTech credit) between 2013 and 2019. Cornelli et al. (2020) estimate that in 2019 global total of the flow of the new forms of FinTech credit was estimated at $795 billion, making up $223 billion and $572 billion, respectively.

Another global analysis of total global market volume by Ziegler et al. (2020) indicate that the global alternative finance industry raised via FinTech credit platform for consumers, business and other fundraisers, facilitated USD $304.5 billion in transaction volume in 2018, a 27% annual decline from the $419 billion recorded in 2017. Ziegler et al. (2021) further document a global decline of 42% from $304.5 billion in 2018 to $176 billion in 2019. Similar to the global total FinTech credit market volume, FinTech credit business funding for start-ups and SMMEs fell by $82 billion in 2018 from $153 billion recorded in 2017, a significant reduction largely due to the sharp decline in business-focused funding activity in China (Ziegler et al. 2020). Based on the data used in this study, the sample size for 25 economies is estimated at $217.5 billion in 2019, after reaching a high of $463.8 billion in 2017. The major decline in global volume in all instances was entirely attributed to a sharp decline in alternative finance activities in China (Cornelli et al. 2021; Ziegler et al. 2021, 2020).

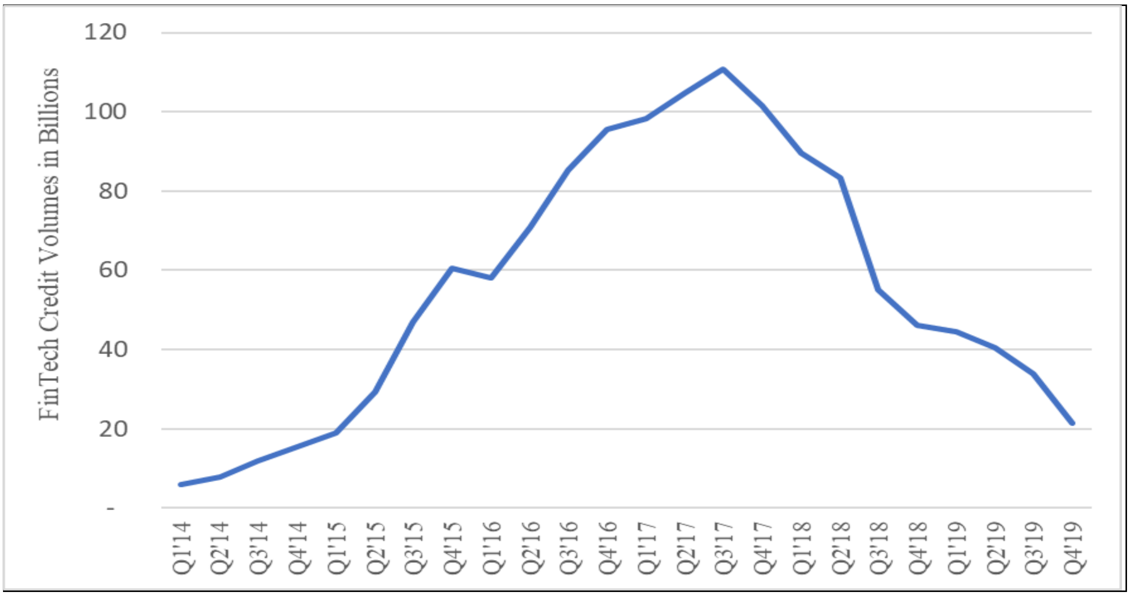
On the other hand, a different trend is observed where BigTechs expanded their remit of action in the provision of credit lending at a time when Chinese FinTech credit lending was declining (Cornelli et al. 2020). However, the data also show that since 2018, BigTech credit has overtaken FinTech credit in total size (Cornelli et al. 2020). China was among the economies with the largest markets for BigTech credit in absolute terms (Cornelli et al. 2021). This study thus infers that the decline in FinTech credit may partly be caused by the emergence of BigTech credit which is not included in this study. A brief overview of this decline is discussed in *Box A* below.

Box A: The Case of China's collapse of Fintech credit

The FinTech credit industry in China is large and very fragmented. China, one of the leading giants in the size of alternative finance and has experienced numerous and fast-growing in the period through 2017 but experienced a substantial decline in both the stock and flow of FinTech lending and its global market share, causing an overall contraction in the global FinTech credit volumes between 2018 and 2019 (Cornelli et al. 2021; 2020; Ziegler et al. 2021). This was largely due to several structural and regulatory reforms following a series of platform failures and exists, fraudulent activities and malpractices (Ziegler et al. 2021; Cornelli et al. 2021; 2020; Claessens et al. 2018).

China experienced a series of defaults and platform failures that took their toll on the FinTech sector (Cornelli et al. 2020), leading to the imposition of several regulatory restrictions for FinTech credit intermediaries to guard against lending concentration (FSB 2017). The P2P industry saw a sharp rise in the number of "problem platforms" where many platforms promised unrealistic returns and or "rigid redemptions" (Claessens et al. 2018). These "problematic" issues, together with the heightened regulation and measures designed to encourage the exit of non-qualified P2P platforms, contributed to a significant decline in entrants and a surge in platform exits between 2015 and 2016 (Claessens et al. 2018). In 2017, further specific measures were taken, such as banning new student loans and the regulation for cash loans was tightened (Claessens et al. 2018). The BIS report observes that the number of operating China's FinTech platforms fell from its peak of 3,800 in 2015 to 1,836 in June 2018. This left only 343 platforms in operation in 2019, but still with steady exits but no new platform entries since September 2018 (Cornelli et al. 2020). This is consistent with the data from a Chinese Wang Dai Zhi Jia (WDZ) website (an online data platform) presented in *Figure 2.4*

Figure 2.4: Total FinTech credit volumes in China (2014Q1-2019Q4) (in USD Billions)

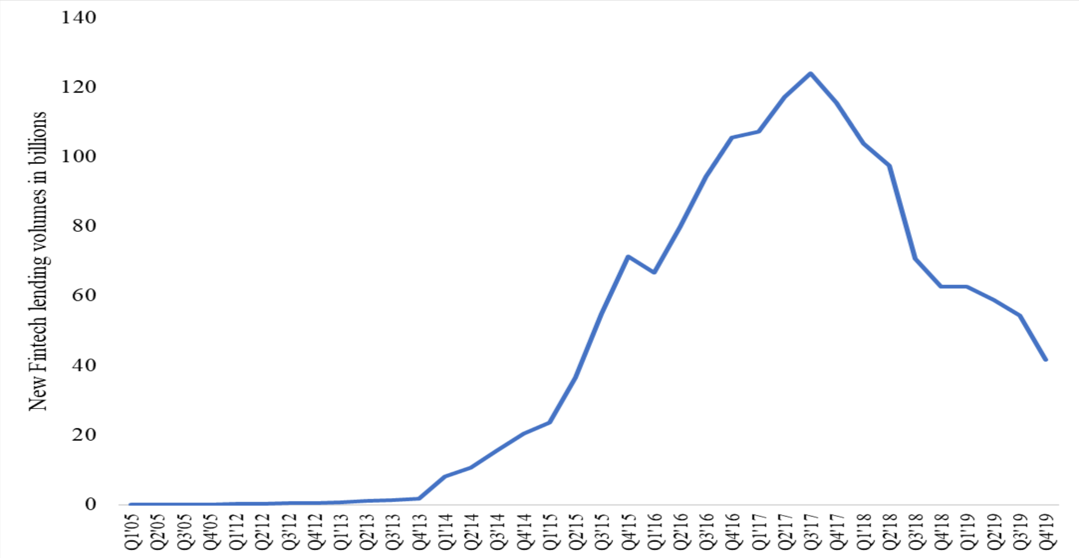


Source: Author's own data calculations

Until 2018, China remained the largest and fastest-growing FinTech credit market globally (Cornelli et al. 2020; Frost et al. 2019), accounting for 88% of the alternative lending market in 2018 (Statista 2020). At the time, China generated a total of $215.37 billion in 2018, followed by the US ($61) billion and UK ($10.4 billion, respectively (Ziegler et al. 2020). However, the FinTech credit market share declined by 48% in 2019 and now only 1% in 2020 (Ziegler et al. 2021).[12] This is consistent with the data in this study that shows that China dominated global FinTech credit volumes by 81.97% in 2018 and 64.51% in 2019. Accordingly, in this study, the inclusion of Chinese volumes in the total global market volume notably confirms a decline in FinTech lending volumes by 35% in 2019. Due to the significant size of the Chinese FinTech credit market, this decline has largely impacted the size of global FinTech credit. *Figures 2.5* and *2.6* thus present a picture of the global or total FinTech credit volumes (with China included). Similarly, the data trends of this study are relatively comparable with the current BIS (annual) database released by Cornelli et al. (2021; 2020) from 2013 to 2019 and the CCAF database by Ziegler et al. (2021; 2020). Figure 2.6 shows the global FinTech credit trends captured by this study, which is also comparable and consistent with the CCFA (e.g., Zieglar et al. 2021; 2020) and BIS (Cornelli et al. 2020; 2021) FinTech credit databases. However, The CCFA and BIS databases provide annual data series from 2013.

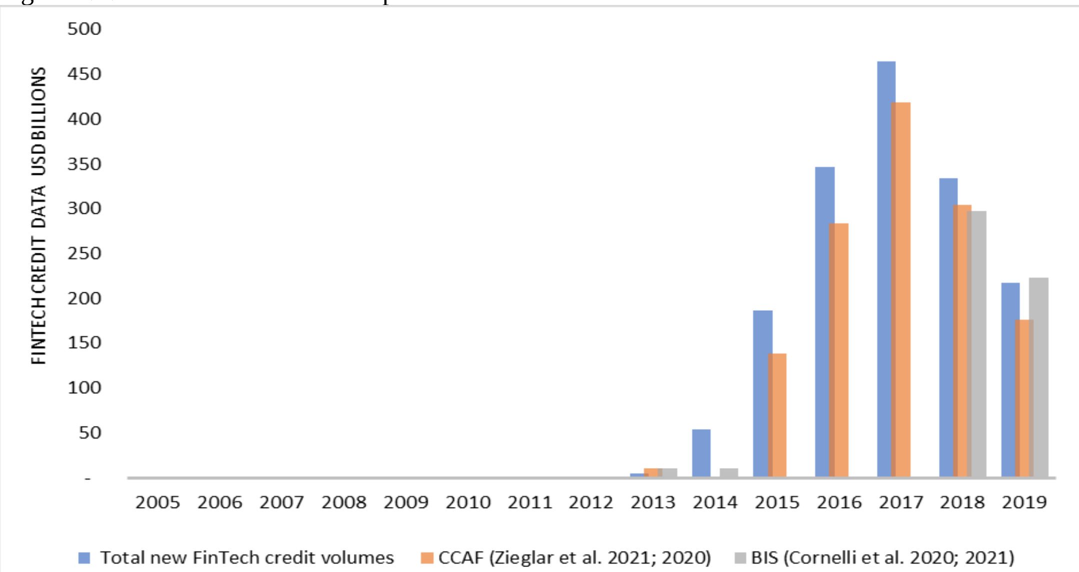
[12] In 2016, Chinese volumes corresponded to about 20% of consumption loans to households provided by traditional banks

Figure 2.5:Global new FinTech credit volumes from 2005Q1 to 2019Q4 (in USD Billions)



Source: Author's own data calculations

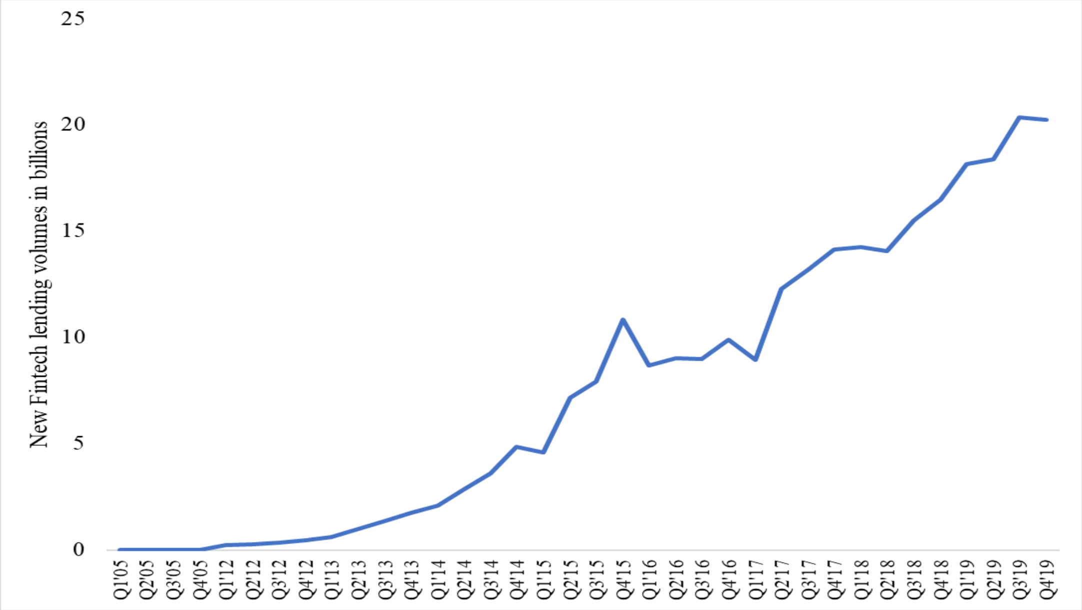
Figure 2.6: FinTech credit data comparison



Source: Zieglar et al. (2021; 2020); Cornelli et al. (2020; 2021); Author's own data calculations

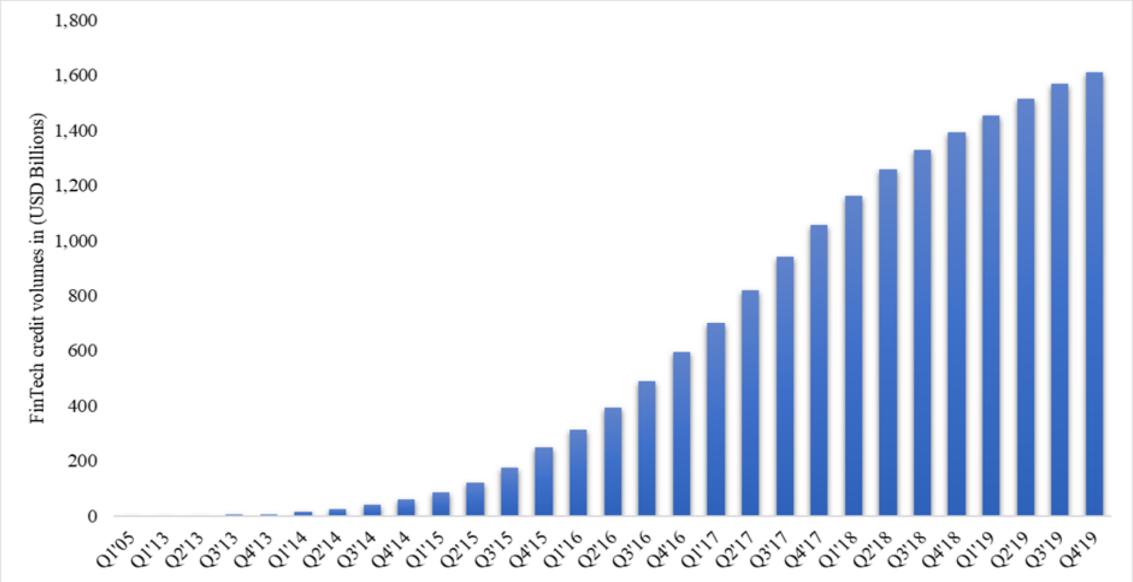
While the global FinTech credit volumes in China declined from 2018 to 2019, FinTech credit was still growing sharply outside China. When the FinTech credit data from China is excluded from the global dataset, a different pattern is observed. For example, it emerges that global online alternative finance market volume grew by 48% year-on-year, from $60 billion in 2017 to $89 billion in 2018 (Ziegler et al. 2020) and 3% amounting to $91 billion in 2019 and a further 24% year-on-year to reach $113 billion in 2020 despite COVID-19 (Ziegler et al. 2021). Even in a global business funding model, the exclusion of Chinese data shows an increase from $21 billion in 2017 to $31 billion in 2018, a 47% annual increase from the previous year (Ziegler et al. 2020). Ziegler et al. (2021) also observed that the exclusion of the Chinese FinTech credit market reveals that the global FinTech credit market had grown rapidly and consistently over time, consistent with *Figure 2.7.* The FinTech lending data used in this study indicate that *Figures 2.6* and *2.7* are based on estimates of new FinTech lending, as opposed to the stock of accumulated loans in *Figure 2.8.*

Figure 2.7:Total new FinTech credit volumes (2005-2019) *excluding China (in USD Billions)



Source: Author’s own data calculations

Figure 2.8: Global cumulative FinTech credit volumes from 2005Q1 to 2019Q4 (in USD billions)



Source: Author’s own data calculations

The rise of nonbank players, such as FinTech credit, has become a global trend, reaching the advanced and EMDEs alike (Molnár 2018). FinTech credit is increasingly becoming economically relevant in some markets (Stulz 2019) as it matures and moves further into the mainstream (Milne and Parboteeah 2016; Wardrop et al. 2015). The growth of FinTech in the credit market structure indicates a broader shift in financial intermediation, particularly from traditional banks. FinTech credit has grown in various market economies at varying levels of adoption. Its growth is also largely predominant in advanced economies than in EMDEs. However, FinTech credit is also becoming economically relevant in some EMDEs, particularly for specific segments such as MSMEs (Adian et al. 2020; Cornelli et al. 2019).

FinTech credit tends to be more prevalent in economies with a balanced mixture of a strong and well-developed financial system, i.e., its banking and capital markets and a mature cross boarder financial integration network. For instance, the regulatory landscape of the European alternative finance market, which allows innovation to flourish, is fluid and multidimensional (Wardrop et al. 2015). Europe, which has the largest representation in the sample, is home to prominent start-ups and innovation hubs, thereby providing diverse and increasing growth patterns in the FinTech sector and a well-known for a long record of FinTech activities such as alternative lending.

The North American region accounts for the largest global alternative market volume. The US, therefore, serves as a natural starting point because it is a major market for FinTech lending in the region. Moreover, FinTech data availability and quality fare better than in most other countries (Berg et al. 2022). According to Ziegler et al. (2021), the region with the largest online alternative finance market is the US and Canada, at $73.93 billion combined. The US alone led by $73.62 billion and accounted for 65% of the global FinTech credit market volume. The US FinTech credit market primarily consists of consumer lending and is largely dominated by institutional investors. Since 2013, the rapid growth in US unsecured personal loans has been driven by the arrival of FinTech credit (Beiseitov 2019).

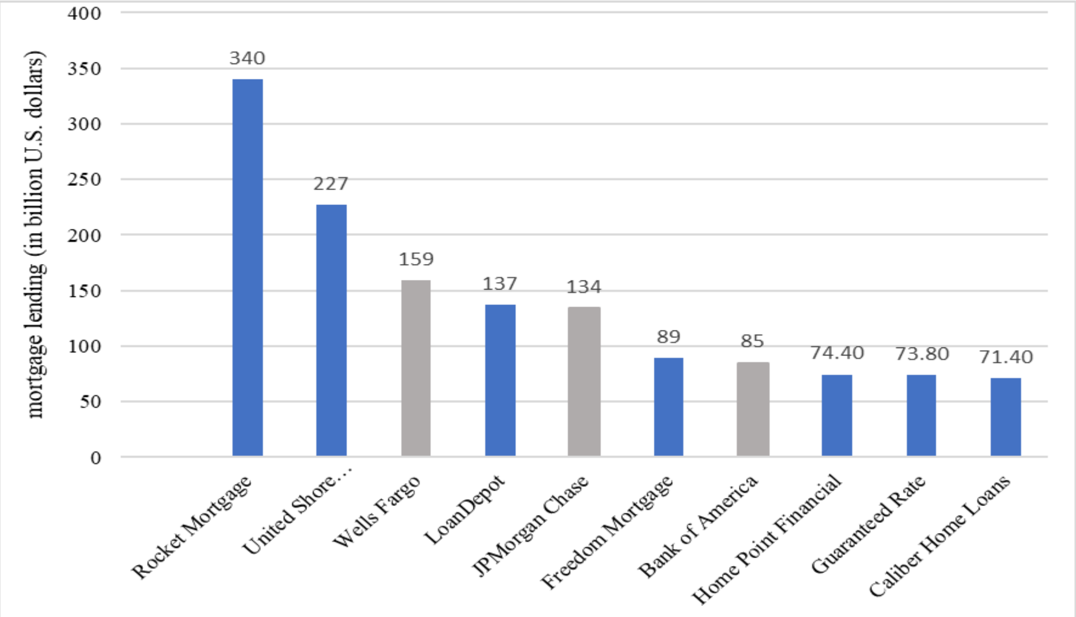
Even more remarkably, in 2013, the overall share of FinTech credit had originated just 5% of unsecured personal loans (Beiseitov 2019; TransUnion 2018). At the time, the FinTech credit share exceeded traditional banks’ share, which fell from 40% in 2013 to 28% in 2018 (Beiseitov 2019). Jiang (2019) reveals a key distinguishing feature of shadow banks’ funding sources being funded by the very banks they compete with in originating mortgages. The author further reveals that banks with in-house mortgage origination provided about 70% of total warehouse credit lines to shadow banks from 2011 to 2017. However, due to lighter regulatory requirements on these lending competitors, they tend to offer risky business loans. They are willing to lend to borrowers with slightly lower credit scores or higher levels of debt compared to their income (Jiang 2019). Furthermore, the US S&P GMI report (2021) estimates that the SMME-focused FinTech originations loans at a total of roughly $13 billion, a 5% market share of loan volume. While total FinTech credit volume may seem relatively smaller, these figures may underestimate the potential impact of FinTech lending. For instance, the number of SMMEs using FinTech loans is large, and the recent survey by the US Federal Reserve shows that 1 in 5 businesses have used an online lender in the last five years. The Bank of England (2017) also suggests that the growth and impact of FinTech credit on incumbent banks' business models may have been underestimated.

FinTech credit lenders have increasingly established themselves as major players in the US housing or mortgage markets (Berg et al. 2022; Buchak et al. 2018; Fuster et al. 2019). For instance, FinTech credit has particularly become an important player in the US mortgage market (Fuster et al. 2019; Buchak et al. 2018), outperforming the market share of some traditional intermediaries by approximately 36% and 38% of all unsecured personal loan balances in 2017 and 2018, respectively (TransUnion 2019). Moreover, in the US alone, one FinTech mortgage originator, Quicken online loans, which owns the online lender Rocket Mortgage, accounted for about 8-12% of new mortgage loan originations (Fuster et al. 2019; Buchak et al. 2018). This made it the US single largest mortgage lender estimated at $86 billion in mortgages in 2017 (Sharf 2018), an eight-fold growth since 2008 and is now among the three biggest mortgage originators in the nation, even above Wells Fargo bank at the time.

The US residential mortgage market currently constitutes the world's largest consumer finance market (Seru 2019). Within the ten trillion-dollar US residential mortgage market, non-depository lenders have originated more than half of the total new loans every year since 2017, with six (6) of the largest ten (10) mortgage lenders being shadow banks (Buchak et al. 2018) and seven (7) in 2021. Seru (2019) also observes that the share of the shadow bank market share in residential mortgage origination has more than doubled from 2007 to 2017, a substantial portion of which was from online FinTech lenders that rely on technology. Estimations based on a list of ten FinTech mortgage lenders used by Jagtiani et al. (2021), Buchak et al. (2018) and Fuster et al. (2019) suggest that the FinTech market share of new lending origination (including refinancings) reached a new high of about 14% in 2020 from 9% in 2016.

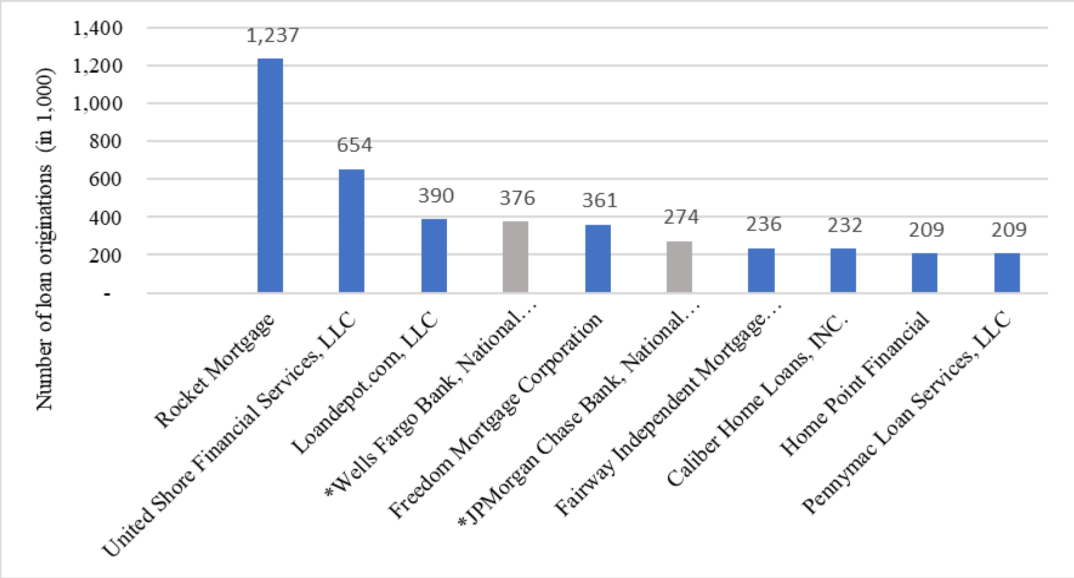
However, it is assumed that due to data limitations, the 14% market share most likely understates the "true" market share of current FinTech lenders (Berg et al. 2022). The unprecedented similar growth trend was also visible in the US consumer personal loan market. According to TransUnion (2019), US FinTech loans accounted for 36% and 38% of all unsecured personal loan balances in 2017 and 2018, respectively, making it the largest market share compared to traditional financial intermediaries. Lately, mortgage lending has been coming from online lending companies such as Quicken Loans, loanDepot and Caliber Home Loans (Jiang 2019). In 2021, Rocket Mortgage accounted for approximately 340 billion U.S. dollars in mortgage lending and also ranked the highest in terms of the number of mortgage originations, as seen in *Figures 2.9 and 2.10* (Bankrate 2022).

Figure 2.9 US Top 10 Leading mortgage lenders in the US in 2021, by value of mortgage lending



Source: Bankrate (2022).

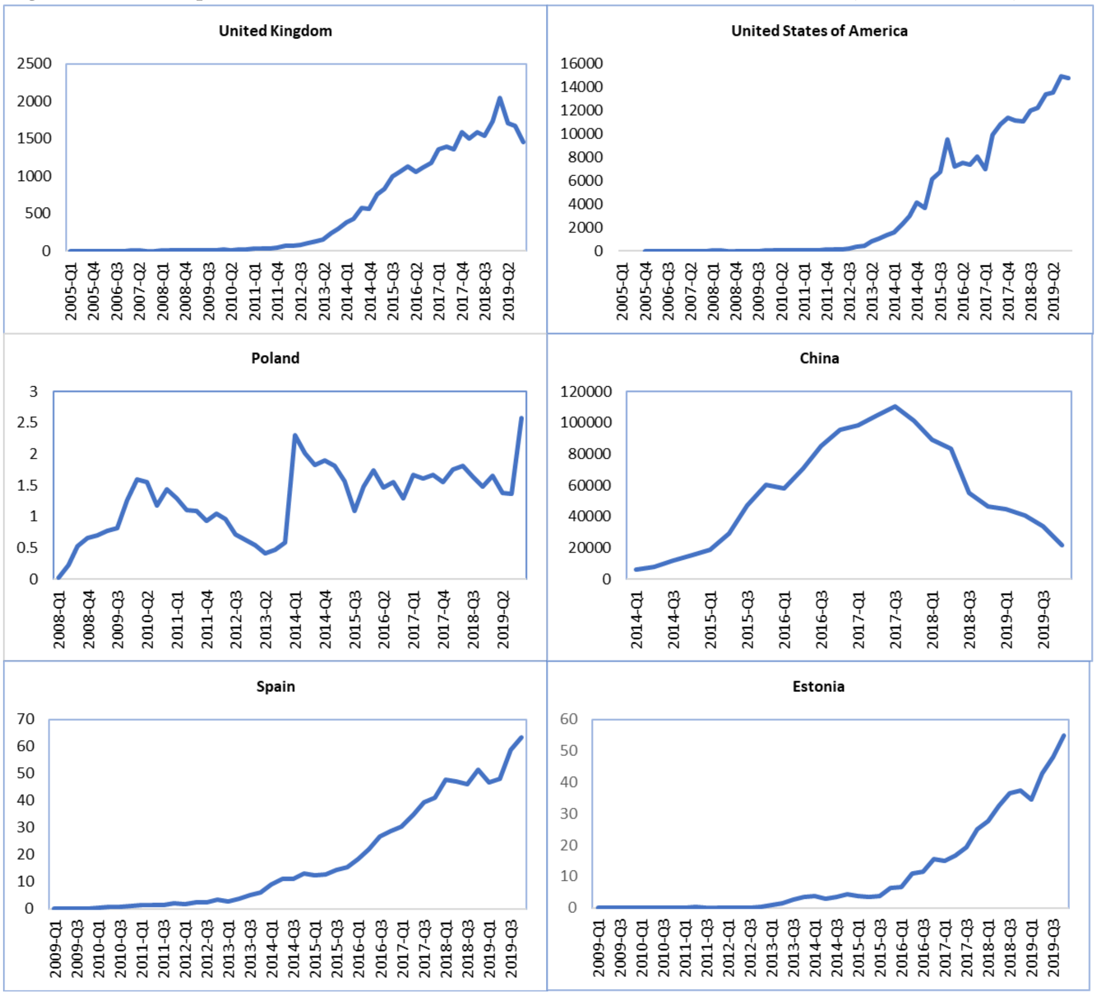
Figure 2.10: US Top 10 US Leading residential mortgage lenders in 2021, by volume in 1,000



Source: Bankrate (2022).

The North American region is followed by other advanced economies, with the UK at $12.64 billion and the EU (excluding the UK) at $10.12 billion. The UK FinTech credit volumes were estimated at $11.5 billion in 2019 (an increase from $9.3 billion in 2018), dominated by a combination of FinTech credit in business, consumer and property lending and significantly smaller volumes of balance sheet lending and invoice trading. The UK market alone was considered to have recorded unique developments in financial innovation and unmatched growth in years since the global financial crisis in 2017 (Vives 2016). The UK lending flow of equivalent bank credit to MSMEs was estimated at 27.7% in 2018 (Ziegler et al. 2020), a significant rise from about 15% in 2016 (CCAF 2017). FinTech credit continues to grow at various pace in different countries, as depicted in *Figure 2.11* below. Several EU countries (e.g., Poland, Estonia and Spain) showed continuous rapid growth even when FinTech credit volumes in the UK and the US plateaued and when they declined in China in 2019, which is consistent with the new dataset by Cornelli et al. (2020) and new publications by (Ziegler et al. 2020;2021).

Figure 2.11:Example of trends in FinTech credit volumes in selected countries (in US millions)



Source: Author's calculations based on data collected

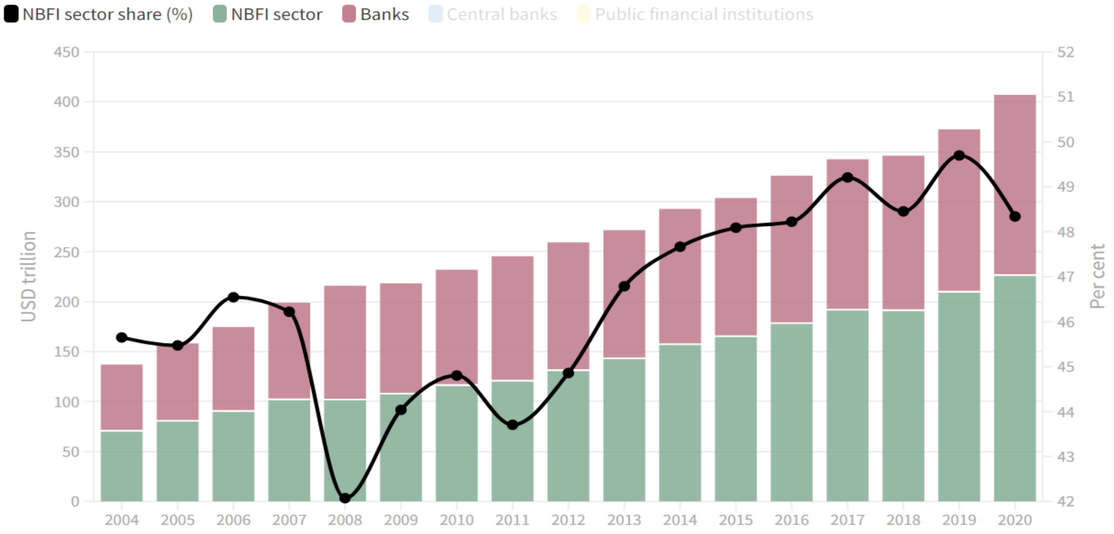
Advanced economies are followed by the majority of the EMDEs led by the Asia Pacific (excluding China) at $8.90 billion, followed by Latin America and the Caribbean (LAC) ($5.27 billion), Sub-Saharan African (SSA) ($1.22 billion), and the Middle East and North Africa (MENA) ($0.59 billion). According to Zieglar et al. (2021), the total volume of alternative finance in China once reached its all-time peak of $111.8 billion in 2017 before it declined to $14.2 billion in 2019 and eventually $0.02 billion in 2020. This may be because FinTech credit provision is not the primary business of EMDEs. What is rather prevalent in some EMDEs is the expansion of the recent emerging giants known as "BigTech credit", particularly in Latin America, Southeast Asia, and East Africa and particularly the largest in China (Frost et al. 2019).

The evolving aspect of FinTech credit in the form of "BigTechs" even have wider access to a range of customer data, useful for improving risk assessments and screening of borrowers (Frost et al. 2019). They are usually non-financial institutions and large firms with expertise in social data analytics and automation of underwriting processes, making their processes more efficient and cost-effective. Emerging studies show that FinTech credit arising from 'BigTech' firm entry may even become greater than the FinTech credit stream due to their size and established network, with potentially widespread implications for financial stability (Frost et al. 2019). In fact, Cornelli et al. (2020) suggest that BigTech credit has outpaced FinTech credit globally since 2018.[13] BigTechs also leveraged their size and established network (Cornelli et al. 2020), a growth that was even more pronounced in 2019 due to the rapid growth in Asian countries (China, Japan, Korea, and Southeast Asia), some African countries, and Latin America. A handful of detailed literature concerning FinTech credit and its different forms (Rau 2021; Farag and Johan 2021; Block et al. 2020; 2018; Goldstein et al. 2019).

By far, the global NBFI financial assets accounted for 49.3% and 48.3% of the global financial system in 2019 and 2020, respectively, compared to 42% in 2008 (FSB 2022). In terms of size, several NBFIs, such as MMFs, are far larger than the size of FinTech credit. This could be due to most NBFIs having been around longer than NBFIs. Its global growth of assets now surpasses bank assets, especially in advanced economies (Buch 2020; Quarles 2020; FSB 2020a, 2020b; 2019b). Moreover, the NBFI sector is relatively larger in advanced economies, averaging 56% of total financial assets than 27% in EMDEs (FSB 2020a). In the US, NBFIs now undertake a significant portion of lending (Chernenko et al. 2019). *Figure 2.12* illustrates the global NBFI assets versus the bank assets.

[13] The recent BIS study by Cornelli et al. (2020) shows that in 2019 global total alternative credit (FinTech credit and BigTech credit) was estimated at $795 billion, making up $223 billion and $572 billion, respectively.

Figure 2.12: Total global NBFI financial assets



Source: FSB (2022)

FinTech credit remains a subset of the overarching NBFI. The NBFI (previously known as "shadow banking") is a broad term comprising a diverse set of financial entities, infrastructures, and bank-like activities (mainly lending) that fall outside the traditional banking sector (FSB 2020b). Shadow banking is now widely referred to as an NBFI or market-based finance. The wide array of entities encompasses diverse business models that include insurance companies and pension funds, money market funds, hedge funds, finance companies, broker-dealers, securitisations, special purpose vehicles, and other financial intermediaries. Based on the current scope of NBFI, non-bank credit is broader than shadow banking. The FSB 2018 Global monitoring report on NBFI has also moved away from the term "shadow banking" to adopt NBFI in order to accommodate a forward-looking approach (see., FSB 2019c). A narrow measure of NBFI has been developed by the FSB since 2011 in order to identify a subset of NBFI entities that perform economic functions that may pose bank-like financial stability risks (i.e., leverage, maturity, and liquidity transformation) and/or regulatory arbitrage (FSB., 2020b).[14] The economic functions are illustrated in *Table 2.4.*

[14] Claessens et al. (2021) also use the narrow measure of NBFIs.

Table 2.4: Classification by Economic Functions (EFs)

EF	DEFINITION	TYPICAL ENTITY TYPES
EF1	Management of collective investment vehicles with features that make them susceptible to runs	MMFs, fixed-income funds, mixed funds, credit hedge funds, real estate funds
EF2	Loan provision that is dependent on short-term funding	Finance companies, leasing/factoring companies, consumer credit companies[15]
EF3	Intermediation of market activities that is dependent on short-term funding or on secured funding of client assets	Broker-dealers, custodial accounts, securities finance companies
EF4	Facilitation of credit creation	Credit insurance companies, financial guarantors, monoline insurers
EF5	Securitisation-based credit intermediation and funding of financial entities	Securitisation vehicles, structured finance vehicles, asset-backed securities

Source: FSB (2020b)

There is a blurry difference between FinTech companies and traditional NBFIs. The major difference between FinTech credit and traditional NBFIs stems from the primary use of digital or online technology in financial services. The FinTech innovation as a segment of NBFIs cuts across different economic functions outlined in the above-mentioned *Table 2.4* due to its varying economic and financing models. FinTech serves as a bridging gap between traditional financial intermediaries and other NBFIs. FinTech, by definition, combines finance with technological advancements to offer effective risk management to enhance its effectiveness and the delivery of products and services relating to financial services.

The abovementioned FinTech entities or activities are drawn from the conventional economic functions normally undertaken by NBFIs and even banks. However, the key distinction is that FinTech entities are innovative and embody a new set of products tailored to the needs of small businesses and are more customer-oriented (WEF 2015). Based on various definitions of Fintech, it involves the use of technology-enabled innovation in financial services that have the potential to transform the provision of financial services spurring the development of new business models, applications, processes, and products (IMF-WBG 2018; FSB 2017). FinTech can also be understood as new technology-driven players that aim to compete with traditional financial institutions in the delivery of financial services (Beck 2020). This is because FinTech entities are heavily dependent on new technologies and may adopt any existing economic

[15] The FSB (2020b) Global monitoring report on NBFI refers to FinTech lending as consumer credit.

function or business model. For instance, leading data-native companies or Big-Tech co companies such as Amazon, Google and Paypal have managed to roll out niche products targeted at the millennial segment, enabled by the concept of FinTech.

FinTech innovation, therefore, leverages sophisticated risk models enabled by the use of new cutting-edge credit models backed by complex and sophisticated complex technologies such as distributed ledger technologies (DLT), new application programming interfaces (APIs), artificial intelligence (AI), machine learning and big data firms (Demertzis et al. 2018; OECD 2018; IMF 2019; FSB 2017), to create new financial solutions and delivery channels that can accurately estimate risks. For instance, FinTech lenders are better able to screen potential borrowers, leveraging alternative sources of information and the big data approaches inherent in technology-based lending (Buchaek et al. 2018). The use of such data-driven underwriting and risk management has been an essential application of FinTech, increasing risk estimation and thus reducing the vulnerability in the financial system (WBG 2022; FSB 2017).

According to Buchaek et al. (2018)'s technology hypothesis, improving lending technology, particularly among new shadow bank entrants, has not only driven the shift away from traditional banks but increased FinTech credit market shares due to their technology, allowing them to lend more cheaply or to provide better products. In a nutshell, technology has played a critical role in why such FinTech credit intermediaries are able to provide products that have not been provided before, consequently facilitating a massive expansion of non-bank institutions (Seru 2021). Seru (2019) also argues that the increased regulatory burden faced by traditional banks and the technological changes adopted by shadow banks are some of the main factors that explain the growth of shadow banks, many of them "FinTech shadow banks".

The FinTech revolution has given rise to a vast number of technology-oriented market entrants who contests with many segments of the financial services sector (Huebner et al. 2019). FinTech has particularly disrupted almost every aspect of traditional banking activity, from lending to payments to wealth management and investment banking and further extends to other NBFIs. In particular, FinTech credit has revolutionised nonbank lending by tapping into technological advancement to facilitate loans online or digitally. The technological advantage separates FinTech from the traditional NBFIs and also enables it to tap into various non-bank activities. The FinTech disruption is greater in most of these segments — for instance, in household lending, the mortgage market in the US alone is led by a FinTech lender, Quicken loans. More often than not, the Fintech innovations come as an extension of most existing NBFIs, coupled with new processing models that are deemed more efficient that the traditional system. This has been evident in the progression of the FinTech concept, which engulfs most nonbank activities such as alternative finance, payments, insurance, investment etc. Moreover, the heavy reliance on technology to tap into the credit market has attracted even large non-finance companies such as BigTechs and other activities such as securitisation of loans. This has led to further growth of the total alternative finance or Fintech credit.

2.6. Summary and conclusions

This chapter provides a global overview of the FinTech credit industry, including various definitions of FinTech and FinTech credit developed over time. Despite the lack of an official definition of FinTech, there is a general consensus that binds FinTech to the combined use of technological advancements in financial services - outside the traditional banking scope, leading to the development of new business models, applications, processes, instruments, channels and systems. The shortcomings regarding the definitions and categorisations of Fintech underscore the need to develop a more comprehensive framework to help guide policymakers in addressing the topic of the "digitalisation" of financial services (OECD 2018). While it may be beneficial to have a basic understanding of the technology, policymakers and regulators should be more concerned about the applications of new digital technologies and their implications for the financial system.

The working FinTech taxonomy reveals that the current FinTech market segment is diverse and embodies several segments. Regarding FinTech credit, which forms the area of focus of this study, this chapter presents the various business models that offer loans to consumers, businesses, real estate and invoice trading. Over time, the concept of FinTech credit has progressed, migrating from simple or traditional P2P lending to institutional lending and other forms of sophisticated lending models. Moreover, FinTech credit has experienced tremendous growth since the global financial crisis. These developments have since attracted the attention of regulators, policymakers and academia due to their possible implications for financial and bank stability.

There is still substantial uncertainty over the growth of the FinTech credit markets. FinTech intermediaries have facilitated the massive expansion of NBFIs in various segments of the financial sector. FinTech credit, in particular, provides additional and or alternative sources of financing for households and corporates. FinTech innovation continues to evolve and grow in size and scope. Regulators and policymakers continue to keep an eye on the growth of credit intermediation in the nonbank sector. However, estimating the overall size and the depth of the FinTech lending market remains a challenge due to the lack of official FinTech credit data and data on the stock of FinTech lending makes it difficult to estimate the growth of global Fintech credit (Ziegler et al. 2021). The current global trends indicate that FinTech credit activities display potential growth over different regions at varying depths, scopes and sizes. The currently global FinTech credit size currently constitutes a relatively smaller share of overall lending compared to traditional bank credit across jurisdictions (BIS and FSB 2017). However, its growth has outpaced traditional lending growth rates (Berg et al. 2022). Apart from the declining volumes of FinTech credit in China, the rest of the global economies have shown evidence of exponential growth since the global crisis.

This chapter provides a distinction between FinTech and bank credits, as well as other NBFIs. As the rise of FinTech credit increasingly becomes economically relevant in some markets (Stulz 2019), its growth in the credit market structure indicates a broader shift in financial intermediation and potential implications for financial stability. By far, the global NBFI financial assets have outpaced traditional bank assets, especially in advanced economies (Buch 2020; Quarles 2020; FSB 2020a, 2020b; 2019b). Similarly, FinTech credit remains a subset of NBFI, and its growth patterns correspond to the growing global NBFI assets.

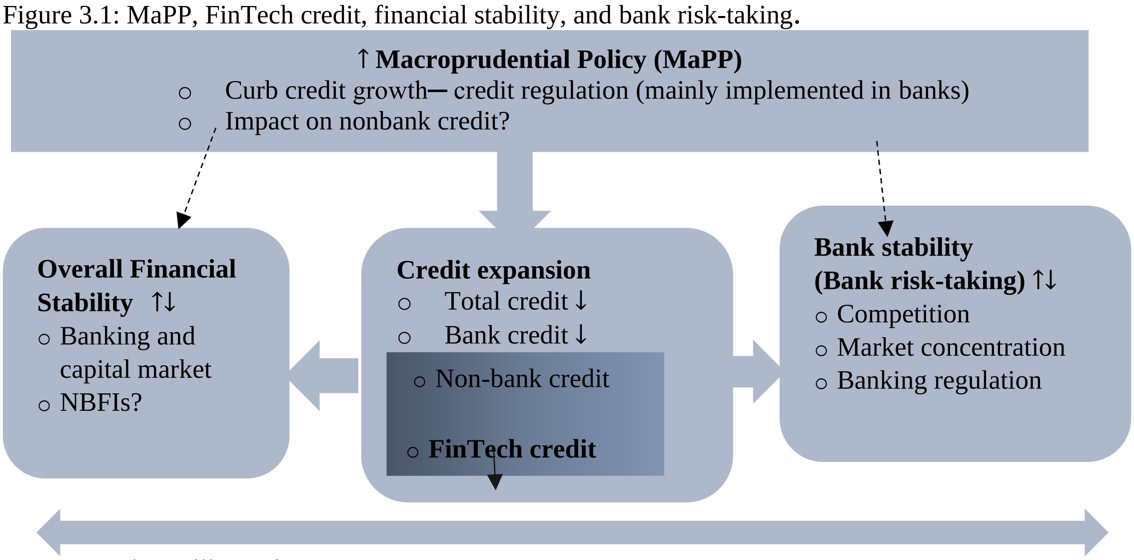
CHAPTER 3: LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

3.1. Introduction

This chapter reviews the literature and develops the hypothesis. Section 3.2 provides a general overview of FinTech credit and NBFIs. Sections 3.3 to 3.5 focus on relevant theoretical literature reviews for the respective themes of this study that may help explain the objectives of this study. It explains the underlying theories behind the interaction of such relationships and their directions. It also outlines the empirical literature by providing summaries of previous pertinent work and knowledge gaps. Section 3.6 elaborates on the theoretical framework for the empirical model and highlights the different hypotheses to be tested. In light of the prior literature, discussions and conjectures, several hypotheses in alternative outlines are formed to address the research questions and objectives of this study.

In order to understand the association between FinTech credit and financial stability, it is necessary to understand the nature of the interaction of nonbank credit intermediation with various aspects of the financial system. In this respect, the study highlights three key relationships based on four main strands of the literature, as depicted in Figure *3.1*. It illustrates how FinTech credit is associated with (i) overall financial stability, (ii) bank stability (bank risk-taking) and (iii) MaPP.

Figure 3.1: MaPP, FinTech credit, financial stability, and bank risk-taking.



Source: Author's illustration

3.2. Overview of FinTech credit and non-bank financial intermediation

The rise in non-bank credit intermediation has become one of the most notable features of modern finance. The financial intermediation theory sheds some light regarding FinTech credit. However, FinTech activities are often misunderstood, and there are evidently various interpretations of what the FinTech term means (Thakor 2020). Existing theories of financial intermediation and the financial system architecture reflect the existing interaction between traditional banks and financial markets (e.g., Song and Thakor 2010). The major question that most studies try to address is regarding the role played by FinTech credit in the economy from a perspective of financial intermediation theory. One key question is how the theories of financial intermediation can be modified to accommodate traditional banks, shadow banks and NBFIs (Thakor 2020). Until now, literature on FinTech innovations has simply bootstrapped FinTech credit platforms to models of financial intermediary existence (de Roure et al. 2022), or merely discussed the implications of financial intermediation for emerging technological innovations (Molnár 2018).

However, theories on the emergence and interaction of banks and non-banks are still evolving, particularly with regard to the emergence of technological innovation. For instance, Donaldson et al. (2021) present a general equilibrium theory of how traditional banks and non-banks arise endogenously to segment the credit market. Thakor (2020) reviews the literature on FinTech and how it interacts with the traditional banking system. The author notes that the main challenge with the theories of financial intermediation and existing financial policies is how they could be modified and adapted to accommodate all players, i.e., traditional banks, shadow banks, and or NBFIs. So far, the FinTech literature has simply bootstrapped FinTech credit platforms to models of the existence of financial intermediation (de Roure et al. 2022). Molnár (2018) discusses the implications of new market entrants (FinTech models) in the context of the financial intermediation literature. Several other academic studies have also discussed the role of FinTech credit in financial intermediation (Milne and Parboteeah 2016). Other recent overview articles include Berg et al. (2022), Agarwal and Zhang (2020), Thakor (2020), and Vives (2019). The main question is whether new market players disintermediate mainstream banks as complements, rivals or just new forms of credit.

Evolving literature attempts to theorise how banks and non-banks co-exist in a general equilibrium even though non-banks have a higher cost of capital than banks. Donaldson et al. (2021) maintain that while non-banks may not necessarily take over the entire credit market, they tend to coexist with banks in equilibrium. Cerqueiro et al. (2020) prove that banks are unique in lending. Thakor and Merton (2018) develop a theory of bank and non-bank credit in which banks have an endogenous advantage over non-bank lenders (including FinTech credit platforms) in developing investor trust due to their unique access to low-cost deposit funding. This is consistent with Donaldson et al. (2021). Bunderson and Thakor (2021) also suggest that traditional banks tend to have a funding cost advantage over non-bank, which may be enabled by their access to safety nets such as deposit insurance. Nonetheless, the equilibrium success of probability is largely dependent on the heterogeneity of the lender's cost of capital since non-banks are mostly not subject to the same regulatory capital requirements as banks (Bunderson and Thakor 2021). However, Bunderson and Thakor (2021) argue that this can also be a disadvantage to banks, generating a "soft-budget-constraint" problem that prevents banks from credibly threatening to withhold additional funding to failed projects− a problem nonbanks emerged to solve.

FinTech credit is largely not subjected to stringent prudential regulations in most jurisdictions (Frost et al. 2019; Claessens et al. 2018). They are mostly not or only partially captured by existing regulations in several jurisdictions and may benefit from a lower regulatory burden (Bertsch and Rosenvinge 2019). This may create a possible regulatory advantage over the incumbents (Braggion et al. 2021; de Roure et al. 2022) that is partly motivated by stricter existing regulatory frameworks that have a strong focus on bank-based financial intermediation (Darst et al. 2020; Bertsch and Rosenvinge 2019; Adrian and Jones 2018).

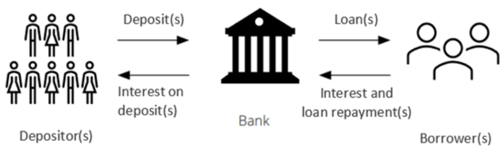
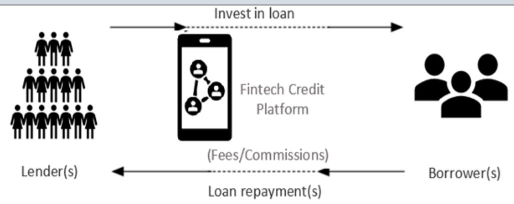
FinTech credit platforms also benefit from the structural cost, competition and regulatory advantage, allowing them to offer improved efficiency with innovation, enhanced diversity in credit access and supply and lower-cost refinancing alternatives to borrowers that would otherwise be unprofitable for banks to serve (Hikida and Perry 2020). This may create higher funding costs that erode the subsidised bank deposit insurance, providing an enabling environment for non-banks to compete (Darst et al. 2020). Furthermore, enhanced knowledge of technological advancements and liquidity transformation could prompt the entry of nonbanks into credit markets (Buchak et al. 2018; Moreira and Savov 2017). Thus, a confluence of various factors can further create a fertile environment for FinTech credit to grow. Moreover, this may suggest that leverage is not as attractive for non-banks as it is for banks (Bunderson and Thakor 2021) and faces a higher probability of failure from operating with lower capital.

The reluctance and inability of mainstream banks in the post-crisis period to provide credit, especially to start-ups and micro, small and medium-sized enterprises (MSMEs), has spurred the latest wave of new financial innovation in the form of FinTech credit (Bavoso 2020). FinTech credit fills this gap by acting as an intermediary between depositors and borrowers, thereby mediating the transaction costs and risks of liquidity and maturity transformation between shorter-term deposits and longer-term loans (Hikida and Perry 2020). As a result, it transforms the credit supply and how value is created and delivered beyond traditional patterns. In the broader context, the boundaries of such intermediation activities allow new firms to source deposits, evaluate credit evaluation, originate loans, and offer business lines of credit without the middleman.

To better understand the main similarities and differences between traditional banking and FinTech credit intermediation, Thakor (2020) underscores the need for an integrated theory of intermediated and non-intermediated lending in which the basic institutional facts are outlined and used. The author reiterated that this would reflect both the economic functions of financial intermediation embedded in the existing theories and also capture activities of FinTech credit platforms. This may further be used to redesign the theories of financial system architecture that include not only banks and capital markets but FinTech developments. To develop a coherent theory of financial intermediation that includes nonbanks such as FinTech credit, FinTech credit platforms must be viewed as both a technological platform and a potential profit-maximising entity that faces incentive conflicts *vis-à-vis* borrowers (Thakor 2020; Merton 2018).

FinTech credit differs from bank credit on multiple dimensions. In essence, FinTech credit lenders are non-deposit-taking institutions or NBFIs that facilitate loans online either directly or through online platforms. Unlike traditional banks, FinTech credit platforms do not rely on deposits to finance their lending; instead, they tend to raise capital through equity markets, public debt, private equity, bank credit facilities and securitization. FinTech lenders are also not subject to most traditional bank regulations, normally in the form of capital requirements, financial reporting and disclosures. The lack of regulations or lighter regulation, coupled with technological advantages, has, in part, enabled FinTech lenders to enjoy spectacular growth at the expense of their brick-and-mortar contenders. Empirical evidence corroborates the fact that FinTech lenders are subject to lighter regulation than the incumbents play an important role in their growth (Buchak et al. 2018). *Figure 3.2* below summarises the basic framework of financial intermediation services to illustrate the difference between traditional bank credit and FinTech credit models. Berg et al. (2022) also provide a detailed distinction between FinTech and traditional bank business models. Following Thakor (2020) and Foottit et al. (2016), the illustration includes some of the frictions and incentive problems banks and FinTech credit platforms face.

Figure 3.2: Bank credit vs FinTech credit.

Traditional Bank Credit Model	**FinTech credit Model**
	
A. *Services provided (as depicted in existing theories).*	**A. *Services provided.***
• Act as an intermediary between borrowers and depositors.	• Directly match lenders with borrowers via online platforms.
• Engages in maturity transformation.	• Generally, by design, there is no maturity transformation involved.
• Generate income by taking risks onto their balance sheets and managing spreads between the interest banks charge on loans and paid on savings. This risk-taking requires them to hold capital to absorb potential losses.	• Do not lend themselves, hence earns no interest and do not need to hold capital to absorb any losses. However, some use own balance sheets to fund the loans they make.
• Have access to rent-generating deposits and invest their own capital in loans.	• FinTech credit platforms have no deposits and are all-equity lenders.
• Improved risk-sharing and consumption insurance (Diamond and Dybvig 1983).	• No.
• Screening (Coval and Thakor 2005).	• Yes.
• Monitoring (Mehran and Thakor 2011).	• No.
• Funding liquidity creation (Donaldson et al., 2018).	• No.
• Loan commitments (credit rationing insurance) and other off-balance-sheet puts and guarantees (Thakor 2005).	• No.
B. *Capital structure.*	**B. *Capital structure.***
• High leverage with little bank equity capital.	• All equity-financed: no equity capital invested by the lending platform, so investors are equity holders in loans.
C. *Incentive problems.*	**C. *Incentive problems***
• Insufficient screening.	• Yes.
• Insufficient monitoring.	• No.
• Insufficient funding liquidity creation.	• No.
• Excessive risk-taking due to high leverage and safety nets.	• No.
• Over-lending and excessive growth due to incentives distorted by safety nets and too little capital.	• Over-lending and excessive growth due to profit-maximisation motives.
• Insufficient capital due to safety nets.	• No.
• Incentives to renege on off-balance-sheet commitments.	• No.
• Depositors have limited control or visibility over how their money is used.	• Uses traditional, bank-like, credit-scoring approaches and publicises these credit risk scores. • Offer transparency and control to lenders, e.g., disclosure on recipients of funds lent out.
D. *Regulation*	**D. *Regulation***
• Heavily regulated by central banks.	• No direct supervision from central banks.
• Deposit insurance and capital regulation.	• Not required to hold capital or liquidity as banks do. Mostly receives lighter regulation.
• High regulatory costs and restrictions.	• Lower regulatory burden.
E. *Objective function*	**E. *Objective function***
• Maximise bank equity value.	• Maximise the value of the FinTech credit platform's owners' claim consisting of origination and other fees plus a fraction of borrower repayments.

Source: Foottit et al. (2016); Thakor (2020); Author's illustration

3.3. FinTech credit and financial stability

The concept of financial stability remains a multifaceted and elusive concept that is still difficult to define and measure (Puig et al. 2010; Gadanecz and Jayaram 2008). It is a financial system that can be portrayed as stable in the absence of excessive volatility, stress or crises (Gadanecz and Jayaram 2008). It can be broadly expressed in the absence of episodes of system-wide failures and vulnerabilities, thereby becoming more pronounced during periods of instability (World Bank 2016b; Crockett 1996). The reality of financial instability pre-exists, and endogenous risk may ultimately manifest itself in the financial system through various amplification mechanisms such as systemic risk, banking failures, market volatility, intense asset price and the collapse of market liquidity if not timely addressed.

The notion of financial stability also rests in the core of the macroprudential framework that places great emphasis on safeguarding the broader financial system from vulnerabilities and increasing sufficient resilience of a financial system to disturbances that are less likely to amplify adverse shocks. The macroprudential perspective stems from the market's failure to deal with aggregate risks, thus placing financial stability as the core priority to ensure that these risks are acknowledged and contained. Therefore, it is imperative to review the conceptual fundamentals for the existence of FinTech activities as a financial intermediary, why they coexist with financial markets and the justification of prudential regulation and oversight. Consideration of the economics and implications of emerging market players, such as FinTech innovation with respect to how it refines financial services, is critical, particularly the underlying economics of finance and its implications for financial stability (Llewellyn 2009).

Previous literature on the link between overall credit growth, financial innovation and financial stability provides the basis to understand emerging literature relating to the implication of NBFIs on financial stability. However, empirical literature linking FinTech credit and financial stability is still nascent and under-studied. By and large, the recent empirical literature on FinTech credit has mainly focused on several key research areas.[16]

[16] A greater aspect of the literature widely researched explore the drivers or determinants of FinTech credit growth (see., Cornelli et al. 2021; Havrylchyk et al. 2020; Rau 2020; Bazarbash et al. 2020; Frost et al. 2019; Haddad and Hornuf 2019). Others examine the impact of FinTech credit on bank credit (Li et al. 2017; Cornaggia et al. 2018; Vives 2019a; Tang 2019).

Furthermore, the existing literature mainly focuses on various aspects of FinTech using micro or individual country data (Braggion et al. 2021; Jagtiani and Lemieux 2018; Zhang et al. 2017). However, few cross-country data studies exist (Ziegler et al. 2021; Cornelli et al. 2020; Bazarbash et al. 2020; Frost et al. 2019; Claessens et al. 2018). Cornelli et al. (2020) provide the first comprehensive annual country panel database for total alternative credit volumes (FinTech and BigTech credit) for 79 countries from 2013 to 2019.

A vast amount of literature suggests the existence of a relationship between credit growth and financial stability, as well as the contrasting effects of credit growth and leverage. The extensive literature supports this financial innovation theory which suggests a strong *two-sided* association between financial innovation and economic growth and fragility (Beck et al. 2016). Such contrast is explained through the "innovation-growth" and the "innovation-fragility" views. The contrasting views highlight the nature of financial innovation and its potential to enhance financial stability through the functions of financial intermediation and risk shifting but may also disrupt such stability (Llewellyn 2009).

The traditional "innovation-growth" hypothesis portrays the greater potential of financial innovation in promoting economic growth and stability, which will ultimately foster a healthier and more resilient financial system with positive spillovers for economic growth (Wall 2018). Financial innovation presents itself as a driving force behind financial deepening and economic growth and development over the past decades (Laeven et al. 2015). It also helps economies exploit growth opportunities (Beck et al. 2012) and reduces economic activity volatility in the last decades (Dynan et al. 2006).

The emergence of FinTech credit presents a useful illustration of how FinTech innovation may improve access to credit and the economic efficiency of financial intermediation (Hikida and Perry 2020), thus promoting financial stability. This draws from the economic theory that indicates that credit markets and credit growth promote household consumption and stimulate economic growth through the credit channel. Credit growth thus represents an increase in demand for household and business credit (Adrian and Liang 2018). FinTech credit is fundamental for financial and credit markets and essential for deepening financial systems in emerging and advanced economies (Taylor et al. 2020). This is particularly relevant during economic downturns (Agarwal et al. 2018).

FinTech credit provides socio-economic benefits that promote economic funding in real economies and broaden access to the economies' credit channels (Cornelli et al. 2020; Jagtiani and Lemieux 2018; Carney 2017). Credit expansion widens credit access and greater support for investment and economic growth (Levine 2005) that channels finances to production and consumption, as well as capital formation, subsequently affecting real economic activity. Broadening credit access may alleviate the impact of real shocks and provide an additional source of credit when banks are under stress (Jagtiani and Lemieux 2018; Carney 2017; de Roure et al. 2022).

The "innovation fragility view", by contrast, presents financial innovations as one of the root causes of the global financial crisis (Beck 2014). Financial innovation is seldom associated with ideocratic bank fragility, higher levels of sector growth volatility and bank losses during the financial crisis (Beck et al. 2014; 2016). As with the financial crisis, disruptive innovations such as FinTech tend to be linked to bank crises and financial instability. Therefore, the "innovation fragility view" suggests that FinTech credit may be disruptive and potentially impair financial stability (Demertzis et al. 2018; He et al. 2017; Tarullo 2019; Vives 2019b; 2016; Wall 2018). Financial innovation may also enable regulatory arbitrage, distortion of incentives, and amplified systemic risks (Vives 2019b), leading to increased financial system fragility (Gennaioli et al. 2012; Allen and Carletti 2006). FinTech credit may also lead to more volatile markets that fail to respond appropriately to new information or where informational asymmetries impede informed bargaining.

A growing literature links FinTech credit to financial stability through various direct and indirect channels. The expansion of FinTech activity could also generate larger transmission channels, especially if traditional financial intermediaries have indirect or direct exposures to FinTech entities through their linkages with the wider financial sector (Durdu and Zhong 2022; Marqués et al. 2021; FSB 2020b). Direct exposures between FinTech credit and traditional banks can be through competition and diversification channels (Bertsch and Rosenvinge 2019; FSB 2019a; Bahri and Hamza 2019). According to Fung et al. (2020), FinTech affects the vulnerability of financial institutions through the profitability channel. Increasing interconnectedness between FinTech platforms and other traditional intermediaries may also create new transmission channels that propagate FinTech credit risks to the wider financial system and vice versa (FSB 2017). Moreover, financial stability risks also could be amplified due to existing financial frictions, or new ones may emerge should FinTech innovations lead to larger or new imbalances and contagion channels (FSB 2017; Mnohoghitnei et al. 2019). Other transmission channels may result through regulatory arbitrage channels, which may lead to excessive build-up of household leverage (Braggion et al. 2021). The diversification channel, on the other hand, may enhance financial stability by diversifying some of the risks associated with the traditional banking system (Bertsch and Rosenvinge 2019; FSB 2019a; Carney 2017).

FinTech credit can promote economic growth by serving as a driver to help reduce agency costs and information asymmetries, complete the market, facilitate effective risk allocation, and improve capital allocation efficiency of financial services and a mechanism from which all investment flows (Godoy et al. 2020; Kirchner et al. 2020; Fuster et al. 2019; Mnohoghitnei et al. 2019). Furthermore, the sophisticated and streamlined processes embedded in FinTech innovations are largely driven by lower operating costs and scale economies, which may broaden access to financial services, and increase transparency, convenience and immediacy (Fuster et al. 2019; Jagtiani and Lemieux 2018). Despite the Modigliani-Miller assumption of efficient and optimal capital allocation, this is constantly confronted with the reality of incomplete financial markets and information and contracting problems for financial markets and their intermediaries. The economic theory and policy also posit that the financial market economies on their own are not necessarily efficient, stable or self-correcting (Stiglitz 2014).

As nonbank credit grows and increases in systemic importance, it becomes more important to address financial stability risks beyond banking. A greater share of FinTech-facilitated credit in the financial system may present a mix of risks and opportunities for financial stability. The preliminary report by the FSB, released in 2017, was key in addressing several issues emanating from FinTech developments, highlighting the potential benefits and risks of FinTech to financial stability. While currently, there is no evidence of any adverse systemic impact yet, the FSB report identified the potential risks as both micro-financial (e.g., credit risk, leverage, liquidity risk, maturity mismatch and operational risks) and macro-financial (e.g., unsustainable credit growth, incentives for more risk-taking by traditional institutions, increased interconnectedness or correlation, procyclicality, contagion and systemic importance) (FSB 2017). Among the risks are the potential weakening of lending standards, increased procyclical credit provision, and more risk-taking.

Moreover, the securitisation of FinTech credit obligations into large bundles may potentially increase interconnectedness between FinTech platforms and other traditional intermediaries, thereby creating new transmission channels that propagate FinTech credit risks to the wider financial system and vice versa (FSB 2017). While securitising FinTech loans to MSMEs may play a significant role as an alternative source of funding and additional market liquidity that lowers the cost of funding (Foottit et al. 2016), the use of such securitised products raises concerns regarding the funding stability in events of credit market downturn and the potential excess funding, which may weaken lending standards (Kenney and Zysman 2019; FSB 2017; Wardrop et al. 2015).

Among potential benefits from FinTech innovations are effects associated with the decentralisation and increased intermediation by non-bank and non-financial entities; increased efficiency, transparency, immediacy, competition and resilience of the financial system; and greater financial inclusion and economic growth, particularly in emerging and developing markets (FSB 2017). FinTech could also lower entry barriers which may lead to a more decentralised, diversified and resilient financial system.

Emerging literature suggests that NBFIs may affect financial stability through the migration of credit to the nonbank sector. The outcome of such a shift may reduce or increase risks to financial stability, such as bank risk-taking, through diversification of funding sources or competition pressure (Bertsch and Rosenvinge 2019). However, specific attributes of banks and the degree of concentration of the credit market will determine whether an increase in FinTech credit competition will enhance or diminish financial stability (Thakor 2020). This may enhance financial stability in several ways. For instance, the substitution effects from the activation of MaPP may lower systemic risks (Cizel et al. 2019), the probability of systemic crises and bank default (Altunbas et al. 2018; Dell'Ariccia et al. 2016). The migration of credit to a "more market-based" system, may thus diversify risks and increase the banking system's resilience (Cizel et al. 2019; Bats and Houben 2020; De Fiore and Uhlig 2015). They may also create an advent of market liquidity events between traditional banks and nonbanks (Cizel et al. 2019). NBFIs, such as FinTech credit platforms, are generally less leveraged, involving fewer liquidity or maturity mismatches than banking financing, particularly in the ‘traditional’ P2P model (Cizel et al. 2019; FSB 2017; ESRB 2016). Moreover, nonbank credit is not linked to the systemic functions related to the payments system and market infrastructures. They have no access to public safety nets, such as deposit insurance and central bank liquidity support, thus reducing moral hazard concerns (Cizel et al. 2019).

On the contrary, FinTech credit can become a potential channel through nonbanks that could act as a conduit to avoid existing regulations in the core banking system (Cizel et al. 2019). It can even be rendered less responsive to prudential interventions previously used to remedy threats to financial stability (FSB 2019a). This may further undermine the effectiveness of financial policies such as MaPP and contribute to financial stability risks (Braggion et al. 2021; Claessens et al. 2021; Cizel et al. 2019). The migration may further yield undesired outcomes, especially when excessive debt burdens from households and businesses remain problematic, even if contagion risks decrease (Cizel et al. 2019; Houben et al. 2019). Even when FinTech credit platforms are unleveraged, they may still be prone to spillovers from turbulences in the banking or capital markets (Sahay et al. 2020). de Roure et al. (2022) assert that while banks are “leveraged lenders”, FinTech credit platforms are large “equity lenders”, which may result in risk-shifting and moral hazards in banks that require sufficient equity capital to overcome.

Recent debates contend that FinTech credit may have a greater systemic impact through fundamental transformational mechanisms, such as the disintermediation of traditional financial intermediaries, disaggregation of financial services and decentralisation of networks (Gray and Leibrock 2017). These economic functions, such as credit intermediation, may emerge from excessive credit growth and leverage, liquidity, and maturity mismatches, procyclicality of margins and haircuts or imperfect credit risk transfer (FSB 2020b; FSB 2017; Doyle et al. 2016). Some NBFIs may not be systematically assigned to the financial sector (Godoy et al. 2020; Kirchner et al. 2020), further raising financial stability concerns and undermining the macroeconomic relevance of credit markets (Cornelli et al. 2020). Simultaneously, literature has evolved to add additional frictions to explain the non-bank credit sector and its interactions with other imbalances, such as fragile financial intermediaries (Adrian and Jones 2018).

While the pre-crisis literature presents credit as a catalyst for economic growth, the rapid growth of credit serves as a reliable banking and financial crisis predictor (Röhn et al. 2015; Aikman et al. 2014). It is largely identified as one of the root causes of the banking crisis (Alessi and Detken 2018). In essence, credit can be a catalyst for economic growth as the root cause of systemic crises. Oftentimes the same mechanism that helps reduce agency costs and enhance resource allocation can also be a source of financial fragility (Beck 2014). Innovation activities may be dampened during the crisis (Döner 2017, OECD 2012). Moreover, credit aggregates are directly associated with boom-bust financial cycles (Alessi and Detken 2018; Jordà et al. 2013; Schularick and Taylor 2012). This is even exacerbated during periods of prolonged slow economic growth and extended low-interest rates, coupled with the signs of risk-taking such as rapid credit and increasing asset prices.

Various shocks can amplify vulnerabilities and risks to financial stability. Vulnerability and procyclicality in credit provision could also arise from various sources, including a greater concentration in some market segments, if funding flows on FinTech lending platforms were to become large and unstable. The vulnerability may also emanate through excessive leverage and asset price bubbles, raising concerns about how FinTech credit would fare during periods of rapid credit growth or market stress (FSB 2017; 2019a; Vives 2019b; Claessens et al. 2018). Financial instability tends to rise due to negative shocks amplified by financial vulnerabilities, leading to non-linear outcomes and tail events (Adrian and Liang 2018). At the aggregate level, such vulnerabilities increase the risks of amplifying shocks in the financial system and, in the worst case, systemically cause severe financial and macroeconomic consequences. New sources of fragility may thus disrupt traditional financial and capital markets (Demertzis et al. 2018; Lai and Van Order 2017; Vives 2019b). This can further lead to weaker lending standards and riskier lending, and defaults during upswings, with the potential for a pullback in credit in periods of market stress or economic downturn (FSB 2017; 2019a).

A rapid expansion of credit can potentially usher in new risks to financial stability. When such expansion becomes too fast, it may expose the system to future conventional vulnerabilities associated with the rise in the systemic importance of non-traditional players and the influx of new highly interconnected firms (Aikman et al. 2019; FSB 2019a). Due to the high degree of interconnectedness between banks and nonbanks (through direct exposures), vulnerabilities can potentially materialise simultaneously, further increasing the risks to overall financial stability (ECB 2020). The level of interconnectedness in the financial system plays an important role in financial stability as potential risks could be propagated or amplified across the system (Marqués et al. 2021; Martinez-Jaramillo et al. 2019).

The growing importance of NBFIs has amplified the degree of interconnectedness with other parts of the financial system (particularly banks) in longer and more complex chains of intermediation (FSB 2020a). The extent of this interconnectedness could further be amplified by FinTech credit, as shocks easily spread with increased interconnectedness (Marqués et al. 2021). Generally, banks and nonbanks are often interrelated; hence the FinTech and the banking sector tend to compete in similar market segments and businesses (Brandl and Hornuf 2020; Dorfleitner et al. 2017; Kommel et al. 2019; Yao et al. 2018b). Some incumbents have incorporated FinTech innovations in their business model through joint partnerships, acquisitions, venture capital funding or service outsourcing through alliances, ownerships, and joint ventures (Wójcik 2021; Lai 2020; Hornuf et al. 2021) and as institutional investors (Buch 2019; Lee and Shin 2018). The collaboration is even greater and more common for larger banks (Hornuf et al. 2021).

Credit shocks can also be amplified and transmitted to the broader economy through financial accelerator mechanisms (Punzi 2018; Zabai 2017; Röhn et al. 2015). For instance, adverse shocks to highly indebted households or rising levels of household debt can negatively impact the wider economy and trigger borrowing constraints leading to a deleveraging process. At business cycle frequencies, several studies and the recent experience of the global financial crisis have demonstrated that an increase in private sector credit (including corporate and household debt) can be a source of financial vulnerability. Furthermore, FinTech credit may be subject to strong pro-cyclical self-reinforcing cycles and may even exhibit larger and sharper swings than existing financial institutions (FSB 2019a; 2017).

The financial stability approach accentuates the destabilising effects of excessive leverage build-ups and the relevance of household loan servicing ability, arising from an excessive debt accumulated in the preceding period and becoming burdensome for the borrower when market conditions reverse. Unstable and excessive credit growth, if sustained over long periods, tends to promote the build-up of financial fragilities, and possible emerging credit bubbles may threaten the stability of the financial sector (Boh et al. 2017). History demonstrates that massive build-ups of credit in the private sector tend to precede crisis and often lead to the build-up of systemic risks to financial stability, which may materialise in the form of systemic banking crises (Alessi and Detken 2018; Mian et al. 2017). This may increase the likelihood of a financial crisis once the crisis ensues (Freixas et al. 2015). Moreover, deeper recessions and slower recoveries are usually preceded by more credit-intensive economic expansions (Jordà et al. 2013). However, the severity of such a recession is dependent on the joint build-up of vulnerabilities from different sectors, particularly if the credit boom-bust will result in a full-blown banking crisis. Even in cases where credit booms do not turn into full-blown banking crises, the recoveries are often muted (Dell'Ariccia et al. 2012).

A fragile financial system is susceptible to relatively small negative shocks that can have huge impacts on banking crises and persistent recessions (Boissay et al. 2016). While the resulting economic costs of crises are normally large, even a relatively small shock can become systemic due to amplifying spirals associated with the build-up of several vulnerabilities in the financial sector, such as excessive leverage, interconnectedness, and common exposures (Röhn et al. 2015). As with the financial crisis, a larger exposure of the financial sector to bad loans can cause a banking crisis, with an associated credit crunch hurting the general economy (Röhn et al. 2015; André 2016). Moreover, financial stability risks could be amplified due to existing financial frictions, or new ones may emerge should FinTech innovations lead to larger or new imbalances and contagion channels (FSB 2017; Mnohoghitnei et al. 2019). However, the resilience of the FinTech credit sector to larger exogenous shocks (commonly faced by the banking sector) might be abetted by its relatively low level of interconnectedness (BIS and FSB 2017).

These scenarios are expounded by the "too much finance" literature, also known as the "curse analysis", reflecting credit growth as a two-edged sword. The theoretical underpinning for this credit-stability relationship, in which an estimate of the non-linear association is obtained, gives an opportunity to raise the problem of marginal levels (saturation point) of credit growth relative to financial stability. The "too much finance" hypothesis holds that there is an optimal point above which a growing financial sector may start to hurt economic growth, a variable that has a substantial and direct impact on financial stability (Zhu et al. 2020a; Sahay et al. 2015a; b; Arcand et al. 2015). Other studies document an inverted U-shaped relationship between finance (financial development) and innovation (Zhu et al. 2020a; Law et al. 2018). Mishra and Narayan (2015) also suggest that credit influences financial stability and exerts a positive effect on economic growth when it attains a certain level. Studies also demonstrate that the growth benefits tend to start declining when aggregate leverage is high. In other words, when the credit levels reach these marginal parameters or thresholds, the financial system's ability to maintain its resilience and enforce adequate prudential measures diminishes. This relationship is likely to breed a policy dilemma if they are mutually exclusive and where credit promotes economic growth and triggers financial instability (Koong et al. 2017). The findings are consistent with the "vanishing effect" phenomenon by Gründler (2019).

3.4. FinTech credit and bank risk-taking

The theoretical foundation of the relationship between FinTech credit and bank risk is still evolving. The measures of bank risk-taking demonstrate banks' exposure to the emergence of FinTech credit and express the degree of banks' financial soundness and resilience to threats as far as bank stability is concerned. Therefore, the literature on "excessive" bank risk-taking is fundamental in financial and bank stability debates. For a long time, policymakers have been concerned about excessive risk-taking by banks for several reasons, including misaligned incentives (García-Alcober et al. 2020). This is because the significant impact of banks could cause an accumulation of financial imbalances, potentially increasing vulnerability to adverse shocks by undermining banks' loss-absorbing capacity and their resilience to those shocks (Kawamoto et al. 2020).

Several sources of risk have emerged with the rise of FinTech credit (and BigTech credit) into the traditional banking sector (OECD 2020a). During expansionary periods, banks tend to underestimate risk and engage in risk-taking behaviours that may increase their probability of experiencing financial difficulties in the future (Altunbas et al. 2014; 2012). Hence, the concept of risk-taking also highlights the behavioural finance of banks' response to various risks. Even during the financial crisis period, increased financial innovation in the financial system was associated with higher risk-taking and more volatile bank returns resulting in higher bank losses (Beck et al. 2012). A considerable body of literature has investigated the banks' risk-taking behaviour (Bitar et al. 2018; Bhagat et al. 2015; Laeven and Levine 2009).

The relationship between traditional bank and nonbank credit is often explained by the consumer theory, i.e., substitution and complementary theories. Tang (2019) theorises that when there is a negative shock to bank credit supply, the quality of the FinTech credit borrower pool is dependent on whether FinTech and bank credits are complements or substitutes. The typical competition channel largely aligns with the "substitution" theory, suggesting that a growing share of FinTech credit activities may disrupt or displace incumbents. Evolving empirical literature suggests that FinTech credit may substitute bank credit (Havrylchyk et al. 2020; de Roure et al. 2022; Ziegler et al. 2021). Havrylchyk et al. (2020). Fernández et al. (2018) reveal that non-bank loans (FinTech credit platforms) partially substituted traditional bank loans, especially in countries that were more affected by banks' deleveraging in the wake of the financial crisis. Fuster et al. (2019) suggest that FinTech credit lenders compete with traditional mortgage lenders instead of broadening access to borrowers with low access to traditional lending. Dabrowski (2017) argues that crowdfunding can compete with traditional corporate bonds and venture capital funds. An alternative theoretical view is based on a 'complementary' theory that suggests that FinTech credit complements other traditional forms of credit (rather than substitutes) (Cornelli et al. 2020), such as retail banking services (Demertzis et al. 2018; Cornaggia et al. 2018). Several empirical pieces of evidence support the complementary relationship between FinTech credit and bank credit (Cornelli et al. 2021; 2020; Zhang et al. 2019).

The "substitution" theory suggests the existence of competition, a factor perceived as a possible source of instability in the banking sector (Vives 2019b; Lai and Van Order 2017). Vives (2019a; 2019b) reviews the technological disruption in banking, exploring its impact on competition and its potential to increase efficiency. Related work by de Roure et al. (2022) and Tang (2019) examine why banks may lose loans to FinTech credit platforms. The authors find that FinTech credit competes with bank credit but tends to have a competitive edge when banks suffer temporary shock that limits their credit supply. The effect strengthens when the banks unaffected by the shock are financially weaker or have lower capital (Tang 2019).

A hoary notion in banking literature postulates that excessive competition can lead to socially undesirable outcomes in the form of bank failures, panic, runs, and even crises

(Boyd and De Nicoló 2005). Intense competitive pressure can impact banks' traditional business and operational models, challenging them to re-evaluate their competitive advantage to adjust to the new reality (Jakšič and Marinč 2019; Funk 2019). This may further exert some burden on banks’ business models and profit margins, resulting in banks’ risk-taking, which may inevitably lead to increased risk-taking (OECD 2020a; Vives 2019a; Bertsch and Rosenvinge 2019). They may also reduce bank liquidity by disrupting the stability of deposits and accelerating the weakening of asset quality (Hu et al. 2019). It is without a doubt that the short-run impact of the disruptive technologies will be to erode the banks’ profit margins and increase the contestability of banking markets, while the long-run impact will be dependent on what market structure ultimately prevails (OECD 2020a).

Strong competition in the banking sector tends to lead to higher risks as reduced monopoly rents earned by banks are reduced; hence banks resort to taking more risks due to reduced profits and capital ratios and an increase in asset risk (Phan et al. 2021). Also, FinTech firms may fuel competition to capture the rents in the banking sector (OECD 2020a), and reduced rents for banks from relationship lending may further increase the attractiveness of risky investments (Thakor 2020). FinTech credit advantage may arise if banks collect high intermediation rents, while FinTech credit platforms have more favourable cost structures, such as lower cost of infrastructure and lesser strict regulatory requirements (Bertsch and Rosenvinge 2019). This may further heighten the competitive rift, especially in “riskier borrower” segments and small loan sizes, where screening based on automated credit scoring technologies tends to be more profitable (Einav et al. 2013).

The competition effect is likely to increase as new market players enter the financial sector, but the long-term impact is more open (Darst et al. 2020; OECD 2020a). There is even a potential long-term risk depending on the extent of BigTech firms to dominate the customer interface (OECD 2020a). Cornaggia et al. (2018) find that high-risk FinTech credit substitutes for bank credit and that consumers may substitute one credit provider for another, creating adverse selection problems for traditional lenders. In some instances, there is a growing client base of FinTech credit activities of already banked individuals and customers (Ziegler et al. 2021). For instance, FinTech credit firms in the UK are predominant on banked customers (96%) (Ziegler et al. 2021).[17]

The role of regulation in the interaction of market competition and bank risk-taking cannot be overstated. To the extent that the emergence of FinTech firms reduces the profitability of traditional banks, in an effort to offset the downward pressure on their profits, the latter may resort to taking excessive risks (OECD 2020a). The worst-case scenario may arise from the regulator's response to the rise in contestability and enhanced risk-taking by raising prudential requirements for banks. This may, in turn, raise the incentives to circumvent MaPP interventions and foster an increase in shadow bank activity outside the regulatory boundary (OECD 2020a). For instance, this self-feeding may occur when macroprudential regulation attempts to curb excess credit or limit systemic risk, but the limits to leveraged lending (imposed on banks) may shift leveraged lending toward nonbanks, incentivising the growth of non-bank activities (Claessens et al. 2021; Irani et al. 2021; FSB 2020b; OECD 2020a; Cizel et al. 2019). A living example was experienced by the US with the leverage lending guidance (Kim et al. 2018). Lower regulatory requirements for new market entrants, particularly nonbanks, are likely to foster competition, but at the potential cost of destabilising traditional banks incumbents by decreasing their profitability, increasing the incentive for risk-taking, and transferring systemic risk to the nonbank sector (OECD 2020a).

An alternative theoretical view supports the complementary theory that FinTech credit may benefit the banking system by enabling risk-sharing and fostering technological innovation for future economic growth (Beck et al. 2016; Meierrieks 2014). The diversification channel may reduce over-reliance on the banking system and diversify some of the risks associated with the traditional banking system (Bertsch and Rosenvinge 2019; FSB 2019a; Carney 2017). A greater share of more "market-based" finance may increase the financial system's resilience (Bats and Houben 2020; De Fiore and Uhlig 2015), thereby reducing bank risk-taking. Increased banking competition may influence banks to be more efficient and possibly reduce their bank risk-taking or over-lending (Thakor 2020) and improve their stability by increasing their profitability and asset

[17] Accordingly, the Middle East and North Africa (MENA) (83%) and by Latin America and the Caribbean (LAC) (82%) regions also recorded high levels of banked customers while the Sub-Saharan African (SSA) and the Asia Pacific showed potential for the underserved groups by approximately 49% and 51% underbanked.

quality (Goetz 2018). Zhang et al. (2019) suggest that FinTech credit complements bank lending in the initial regime when FinTech lending balances are still low, subsequently substituting bank credit when FinTech lending increases. Conversely, Kohardinata et al. (2020) found that FinTech credit growth initially substituted the Indonesian banks' credit growth in 2018 but changed into a complementary effect in 2019. Similarly, Hodula (2021) suggests that FinTech credit platforms can act as both complements and substitutes for traditional bank credit.

Several studies reveal a positive relationship between FinTech credit and bank stock returns (Chen et al. 2019; Li et al. 2017). However, Li et al. (2020a) investigate the risk spillovers between the FinTech sector and traditional financial institutions using US stock returns and find a positive correlation, an increase in systemic risk. Thus, the correlation between FinTech and bank risk spillover may suggest that both sectors may be susceptible to similar risks, defeating the complimentary benefits and may have serious consequences for financial stability. However, some studies suggest no significant relationship between FinTech credit and bank credit. For instance, Asmarani and Wijaya (2020) also explore the effect of FinTech (proxied by FinTech funding frequency and FinTech funding value) on banks' stock returns using monthly data from 2016 to 2018 and found no significant effect. In addition, Cornaggia et al. (2018) suggest that while 26.7% of risky FinTech loans displace bank lending, the low-risk loans may be purely expansionary, particularly when addressing the underserved segment.

An emerging strand of literature examines the relationship between FinTech developments and bank risk-taking. The existing studies hold different views regarding the impact of technological advancement on traditional bank stability and risk-taking. Fung et al. (2020) suggest a varying impact of FinTech innovations on bank stability, using a panel sample of listed banks from 84 countries from 2010 to 2017. The authors use FinTech regulatory sandboxes (as an exogenous shock to FinTech innovations) and Z-score. They conclude that FinTech enhances bank stability in emerging markets but undermines it in developed markets. Phan et al. (2021) suggest that FinTech entities (measured as the number of FinTech companies) will upset the balance of traditional financial institutions, thus negatively influencing bank performance. The authors used a two-step GMM system dynamic panel estimator in Indonesia from 1998 to 2017 and four measures of bank performance: net interest margin (NIM), return on assets (ROA), return on equity (ROE) and the yield on earning assets (YEA).

Similarly, Haddad and Hornuf (2021) used NIM, ROA, ROE and Tobin's Q as measures of bank performance to examine the impact of the development of FinTech start-ups (measured as the number of FinTech start-ups founded) on bank performance and default risk. Using a larger sample from 87 countries from 2005 to 2018, Haddad and Hornuf (2021) find a positive relationship between FinTech start-up formations and banks' performance. Their findings also show that FinTech start-ups decrease the incumbent's systemic risk exposure and stock return volatilities. Deng et al. (2021) investigated the association between FinTech (proxied by a digital financial inclusion index) and bank risk-taking from 2011 to 2016. Using a benchmark regression model, the authors find that the development of FinTech significantly decreases the bank risk-taking level of small and medium-sized banks. Prior literature linked the emergence of financial innovations such as "internet finance" with bank risk. The taxonomy of internet finance comprises six major models: third-party payment, P2P loan platforms, big data finance, crowdfunding and wealth management (Deng, 2015). Guo and Shen (2019) used the internet finance index (constructed via text mining) and a sample of 83 commercial banks in China from 2003 to 2016. Using system generalized moment estimation (SYS-GMM), the authors show that the development of internet finance significantly increases the risk-taking level of traditional banks.

Similarly, Dong et al. (2020) employed static and dynamic panel models to examine the impact of internet finance on traditional banks using four dimensions of bank profitability, liquidity, security and growth. They find that developments in internet finance positively impact bank profitability, security and growth but have a negative impact on bank liquidity. Liao (2018) examined a two-way impact mechanism of internet finance on Chinese bank risk exposure and bank risk-taking from 2006 to 2016, using the NPL ratio, loan preparation loss, capital adequacy ratio, Z-index, and expected default rate. The author uses the regression analysis of the GMM model and concludes that internet finance stabilises the banking industry and the overall stability of the financial system.

Several scholars held a compromise point of view that internet finance would increase bank risks in the short term but, in the long term, assume more of the role of cooperation. The short-run impact of the disruptive technologies may erode the banks’ profit margins and increase the contestability of banking markets, while the long-run impact will be dependent on what market structure ultimately prevails (OECD 2020a). Wang et al. (2021) suggest that the impact of internet finance on traditional bank risk-taking is non-linear (U-shaped), using the media’s attention paid to FinTech-related information to measure FinTech development from 2011 to 2018. The authors use Z-score as a proxy of bank risk-taking and present evidence that the development of FinTech exacerbates banks’ risk-taking and that the exiting relationship between FinTech development and banks’ risk-taking is non-linear or U-shaped. The non-linear relationship indicates that FinTech threatens bank profits at the initial development and aggravates their risk-taking. However, at a later time, banks and FinTech firms may cooperate to compete, which may enhance the stability of banks as FinTech challenges banks to upgrade their technology, innovate their businesses, and optimise their services (Wang et al. 2021).

Nevertheless, these indicators do not specifically capture the FinTech credit market. The common thing about these studies (e.g., Dong et al. 2020) is that their proxy for the development of internet finance is constructed as an index based on “text mining” or search engine such as “Baidu's search index”.[18] Li et al. (2020c) also carried out a co-word analysis of the literature, which showed the main modes of internet finance. Furthermore, Wang et al. (2021) use the media's attention as a proxy for FinTech development, while Phan et al. (2021) have adopted the “number of FinTech firms”.[19] Furthermore, some of these studies have linked FinTech innovation to the rise of “internet finance” within the banking sector, a concept broadly used by several Chinese-based studies (e.g., Dong et al. 2020; Li et al. 2020b; Hu et al. 2019; Funk 2019).[20] Several of these studies categorise major models of internet finance under an umbrella term, which include third-party payments and mobile payments, internet banking, digital currency,

[18] The annual word frequency statistics of “text mining” of the initial keyword is searched in Baidu's database as the basis of the Internet finance index.
[19] The “number of FinTech firms” includes firms offering different bank related activities, of which lending constitute around 45%, followed by payments 38% and the rest being personal finance management, crowdfunding, and cryptocurrencies.
[20] However, some studies narrow the term “internet finance” to electronic finance adopted by traditional banks and argue that they can potentially alter banks’ risk-taking. For instance, Ky et al. (2019) show that the successful implementation of FinTech products in banks increases their profitability and efficiency.

P2P lending, crowdfunding, and the use of technological innovations such as big data in financial activities (e.g., Li et al. 2020b; Deng 2015).

3.5. Macroprudential policy and FinTech credit

It is widely accepted that the primary aim of MaPP is to enhance the financial system's resilience and reduce financial stability risks (IMF 2013). Thus, an effective MaPP intervention should stabilise its underlying target variable, such as credit growth or house price growth, which, among others, can manifest through a decline in the volatility of the target variable. Galati and Moessner (2018) provide an in-depth review of the literature on existing studies associated with the implications of MaPP. While various economies have increasingly adopted MaPP following the global financial crisis, their potency in the allocation of credit intermediation still lacks a full understanding. More specifically, existing MaPP tools are largely targeted at the traditional banking system and may become limited in restraining credit growth emanating from the nonbank sector. One of the reasons that such policy analysis fails to fully fulfil their policy agendas is because intermediation in the lending market has undergone a dramatic shift due to the entry and growth of "shadow banks" (Claessens et al. 2018).

Banks are traditionally exposed to stringent macroprudential regulations such as Basel III, while non-banks are mostly left lightly regulated and sometimes even unregulated. This gap has been filled in part by NBFIs such as shadow banks and FinTech credit, which are not subject to such restrictions. This is affirmed by Goodhart (2008) that the more a regulation becomes effective, the more incentives to find ways around it. At a higher policy level, a relaxed regulatory approach to FinTech development may raise systemic risk concerns and open up non-negligible regulatory arbitrage channels, which may lead to excessive build-up of household leverage (Braggion et al. 2021). Moreover, the potential regulatory arbitrage, leakages and circumvention also continue to pose challenges, as even borrower-targeted measures are not always applied to all forms of credit or loans (Arena et al. 2020). The pre-crisis literature thus reminds us that risks to financial stability may also emerge outside the banking sector (FSB 2020a, 2019b; ESRB 2020). Moreover, the experience of the financial crisis has also shown that stricter regulatory restrictions on traditional banks significantly contributed to a decline in bank lending.

Previous studies have investigated the effect of MaPP on bank or total credit growth and established that MaPP instruments have the intended effect on reducing bank credit (Akinci and Olmstead-Rumsey 2018; Altunbas et al. 2018; Cerutti et al. 2017a). Prior literature also documents that macroprudential instruments, particularly the tightening ones, exert significant stabilising effects on the financial system by curbing credit expansion and leverage growth and counteracting the incentive of financial institutions' excessive risk-taking (e.g., De Schryder and Opitz 2021; Pochea and Niţoi 2021; Akinci and Olmstead-Rumsey 2018; Altunbas et al. 2018). In a recent comprehensive study, Cerutti et al. (2017a) show that the use of macroprudential instruments is generally associated with the intended downward impact on credit, particularly bank credit.

Similarly, Akinci and Olmstead-Rumsey (2018) reveal that the MaPP index reduces bank credit growth. De Schryder and Opitz (2021) find that a MaPP tightening shock reduces bank credit and household credit-to-GDP. Richter et al. (2019) and Carreras et al. (2018) detail a significant immediate decrease in household credit. Akinci and Olmstead-Rumsey (2018) and Cerutti et al. (2017a) reveal a significantly subjugated aggregate credit growth, particularly household credit growth when MaPP is tightened. However, Cerutti et al. (2017a) warn that the effects tend to be weaker for financially and more developed and open economies.

While the predominant implementation of macroprudential measures on the banking system may have been effective, they may also be subjected to a boundary problem, causing substitution flows to less regulated segments of the financial sector (Claessens et al. 2021; FSB 2020b; Cizel et al. 2019; Kim et al. 2018). An emerging new strand demonstrates this in the literature that sheds light on the relationship between traditional bank credit and nonbank credit from a MaPP perspective. The theory suggests that during the bust phase, activating MaPP in one financial imbalance can trigger the unwinding of others resulting in the "waterbed or substitution effects". As such, the effectiveness of MaPP tends to weaken during the bust phase compared to the boom stage of business cycles. For instance, MaPP actions undertaken to contain corporate credit were also associated with a significant surge in household, housing and consumer credit in the immediate subsequent quarter following the implementation of those measures (BIS 2018). Therefore, the simultaneous unwinding of several imbalances may aggravate the downturn and further deepen the crisis (Röhn et al. 2015). Furthermore, triggering such

MaPP, in turn, appears to be dependent on the non-linear behaviours of the stability of the financial system, particularly during episodes of financial distress.

Several empirical works of the literature suggest the existence of a robust empirical link between macroprudential framework capacity and nonbank credit growth. The evidence suggests that the activation of MaPP may shift leveraged lending towards nonbanks and incentivise the growth of non-bank activities through “cross-sector substitution” and “waterbed” effects (Claessens et al. 2021; Irani et al. 2021; FSB 2020b; OECD 2020a; Cizel et al. 2019). Developments in financial innovation may thus result in some innovative activities (Price Waterhouse Cooper (PwC) 2017) and financial risks (Buch 2020; FSB 2020b; Llewellyn 2009) migrating outside of the regulated banking and insurance sectors. Nonbank credit activities such as the FinTech innovation may take advantage of this shift by enabling new players and business models to enter the credit market (Mnohoghitnei et al. 2019). Hodula and Ngo (2021) assert that several multiple channels (direct or indirect) are likely to be at play. For instance, MaPP tightening generally and directly limits bank credit, which may limit or exclude some borrowers outside the traditional credit intermediation, leading them to turn to alternative forms of credit such as FinTech credit. Moreover, tighter MaPP may increase traditional bank funding costs, which may then raise banks’ incentives to securitize their existing loan contracts (Hodula and Ngo (2021). To prove which of these channels are at play is beyond the scope of this study and remains a potential area for future research.

The closest to this study was Braggion et al. (2021), who examined 20% of Chinese FinTech credit platforms around the tightening of residential mortgage loan-to-value (LTV) caps in several cities in China in 2013. Braggion et al. (2021) suggest that FinTech credit may pose new risks to the financial system by acting as a conduit to avoid LTV caps imposed on traditional credit providers. Relatedly, Buchak et al. (2018) explore whether the US residential mortgage market, whose banks were more subjected to a specific regulatory burden, experienced larger market share gains or growth in FinTech credit. They conclude that the significant increase in the FinTech credit market share was largely attributed to regulatory constraints among traditional banks after the crisis. Similarly, de Roure et al. (2022) document how Fintech credit grows when some banks are faced with exogenously higher regulatory costs, such as stricter bank capital requirements in the German consumer credit market post-2010. On the other hand, Irani et al. (2021) examine the link between bank capital regulation and the prevalence of the lightly regulated nonbank sector (shadow banks) in the US corporate credit market. The authors document that shadow banks or lightly regulated nonbanks tend to substitute capital-constrained banks in the financing of corporate credit — rather than household or consumer credit.

In a more recent close study, Hodula and Ngo (2021) investigate whether MaPP actions affect shadow bank lending using a large dataset covering 23 EU countries and integrate a narrow measure of shadow banking focused on capturing credit intermediation by non-banks. The authors reveal that following a MaPP tightening, shadow bank lending increased. The narrow measure of shadow banking used by Hodula and Ngo (2021) focuses on capturing credit intermediation by non-banks which incorporates loans granted by other financial institutions such as financial vehicle corporations, security and derivative dealers, specialized financial corporations and financial corporations engaged in the lending and residual entities.

Similarly, Claessens et al. (2021) evaluate how MaPP affects non-banks using data from 24 countries participating in the FSB's monitoring exercise from 2002 to 2017. The authors reveal evidence that increases in the MaPP, particularly MaPP tightening, have a positive impact on NBFI activities, partially attributing such an increase to both the reduction in bank assets and an increase in NBFI assets. More specifically, they discover that a net tightening of domestic MaPP leads to an increase of 0.2 percentage points in the share of domestic NBFI assets to total financial assets. The authors also use assets of NBFIs engaged in loan provision or short-term funding and demonstrate that the net tightening in domestic MaPP increased these assets by around 18%.

Relatedly, Irani et al. (2021) investigate the association between capital regulation and the US non-bank credit market and find that a one standard deviation decreases in bank capital leads to a 3.25 percentage point rise in the share of nonbank. Cizel et al. (2019) investigate whether the MaPP prompts substitution toward the nonbank financial sector using the GMM estimator and a quarterly series of bank and nonbank credit data for 40 countries over 40 years span. The authors confirm substantial substitution effect, showing large waterbed effects due to policy restrictions on traditional banks and when economies have well-developed nonbank credit markets. Knot (2018) reiterate the relevance of the substitution effects of stricter bank regulation.

Beyond the overall effects of MaPP, some recent empirical investigations extend to the question of whether MaPP may produce differentiated distributional outcomes (Kang et al. 2021). Prior studies have indicated that macroprudential tools may exhibit instrument- or type-specific outcomes in promoting financial stability but present mixed results on the types of tools that are more effective than the others (Kang et al. 2021). For instance, recent empirical studies that evaluate the effects of macroprudential instruments follow this distinction (Ayyagari et al. 2018; Cerutti et al. 2017b; Claessens et al. 2013). Further grouping macroprudential instruments into various types, Alam et al. (2019) use the latest iMaPP database covering 134 countries from January 1990 to December 2018. The authors postulate that loan-targeted instruments significantly impact household credit. Their findings also note significant and non-linear effects, with a diminishing impact for larger tightening MaPP measures.

The literature also presents mixed results for borrower-based measures, which are predominantly the loan-to-value (LTV) and debt-service-to-income (DSTI) ratios. Morgan et al. (2019) investigated the effects of MaPP on residential mortgage loans using a large sample of more than 4000 banks from 46 countries. Their findings suggest that mortgage loans have been effectively curtailed in economies with an LTV policy. Basto et al. (2019) show that a permanent LTV tightening leads to a long-run decline in lending to the private sector. Dimova et al. (2016) and Claessens et al. (2013) point out that borrower-based measures effectively mitigate the build-up of systemic vulnerabilities compared to those targeted at financial institutions. Jurča et al. (2020) show that the tightening of the LTV limit was the most significant relative to the other borrower-based measures. However, Poghosyan (2020) employs LTV and DSTI ratios in 28 EU countries during the period 1990Q1 to 2018Q2 and notes that MaPP tightening does not reduce total credit to the private sector in the short to medium term but only reaches its peak after three years. Ayyagari et al. (2018), using firm-level data, also observe that the borrower-based measures exhibit a significantly different effect than MaPP targeted at financial institutions. In short, the findings of Ayyagari et al. (2018) are contrary to most studies and lend supportive evidence that MaPP enhances systemic risk as borrowers' credit growth declines in response to tightened macroprudential measures.

However, Kuttner and Shim (2016) employ a large panel data set of 57 countries and conclude that the relationship between most macroprudential measures (including LTVs) is not empirically robust. Instead, the authors suggest DSTI caps as the most consistently effective measure in restraining household credit growth and that household-related taxes slow housing credit. Generally, the most used MaPP tools in both AEs and EMDEs are LTV, debt-to-income (DTI), and concentration limits (Cizel et al. 2019). Carreras et al. (2018) suggest that such instruments as taxes on financial institutions, capital requirements and limits on LTV and DTI ratios are more favourable than other macroprudential tools. Zhang and Zoli (2016) found that the LTV ratio and housing tax curb the growth in credit and housing prices and bank leverage.

Emerging literature suggests that increasing banking regulation incentivises FinTech credit (Cornelli et al. 2021; de Roure et al. 2022; Thakor 2020; Buchak et al. 2018). de Roure et al. (2022) found a direct and indirect effect of an exogenous increase in regulatory burden for traditional banks, causing banks to forego or reduce lending in response to regulatory requirements and as well as increasing regulatory costs. Stricter banking regulation, proxied for the overall stance of financial regulation by Navaretti et al. (2018), is associated with higher FinTech credit (Cornelli et al. 2021). In fact, the FinTech credit market share at the time doubled between 2007 and 2015, an expansion primarily backed by regulatory constraints among banks following the crisis (and, to some extent, technological advancements) (Buchak et al. 2018). Buchak et al. (2018) investigated the rise of shadow banks (notably the FinTech credit) in the US and discovered that regulatory differences or "advantage" accounts for roughly 60% of their growth, followed by technology at only 30%.

Academic literature presents evidence suggesting that linkages between traditional financial intermediaries and NBFIs may be associated with regulatory arbitrage opportunities (Braggion et al. 2021; de Roure et al. 2022; Tang 2019). Indeed, Adrian and Jones (2018) also observe that such regulatory arbitrage may occur where a liquidity, capital, taxation or information requirement can potentially be circumvented to make certain activities more profitable than they would otherwise not be. Therefore, regulatory leakages may intensify should traditional banks shift their risky and capital-intensive lending activities to online lending platforms (Bertsch and Rosenvinge 2019; PwC 2017).

Kim et al. (2018) also reveal that U.S nonbanks increased their leveraged loan activity subsequent to the introduction of the interagency guidance in 2013, while larger banks reduced their leveraged loans. Claessens et al. (2021) assert that tightening MaPP increases NBFI activities but decreases bank assets, thus raising the overall share of NBFI in total financial assets. Rau (2020) also links the introduction of explicit legal regulation on debt and equity crowdfunding to a significant increase crowdfunding volume. This is consistent with post-crisis literature, which argues that stricter regulatory restrictions on traditional banks significantly contributed to a decline in bank lending.

Another strand of emerging literature suggests that the growth of nonbank credit may undermine the effectiveness of credit regulations such as MaPP (Braggion et al. 2021; Claessens et al. 2021; Cizel et al. 2019). Cizel et al. (2019), in particular, suggest that the substitution effect may partially offset the reduction in bank credit, thus inhibiting the intended effects of MaPP on total credit. Claessens et al. (2021) also reveal that the development of a large share of the NBFI sector may limit the effectiveness of MaPP for overall financial stability. Arena et al. (2020) suggest that macroprudential measures may have been partly circumvented through nonbanks that are subjected to less strict regulations. Braggion et al. (2021) employ 2013 loan transaction data from one of the leading FinTech credit platforms in various Chinese cities (RenrenDai). The authors assess the extent to which FinTech credit poses vulnerability to loan-to-value (LTV) based policies and contributes to fuelling household debt creation. Their findings suggest that FinTech credit may pose new risks to the financial system by acting as a conduit to avoid LTV caps imposed on traditional credit providers. Dimova et al. (2016) find that certain macroprudential measures were imposed on Bulgarian and Romanian banks to curb credit growth before the GFC was partially evaded through loan booking with NBFIs.

On a different note, measuring the effects of MaPP on traditional bank credit may be subjected to endogeneity problems, as MaPP decisions are undertaken in response to credit and financial cycles (Cizel et al. 2019). However, concentrating on the MaPP effects on nonbank credit (as in this study) tends to alleviate these concerns, as developments in the non-bank credit market are not likely to have a major influence on prudential policies applicable to traditional banks. Even so, policy intervention may not be completely orthogonal to developments in nonbank credit as both nonbank and bank credit may be correlated and may consequently influence policy decisions due to their effect on total credit (Cizel et al. 2019). This validates the need to incorporate the contribution of the nonbank sector in policy measures, particularly with regard to the increasing nonbank credit.

3.6. Hypothesis development

Since the crisis, there has been an increasing need to raise awareness regarding the potential risks that FinTech credit could pose to financial stability, notwithstanding that FinTech credit activity could benefit financial stability (BIS and FSB 2017). Despite the lack of empirical evidence linking FinTech credit and financial stability, theoretical underpinnings relating to FinTech credit and financial stability remains ambiguous and provide contrasting views regarding potential benefits and threats posed by FinTech credit on the financial system.

The first view broadly draws on the potential benefits of FinTech credit, which may suggest its potential to enhance financial stability (Cornelli et al. 2020; Bertsch and Rosenvinge 2019; Mnohoghitnei et al. 2019; FSB 2017). FinTech credit is largely associated with the concepts of being revolutionary, innovative (Chishti and Barberis 2016), decentralised and disintermediated (Ehrentraud et al. 2020b; Minto et al. 2017). The second view reflects the disruptive capability of FinTech innovation associated with credit disintermediation that poses a greater potential to endanger financial stability (Delabarre 2021; Cornelli et al. 2020; Palmié et al. 2020). The underlying cross-cutting technologies may be subject to policy trade-offs when they enhance speed, efficiency and more accurate assessment but could potentially produce unanticipated outcomes that may cause market instability or discriminatory outcomes (Perkins et al. 2020).

The third view suggests that FinTech credit poses no significant and immediate threat to financial stability, citing a lack of evidence and that the FinTech credit market is still too small to pose significant risks to financial stability ((Bertsch and Rosenvinge 2019; Braggion et al. 2021; Demertzis et al. 2018; FSB 2017). Others hold that it is too early to properly evaluate its impact on financial stability (Bertsch and Rosenvinge 2019; Claessens et al. 2018). Another view holds that FinTech innovation is not likely to threaten UK financial stability in the medium term (Bank of England (BOE) 2018). The absence of an impact may reflect FinTech credit as purely expansionary or a new credit channel, particularly when they attract customers underserved by traditional banks (Cornaggia et al. 2018; Li et al. 2017). The above discussion suggests that the relationship between FinTech credit and overall financial stability may be either positive, negative or non-existent. Therefore, this study hypothesises that FinTech credit impacts financial stability. Thus, this study put forward the following hypothesis:

H_1: FinTech credit has a significant impact on financial stability.

The theoretical foundation of the relationship between FinTech credit and bank risk is still evolving. The banking theory demonstrates this scenario through two contrasting views: the "substitution" and "complementary" effects. The "substitution" theory suggests that a significant growing share of FinTech credit may disrupt traditional banks. This suggests the existence of competition, a factor perceived as a possible source of instability in the banking and financial sector (Vives 2019b; Lai and Van Order 2017). Beck et al. (2012) reveal that higher financial innovations were associated with higher risk-taking and more volatile bank returns resulting in higher bank losses during the crisis. Empirically evidence also shows that FinTech credit may increase bank risk-taking (Liao 2018; Phan et al. 2021).

On the other hand, the "complementary" theory suggests that FinTech credit complements retail banking services (Cornelli et al. 2021; 2020; Tang 2019; Demertzis et al. 2018; Cornaggia et al. 2018). FinTech credit may reduce over-reliance on the banking system through the diversification channel and diversify some of the risks associated with the traditional banking system (Bertsch and Rosenvinge 2019; FSB 2019a; Carney 2017). Also, empirical literature supports this theory, where evidence shows that FinTech credit reduces bank risk-taking and enhances bank profitability (Dong et al. 2020; Fung et al. 2020; Deng et al. 2021; Haddad and Hornuf 2021). The following hypothesis is derived.

H_2: FinTech credit influences bank risk-taking.

Traditional literature documents substantial literature on the effectiveness of MaPP measures in curbing credit growth (e.g., De Schryder and Opitz 2021; Pochea and Niţoi 2021; Akinci and Olmstead-Rumsey 2018). However, another piece of the literature suggests that MaPP may be subjected to "cross-sector substitution" which causes credit activities to shift towards the non-bank sector (Claessens et al. 2021; Irani et al. 2021; Cizel et al. 2019). Modern literature thus links MaPP to the growth of NBFIs (Claessens et al. 2021; Irani et al. 2021; Hodula and Ngo 2021). Cizel et al. (2019), in particular, show evidence that a tightening of MaPP may shift credit activities towards the NBFI. Braggion et al. (2021) suggest that FinTech credit may circumvent credit regulation. Fewer studies attempting to explore the effect of MaPP on FinTech credit conclude that MaPP policies increase NBFIs (Buchak et al. 2018; Braggion et al. 2021; de Roure et al. 2022; Irani et al. 2021). The literature on the effect of MaPP on FinTech credit growth is, therefore, still in its infancy. Based on this limited literature relating to nonbanks, the study develops the following hypothesis:

H_3: MaPP influences FinTech credit growth.

3.7. Summary and conclusions

This chapter provides empirical and theoretical reviews of literature in relation to FinTech credit. There is a growing interest and deliberations on the latest thinking and trending issues surrounding the FinTech revolution. However, emerging empirical literature and knowledge base of FinTech credit is still in the infancy of the established body of research on its impact on financial stability. This may partly be due to the fact that the resilience of FinTech credit processes and entities has not yet been tested over a full economic and credit cycle; hence, it remains unclear how FinTech credit will perform when conditions deteriorate (Claessens et al. 2018). In the absence of current empirical literature linking Fintech credit and financial stability, the study provides a general view of the theological underpinnings and various related theories that explains the potential relationship between Fintech credit – a subset of NBFIs, and its implication on financial stability.

The chapter begins by providing an overall overview of FinTech credit and NBFI. Due to the rise in NBFI (FinTech innovation included) and increasing potential growing impact on financial stability, there is an emerging interest in financial intermediation theory and NBFIs. However, theories on the emergence and interaction of banks and non-banks are still evolving, particularly with regard to the emergence of technological innovation. While existing theories of financial intermediation and the financial system architecture reflect the existing interaction between traditional banks and financial markets, there is still a limited understanding regarding the role played by nonbanks, such as FinTech credit, from a perspective of financial intermediation theory. Thakor (2020) underscores the need for financial intermediation theories to be modified to accommodate traditional banks, shadow banks and NBFIs.

The chapter also attempts to deliberate on the literature regarding the relationship between FinTech credit and overall financial stability. In the absence of specific studies that empirically assess the association between Fintech credit and financial stability, the study draws on various related studies and theories to provide the basis to understand the implication of NBFIs on financial stability. For instance, this includes the links between overall credit growth, financial innovation and financial stability. Overall, the literature has established the potential *two-sided* association between financial innovation and economic growth and fragility, as explained by the "innovation-growth" and "innovation-fragility" views (Beck et al. 2016), which may enhance financial stability through the functions of financial intermediation and risk shifting but may also disrupt such stability (Llewellyn 2009).

The chapter also looks at various direct and indirect channels through which FinTech credit may affect financial stability. Through these transmission channels, the expansion of FinTech activity could be exacerbated and impact financial stability, especially if traditional financial intermediaries have indirect or direct exposures and connections to FinTech entities through their linkages with the wider financial sector (Durdu and Zhong 2022; Marqués et al. 2021; FSB 2020b). Literature thus identifies direct exposures between FinTech credit and traditional banks as the competition and the diversification channels (Bertsch and Rosenvinge 2019; FSB 2019a; Bahri and Hamza 2019) and the regulatory arbitrage channels (Braggion et al. 2021). Moreover, existing financial frictions or emerging new ones may also amplify financial stability risks (FSB 2017; Mnohoghitnei et al. 2019).

The theoretical underpinnings of the association between FinTech credit and bank risk are still evolving. The study first deliberates on the relationship between traditional bank and nonbank credit is often explained by the consumer theory, i.e., substitution (Havrylchyk et al. 2020; de Roure et al. 2022; Ziegler et al. 2021) and complementary theories (Cornelli et al. 2021; 2020; Zhang et al. 2019; Demertzis et al. 2018). This literature provides a basis as to how existing literature has linked FinTech credit to traditional bank credit. For instance, the complementary theory holds that FinTech credit may benefit the banking system by enabling risk-sharing and fostering technological innovation for future economic growth (Beck et al. 2016; Meierrieks 2014). A hoary notion based on the "substitution" theory suggests the existence of competition, which can impact banks' traditional business and operational models (Jakšič and Marinč 2019; Funk 2019), which may inevitably lead to increased risk-taking (OECD 2020a; Vives 2019a; Bertsch and Rosenvinge 2019).

The chapter further looks at different measures of bank risk-taking that demonstrate banks' exposure to the emergence of FinTech credit. This follows an emerging strand of literature that examines the relationship between FinTech developments and bank risk-taking. However, the literature in this area is still evolving. The few existing studies tend to use indicators that do not specifically capture the FinTech credit market. For instance, one common thing about these studies (e.g., Dong et al. 2020) is that their proxy for the development of "internet finance" is constructed as an index based on "text mining" or search engine such as "Baidu's search index". Several of these studies categorise major models of internet finance under an umbrella term, which includes various FinTech models such as third-party payments and mobile payments, internet banking, digital currency, P2P lending, crowdfunding, and the use of technological innovations such as big data in financial activities (e.g., Li et al. 2020b; Deng 2015).

The existing literature between FinTech credit and bank risk-taking is ambiguous. For instance, Fung et al. (2020) conclude that FinTech enhances bank stability in emerging markets but undermines it in developed markets. Phan et al. (2021) suggest that FinTech entities may negatively influence bank performance, while Haddad and Hornuf (2021) find a positive relationship between FinTech start-up formations and banks' performance. Deng et al. (2021) found that the development of FinTech significantly decreases the bank risk-taking level of small and medium-sized banks, while Guo and Shen (2019) show that the development of internet finance significantly increases the risk-taking level of traditional banks. Similarly, Dong et al. (2020) find that developments in internet finance positively impact bank profitability, security and growth but have a negative impact on bank liquidity. Liao (2018), on the other hand, concludes that internet finance stabilises the banking industry and the overall stability of the financial system. Several scholars hold a compromise point of view that internet finance would increase bank risks in the short term but, in the long term, assume more of the role of cooperation (e.g., OECD 2020a). However, others specifically suggest a non-linear (U-shaped) relationship between FinTech development and bank risk-taking (Wang et al. 2021).

The chapter also deliberates on the association between MaPP and FinTech credit. This is also an emerging area of interest which has recently been explored, particularly in relation to the link between MaPP and NBFIs (e. g., Claessens et al. 2021; FSB 2020b; Cizel et al. 2019). These studies particularly focus on the potential leakages of MaPP that result in substitution flow to less regulated segments of the financial sector (Claessens et al. 2021; FSB 2020b; Cizel et al. 2019; Kim et al. 2018). Vast knowledge of literature has previously concentrated on the effect of MaPP on bank or total credit growth and established that MaPP instruments have the intended effect of reducing bank credit (Akinci and Olmstead-Rumsey 2018; Altunbas et al. 2018; Cerutti et al. 2017a).

While the predominant implementation of macroprudential measures on the banking system may have been effective, an emerging new strand of the activating MaPP may result in the "waterbed or substitution effects" and weakens the effectiveness of MaPP. This has been confirmed by several empirical works of the literature, suggesting the existence of a robust empirical link between macroprudential framework capacity and nonbank credit growth. An even closer study by Braggion et al. (2021) provide a basis for this study and conclude that FinTech credit may pose new risks to the financial system by acting as a conduit to avoid LTV caps imposed on traditional credit providers. Relatedly, Buchak et al. (2018) attribute the significant increase in the FinTech credit market share to regulatory constraints among traditional banks after the crisis. In more recent close studies, Claessens et al. (2021) and Hodula and Ngo (2021) reveal that MaPP has a positive impact on NBFI activities and shadow banking, respectively.

CHAPTER 4: RESEARCH METHODOLOGY

4.1. Introduction

The study adopts a macro approach due to its interest in examining the overall implication of FinTech credit to financial stability. This standpoint has been motivated by increasing attention to the growing role of NBFIs (e.g., FSB 2020; 2019c), particularly emerging FinTech innovation. The study thus explores different measures of FinTech credit proxied by a share of FinTech credit to total domestic credit (Frost et al. (2019), a percentage of GDP (Bazarbash et al. 2020) and FinTech credit per capita (Cornelli et al. 2021; 2020; Rau 2020; Frost et al. 2019). FinTech credit data was initially sourced as volumes of new loans originated by domestic online or digital FinTech credit platforms.

This chapter presents the framework of the relevant research design and methodology employed to achieve the research objectives of this study. Specifically, this chapter focuses on sample construction and data sources for variables used in econometric estimations. A detailed empirical strategy is presented under each respective empirical chapter. The chapter is organised as follows. Section 4.2 provides details on the selection of the sample, and Section 4.3 presents data collection methods. Section 4.4 presents a summary and conclusion.

4.2. Data sample selection

The target sample of this study was based on FinTech credit activities offered by online lending platforms without a traditional intermediary (Bertsch and Rosenvinge 2019). The selection criteria for FinTech credit data were based on economies with active and or significant FinTech credit activities. The data was therefore extracted from an initial list of the top 40 countries leading in alternative finance by volume per capita. To avoid data bias, the list of countries included mainly depended on the availability of FinTech credit data. Depending on data availability, this study constructs a new dataset from twenty-five (25) advanced and emerging economies with different timelines of FinTech credit adoption. However, limited data availability was a key constraint.

This is partly due to the fact that FinTech credit platforms are still not subjected to regulatory data reporting in most jurisdictions, leading to limitations in the availability of official data (Claessens 2018). Moreover, it is generally difficult to obtain and aggregate

FinTech credit in a way that is consistent and comparable across countries. In order to avoid discrepancies between different countries, the study standardised the data collection methodology by focusing on the FinTech lending sector, in essence excluding other sub-segments of the FinTech innovation such as payments, and money transfer (remittances), investments, insurance, crypto trading, and lending. The study also excluded BigTech credit data due to limitations in data availability.

The CCAF is currently one of the leading pioneers in global alternative finance market data or volume as represented by finance raised via an online alternative finance platform for consumers, businesses and other fundraisers (Ziegler et al. 2021). The study extracted an initial list of the top 40 countries leading in alternative finance by volume per capita. It then generated a total aggregated unbalanced panel dataset comprising a sample of 1500 observations in 25 countries (20 advanced economies and 5 EMDEs) for the period 2005Q1 to 2019Q4. The list of selected countries was extracted from the 2017 global benchmarking report developed by the CCAF based on annual transaction volume. However, due to the limited availability of a key independent variable (MaPP), used in the third empirical chapter only covers the period 2005Q1 to 2018Q4. Moreover, due to limitations on the FinTech data and varying times of FinTech credit adoption, the available FinTech credit variable yielded 673 observations. The list of countries used is presented in *Table 4.1*.

Table 4.1:Countries used for the construction of the sample list

Advanced Economies (AEs)	Emerging Market and Developing Economies (EMDEs)
1) Australia	1) Bulgaria
2) Belgium	2) China
3) Canada	3) Indonesia
4) Estonia	4) Mexico
5) Finland	5) Poland
6) France	
7) Germany	
8) Ireland	
9) Italy	
10) Korea	
11) Latvia	
12) Lithuania	
13) Netherlands	
14) New Zealand	
15) Slovak Republic	
16) Spain	
17) Sweden	
18) Switzerland	
19) United Kingdom	
20) United States	

Source: Author’s illustration

4.3. Data collection methods

4.3.1. Data Sources for FinTech credit variable

To address the objectives of this study, a quantitative approach was adopted. This process includes gathering and tabulating raw data from different sources, which in this study are all secondary. FinTech credit data were collected via web-scraping from respective FinTech credit platform (websites) databases such as publicly availed platform loan books (loan-level data).[21] Additional data were obtained from various sources, such as the countries' P2P associations, private company reports, FinTech reports and platform annual reports. Other data sources include private databases and websites such as the US Standard & Poor's (S&P) Global Market Intelligence and Brismo (formerly known as AltFi data).

The P2P associations include the Alternative Financial Services Association of Latvia (AFSAL), the Korea P2P Finance Association, the Swiss Marketplace Lending Association (SMLA) and the UK P2P Finance Association (P2PFA). The P2P associations are owned mainly by respective members and mainly collate and present statistics on domestic FinTech credit platforms. For instance, the UK P2PFA represents over 80% of the P2P lending market in the UK, including consumer lending, business lending and invoice financing. Data from China was mainly sourced from Chinese Wang Dai Zhi Jia (www.wdzj.com) through the CEIC website, one of China's economic databases on economic and financial indicators. The WDZJ is currently China's largest portal website for the P2P lending industry in China, used by various studies (e.g., Cornelli et al. 2021; 2020; Claessens et al. 2018; Yu and Shen 2019; Huang, R.H., 2018). The data were augmented with data from China Banking and Insurance Regulatory Commission (CBIRC). FinTech data for Sweden was sourced from the Sweden RiksBank survey (Bertsch and Rosenvinge 2019).

Once the FinTech data had been collected, this followed a multi-stage verification process which included cross-checking the data fields for anomalies and inconsistencies. For instance, the raw data was then cleaned and processed into meaningful information with the use of the appropriate analytical tools and methods. In the event of a discrepancy, the study compared the FinTech lending volumes with other publicly available information

[21] The web-scraping technique has been widely used in the CCAF studies to obtain FinTech credit data (see. Frost et al. 2019; Cornelli et al. 2020).

through platform websites, published statistics, press releases and annual reports. The study did not disclose individual platform data but analysed and presented the data in aggregate form. Pure or absolute numbers in the form of new loans or loan origination amounts were simply aggregated together by country to give a total for each quarter where data was available.

The study further addressed the mixed frequencies (daily, monthly and quarterly) of the data collected. FinTech credit values were standardised, aggregated into quarterly frequencies and converted into the US dollar currency. In dealing with a mixed-frequency dataset, in which the vector of endogenous variables comprises both high and low-frequency variables, all data are expressed in the same frequency by aggregating data into quarterly data. In some cases, FinTech credit data was reported in cumulative lending flow over a calendar year or since the inception of their business. Generally, a higher frequency of data allows for an increased number of observations which helps to reduce data "aggregation bias" and also increases the accuracy and precision of the estimate. Following Cornelli et al. (2020), the study obtained total volumes of new loans originated by converting cumulative credit stock to a lending flow. To undertake this, lending figures were converted by taking the differences between the stock of loans reported at the start and end of the period.

4.3.2. Data sources for financial and macroeconomic variables

Data on other financial and macroeconomic variables, such as financial stability variables, bank risk-taking, bank-level and country-level control variables, were obtained from various sources. Data were gathered from the IMF Financial Soundness Indicators (FSI), BIS, Global Financial Development Database (GFDD), OECD, World Bank Institute (WBI) and BankScope. Additional data was obtained from Laeven and Valencia (2020), CEIC; KAOPEN index developed by Chinn and Ito (2006; 2008) and WGI produced by Kaufmann et al. (2011). In the case of missing data, this was augmented with individual Central Bank statistics. More details regarding the financial and macroeconomic variable data sources are discussed further in Section 4.4.

4.3.3. Macroprudential policy data source

MaPP data were sourced from the 2019 integrated Macroprudential Policy (iMaPP) database developed by Alam et al. (2019). The iMaPP dataset encapsulates information from five existing databases drawn from Lim et al. (2011; 2013), Shim et al. (2013), and the Global Macroprudential Policy Instrument (GMPI) survey conducted by the IMF in 2013, the database by ESRB, and the new IMF survey. These were further extended by other databases (e.g., Araujo et al. 2020; Richter et al. 2019; Akinci and Olmstead-Rumsey 2018; Cerutti et al. 2017b; Bruno et al. 2017; Dimova et al. 2016; Kuttner and Shim 2016; Zhang and Zoli 2016).

4.4. Summary and conclusions

This chapter presented sample construction and data sources for key macroeconomic variables. Specifically, this chapter focuses on sample construction and data sources for variables used in econometric estimations. The descriptions of the variables are presented and discussed under each empirical chapter (*Chapters 5 to 7*). This chapter focuses on data collection and sample construction. FinTech data were sourced in the form of loan-level origination volumes by domestic FinTech online platforms via web-scraping from respective FinTech credit platform (websites) databases such as publicly availed platform loan books (loan-level data). The web-scraping technique has been widely used in CCAF studies to obtain FinTech credit data. Additional data were obtained from various sources, such as the countries' P2P associations, private company reports, FinTech reports and platform annual reports. Other data sources include private databases and websites such as the US Standard & Poor's (S&P) Global Market Intelligence and Brismo (formerly known as AltFi data). The study employs three measures of FinTech credit for econometric estimations and robustness checks. The three measures are the share of FinTech credit to total domestic credit (Frost et al. (2019), FinTech credit as a percentage of GDP (Bazarbash et al. 2020) and FinTech credit per capita (Cornelli et al. 2021; 2020; Rau 2020; Frost et al. 2019).

Data on other financial and macroeconomic variables such as financial stability variables, bank risk-taking, bank-level and country-level control variables were obtained from various sources such as the IMF Financial Soundness Indicators (FSI), BIS, Global Financial Development Database (GFDD), OECD, World Bank Institute (WBI) and BankScope. MaPP data were sourced from the 2019 integrated Macroprudential Policy (iMaPP) database developed by Alam et al. (2019). Additional data was obtained from Laeven and Valencia (2020), CEIC; KAOPEN index developed by Chinn and Ito (2006; 2008) and WGI produced by Kaufmann et al. (2011).

The study used FinTech credit activities offered by online lending platforms without a traditional intermediary (Bertsch and Rosenvinge 2019) to construct the sample. The selection criteria for FinTech credit data were based on economies with active and or significant FinTech credit activities. The final sample comprised twenty-five (25) advanced and emerging economies, with different durations or times of FinTech credit adoption, totalling 673 observations. The low sample is partly due to the fact that FinTech credit platforms are still not subjected to regulatory data reporting in most jurisdictions, leading to limitations in the availability of official data (Claessens 2018). Moreover, it is generally difficult to obtain and aggregate FinTech credit in a consistent and comparable way across countries. The study standardised the data collection methodology by focusing on the FinTech lending sector, excluding other sub-segments of the FinTech innovation such as payments, money transfer (remittances), investments, insurance, crypto trading, and lending, to avoid discrepancies between different countries. The study also excluded BigTech credit data due to limitations in data availability.

CHAPTER 5: DOES FINTECH CREDIT ENHANCE OR DISRUPT FINANCIAL STABILITY?

5.1. Introduction

The emergence and the increasing footprint of FinTech credit have attracted the attention of policymakers and academia regarding its implication for overall financial stability (Braggion et al. 2021; Fung et al. 2020; Li et al. 2020a). The pending debate is whether FinTech credit can potentially enhance or disrupt financial stability. A quick peek into existing literature and policy debates regarding the implication of FinTech credit to financial stability is presented with mixed views. FinTech credit appears as a tale of two extremes, offering a vast range of potential opportunities to the financial system while also posing potential stability threats to the banking and overall financial system (International Monetary Policy (IMF) 2019; IOSCO 2017). Indeed, credit expansion tends to stimulate economic growth but may also expose the financial system to shocks and increase the likelihood of a financial and banking crisis (Mian et al. 2017; Freixas et al. 2015). Similarly, FinTech credit has become a subset of an evolving financial innovation and is theoretically shown to be potentially disruptive but valuable (Delabarre 2021; Palmié et al. 2020; Zalan and Toufaily 2017).

An optimistic view is that FinTech innovations that provide some core bank-like functions, such as credit, liquidity and maturity transformation, could enhance banking and financial stability, to the extent that these activities may even diversify some of the risks inherent to the traditional banking system (i.e., credit, liquidity, systemic and operational risks) (Bertsch and Rosenvinge 2019; FSB 2017, 2019a; Carney 2017). The FinTech credit model may also enhance efficiency and foster healthy competition in the banking sector (Fuster et al. 2019; Bertsch and Rosenvinge 2019; Mnohoghitnei et al. 2019). FinTech credit offers an unconventional lending mechanism that eases and simplifies the way capital is raised and extends credit to individual consumers, households, and businesses at a time when traditional bank credit is constrained (Braggion et al. 2021; Buchak et al. 2018). It may, therefore, serve as a “spare tire” in the supply of credit in times of systemic banking crises (IMF 2015) and may reduce financial frictions and foster changes in market structure (FSB 2017).

An even lesser optimistic view is that FinTech credit may potentially become disruptive to the banking sector and the overall financial system (Delabarre 2021; Cornelli et al. 2020; Palmié et al. 2020). The increasing share of FinTech credit to total domestic credit could undermine financial stability and increase the likelihood of banking and financial crises (Frost et al. 2019; Claessens et al. 2018; FSB 2017). Given FinTech credit's economic function of credit intermediation, policymakers are becoming increasingly concerned about the potential bank-like financial stability risks that FinTech activities may pose to the financial market infrastructure, regulatory and supervisory frameworks, and, more critically during stressed events (FSB 2019a, 2019b, 2020a). The regulatory burden placed on banks, coupled with the emergence of unconventional rivals such as FinTech credit, may affect banks' risk-taking and impair their stability (Vives 2019a; Bertsch and Rosenvinge 2019).

This study seeks to synthesise the two sides of the same coin that depicts FinTech credit as a potential driver and disruptor of financial stability (Delabarre 2021). This follows several viewpoints that suggest that FinTech credit may endanger financial stability (Cornelli et al. 2020; Tarullo 2019; Vives 2019b). Other views hold that FinTech credit may be beneficial to the financial system, which may enhance financial stability or reduce risks to financial stability (Cornelli et al. 2020; Bertsch and Rosenvinge 2019). Furthermore, the lack of consensus on the varying viewpoints may, to some extent, suggest a possible existence of a non-linear relationship between FinTech credit and overall financial stability. However, whether FinTech credit can enhance or disrupt the overall stability of the financial system, in reality, remains an empirical subject matter. In this regard, the study seeks to investigate whether FinTech credit enhances or disrupts the overall financial stability. The remainder of the chapter is structured as follows. *Section 5.2* presents variable definitions and descriptions, followed by *Section 5.3*, presenting descriptive statistics. *Section 5.4* presents an empirical approach, while *Section 5.5* presents results and discussions. Last, *Section 5.6* provides conclusions.

5.2. Variable definitions and description

5.2.1. Financial stability index

The dependent variable is the financial stability index (*FSI*). In the realisation that the financial system and the overall economy are intertwined, monitoring and measuring financial stability requires a deep understanding of the relationship between traditional and evolving financial markets and the broader impact of this interaction in the real economy (Brave and Butters 2011). One way to quantify this interaction has been to develop measures such as financial stability indexes. This has resulted in new methodologies being employed by researchers to construct *FSI*, especially in advanced economies (Brave and Butters 2011) and developing economies (Karanovic and Karanovic 2015; Petrovska and Mihajlovska 2013).

This study constructs a composite *FSI* to measure financial stability, a common approach used in literature. The aggregate *FSI* provides several advantages over past measures by exploring an in-depth and broader measure of financial stability. The aggregate views help assess the overall financial stability, while the granular view may help explain the drivers of macroeconomic changes that are helpful to inform policymakers in developing relevant and appropriate measures. The combination of data from various aspects of the financial system also enables the demonstration of the level of financial stability from a multidimensional perspective.

Financial stability is a multidimensional process; hence, excluding other segments of the financial system does not fully capture the complexity of the overall financial stability. In this study, the weighted-sum approach and a broad range of indicators are adopted to construct a financial stability index using quarterly data for the period 2005Q1–2019Q4. The constructed index summarises the information from a set of sub-indexed indicators into a single quantitative aggregate indicator. The index allows for comparisons across different countries, periods, and financial systems and enables the observation of the financial stability level dynamics.

Constructing *FSI* is concerned with the theoretical framework for the selection, definition, and contribution of variables to be included in the index (Karanovic and Karanovic 2015). The key variables capture the macroeconomic, financial, and market-based indicators commonly used in the empirical literature and are suitable for most countries to allow for international comparison (Matkovskyy et al. 2016). The suggested indicators can be used to identify and examine risks in the financial sector. Moreover, the interaction between shocks, financial vulnerabilities, and growth suggests that financial indicators can provide vital information regarding risks to financial and economic stability (IMF 2017). The composition of an aggregated FSI measure includes three dimensions, namely: the banking-system stability index (*BSI*), financial development index (*FDI*) and financial conditions index (*FCI*).

The selection of variables and development of sub-indexes included in the *FSI* is based on the theory that their developments have potential implications for financial stability (Matkovskyy et al. 2016) and economic similarity (IMF 2017). Separating indicators into separate sub-indices allows various groups of indicators to provide separate signals about risks at different horizons. In addition, separating indicators allows for a more direct and specific economic interpretation of the various sub-indices, thus avoiding suppressing some of the information provided by certain variables when commingled with others (IMF 2017)[22]. A total of nineteen (19) indicators from three (3) sub-indices are included in the aggregate *FSI*. *Table 4.3* describes the indicators according to their respective sub-indices.

5.2.1.1. Banking stability index (BSI)

An efficient and effective financial system strives for the efficient and stable performance of its banks (Gavurova et al. 2017), necessitating the need for sound risk indicators for banks (Powell and Vo 2020). Such indicators highlight vulnerabilities in the financial system caused by emerging and increasing banking system risks and other adverse financial and macroeconomic conditions. Stability indicators, also referred to as "financial soundness indicators", provide insight into the healthiness and soundness of a country's financial institutions and support financial and economic stability analysis (IMF 2018). They may also depict information on the general financial health and various financial risks in the banking system (Keffala 2020).

Therefore, an aggregate BSI is constructed using accounting-based bank risk variables contained in the bank's balance sheet. The *BSI* is widely used to construct a financial stability index and is sometimes used solely as a proxy for the bank or financial stability. The inclusion of the *BSI* is because the banking system significantly accounts for the stability of the financial system. The *BSI,* therefore, captures the soundness and healthiness of a country's banking sector in terms of the strength of the banking system

[22] High volatile indicators and higher variable such as asset prices and risk spreads may dominate an index and suppressing some variables such as credit aggregates which may carry significant information about risks to growth at longer horizons (IMF 2017).

(performance and capital adequacy) and the main bank risks (credit and liquidity) (Kočišová and Stavárek 2018).

Various indicators for 'risk exposure' or bank risk-taking and financial stability are considered in determining the bank risk measures. Numerous studies provide insight into the sources of bank fragility or instability. The literature identifies several risk indicators for banks that are believed to influence banks' risk-taking (Ashraf et al. 2016). Swamy (2014) examines banking stability using a restructured vector autoregressive (VAR) model and validates the significant interrelationship between and within bank-specific variables, such as capital adequacy, asset quality, liquidity and profitability, from which bank risk variables can be derived. These variables have been extensively used in banking risk literature (e.g., Saif-Alyousfi et al. 2020; Ashraf et al. 2016).

Bank risk variables are aggregated to the banking sector level and represent various aspects of bank risk. While most bank risk and stability literature usually employ a one-dimensional risk indicator, such as the Z-score, capital ratios, and the share of non-performing loans (*NPL*), there are some uncertainties about whether these indicators fully capture bank risk; suggesting that bank risk is multidimensional in nature (Klomp and de Haan 2014). Therefore, five (5) variables of macroprudential relevance are incorporated (Davis et al. 2020) to capture significant bank risk factors: insolvency, credit, liquidity, portfolio and leverage risk (Al-Shboul et al. 2020).

Following extensive literature, the insolvency risk is measured using the natural logarithm of the Z-score computed using the sum of a bank's return on assets (*ROA*) and equity to total assets ratio over the standard deviation of the bank's *ROA.* Several empirical studies used the Z-score as a bank risk or stability indicator to assess the determinants of bank risk-taking pre and post-crisis period (e.g., Davis et al. 2020; Davis and Karim 2019; de-Ramon et al. 2018; Degl'Innocenti et al. 2018; Noman et al. 2018). The time-varying *Z*-score measures a bank's distance from insolvency (Noman et al. 2018) and captures the probability of default of a country's domestic banking system (Davis et al. 2020; Siddik and Kabiraj 2018).

The *Z*-score is also used to compare capital buffers and returns with the potential for risk (volatility of returns) (e.g., Noman et al. 2018; Morgan and Pontines 2014). This accounting-based stability measure has been widely and frequently applied in empirical research but less so in macroprudential policy circles (Davis et al. 2020). However, the inverse Z-score can be used to approximate the bank's probability of default (Ahamed and Mallick 2019; Fang et al. 2014), assuming bank profits are normally distributed (Roy 1952). A higher Z-score suggests a lower probability of a country's banking system becoming financially distressed or insolvent, implying greater financial stability and lower risk (Degl'Innocenti et al. 2018; Li et al. 2017; Fang et al. 2014). Therefore, *Z-score* is expected to have a positive relationship with financial stability.

Credit risk is measured by the ratio of *NPL* (computed as *NPL* to total gross loans (Davis et al. 2020; Tan and Anchor 2017). It serves as an indicator of asset quality. *NPL* suffocates new lending, reduces banks' income, and constraints banks from further extending credit to the economy, consequently eroding banks' capital, profitability, and solvency (Grasmann et al. 2019; Baudino and Yun 2017). In the worst-case scenario, these effects can question a bank's viability, with potential implications for financial stability (Grasmann et al. 2019). A low diversified loan portfolio and loan concentration in a specific economic sector may signal some level of vulnerability of the financial system. A higher level of *NPL* indicates bank credit risk (Al-Shboul et al. 2020). Therefore, the credit risk indicator is expected to have a negative impact on financial stability.

Liquidity levels influence impacts the banking system's ability to withstand shocks. A conventional liquidity risk measure proxied by the ratio of liquid assets to total assets (*LQ*) is used (Al-Shboul et al. 2020; Tan and Anchor 2017; Singh and Sharma 2016). A higher *LQ* value indicates higher bank liquidity risk and vice versa (Bourgain et al. 2012; Danisman and Demirel 2019). Conversely, a higher value indicates lower bank risk. Thus, liquidity is expected to have a positive influence on financial stability.

The first additive component of *Z-Score*, measured by the ratio of the return on assets (*ROA*) and standard deviation of *ROA* as in Barry et al. (2011), is used to measure portfolio risk (Al-Shboul et al. 2020; Lepetit et al. 2008). This follows a decomposition process used in a series of studies by Lepetit and Tarazi (in Lepetit et al. 2008; Barry et al. 2011). This part considers both the level of returns and the volatility of returns, providing a measure of banks' portfolio risk (Li et al. 2017). A strand of the Z-score-related studies has used Z-score components as alternative stability proxies for banks (e.g., Fung et al. 2020; Beck et al. 2013; Schaeck and Čihák 2014). A higher value indicates lower bank portfolio risk and vice versa. Therefore, the portfolio variable is expected to relate to financial stability positively.

The second additive component of Z-Score represents the leverage part that measures the bank's leverage risk or capital risk (Li et al. 2017), proxied by the ratio of the bank's equity to total assets and standard deviation of *ROA* (Tan and Anchor 2017). The simple leverage ratio is perhaps the most widely used bank risk measure and is a good indication of how robust and resilient the banks are to withstand shocks to their balance sheet. It also reflects the coverage capacity of bank capital for a given level of risk. Studies demonstrate that simple leverage ratios often outperform complex risk-weighted or adjusted capital ratios as a predictor of risk during the crisis period (Davis et al. 2020; Aikman et al. 2019). A higher value indicates lower bank risk. Therefore, leverage is expected to relate to financial stability positively.

5.2.1.2. Financial development index (FDI)

Empirical literature since the 1970s has assessed financial development using the ratio of private credit to GDP and stock market capitalisation as a ratio to GDP. Various researchers have employed variations of these two measures to capture the deepening level of the financial system and development. However, the nature and process of financial development are multidimensional (Oh and Rosenkranz 2020; Svirydzenka 2016). Moreover, in the past decade, the role of financial development in promoting financial innovation has been widely explored (Oh and Rosenkranz 2020). Literature has revealed that the quality of the financial sector and better financing conditions matter for the expansion of FinTech (Oh and Rosenkranz 2020; Navaretti et al. 2018). Rau (2021) underscores the impact of bank profitability on the expansion of crowdfunding, thus suggesting that financial system rents are important for the expansion of FinTech credit. Moreover, alternative credit markets such as FinTech credit tends to flourish more where banks are better capitalised and more developed capital markets and advanced legal system are well developed (Cornelli et al. 2020; 2021).

The *FDI* consists of variables that capture the country's level of financial system development (Karanovic and Karanovic 2015). Seven (7) indicators are included in the construction of this sub-index. They provide financial market information and are considered to have a higher power in predicting future outcomes than the financial indicators (Koong et al. 2017). These market-based indicators are perceived to be more forward-looking compared to the financial indicators because, to some degree, they reflect the views of many highly proactive market participants - for instance, household and business sectors. For instance, credit aggregates (leverage and credit growth) such as the BIS statistics' core debt indicators include credit extended to households, corporations and governments by both banks and nonbanks.

First, market capitalisation (*MC*), measured as a percentage of GDP, is included to capture the development of capital markets (Svirydzenka 2016; Tan and Anchor 2017; Karanovic and Karanovic 2015). *MC* is viewed through the value of listed shares relative to total output; hence it is expected to positively influence the stock market development leading to improved overall economic growth (Karanovic and Karanovic 2015). Second, market-share concentration is included to measure the degree of bank competition using the Herfindal-Hirschmann index (*HHI*) (Karadima and Louri 2020; Karanovic and Karanovic 2015). Theoretically, competition pressures lead to competitive pricing, leading to the higher efficiency of intermediation spread (Were and Wambua 2014). The higher values of HHI reflect more concentrated, less-competitive market conditions. However, such concentration measures can provide poor measures of competition (Bikker et al. 2012), especially since it excludes non-bank market shares, which may represent an important part of some banking markets (de-Ramon et al. 2018).

Concentration implies banking system stability, and thus, a positive relationship with stability is expected (Beck et al. 2006). de-Ramon et al. (2018) reveal that higher market competition promotes better efficiency in the banking market. However, high market competition can also lower barriers to entry for new players, thus positively impacting the adoption of FinTech credit (Oh and Rosenkranz 2020). This may cause FinTech credit to flourish, where there are fewer bank branches per capita and a lower bank credit-to-deposit ratio (Cornelli et al. 2021; 2020). Moreover, lower competition due to expensive banking services or higher banking sector mark-ups may suggest more demand for cheaper credit from FinTech lenders (Cornelli et al. 2021; 2020). However, Havrylchyk et al. (2020) argue that the growth of FinTech credit is slower in economies with high bank concentration.

Third, household debt proxied by total credit to households as a percentage of GDP is included (Kakes and Nijskens 2018). Leverage booms and excessive indebtedness of households during the financial crisis link increasing household debt to financial instability; hence household debt serves as a potential indicator of boom-bust dynamics (Filardo 2009). The IMF (2017) also assert that an increase in household debt serves as a good early warning indicator for banking crises. Several studies in the empirical literature also document evidence suggesting an increase in household debt prior to a banking crisis (see Drehmann and Tsatsaronis 2014; Jordà et al. 2016; IMF 2017). Household debt also plays a critical role in the proliferation of macroeconomic shocks via borrowing constraints in the lending channel (Filardo 2009). Rising household debt levels can negatively impact the broader economy through financial sector mechanisms (Punzi 2018; Zabai 2017), leading to weaker lending standards, riskier lending and banking crises and ultimately causing financial instability (Röhn et al. 2015; André 2016). Literature also supports that household debt may lead to economic vulnerability, financial instability and crisis (Drehmann and Tsatsaronis 2014; Jordà et al. 2016; IMF 2017). Therefore, household debt is expected to relate to financial stability negatively or positively.

Fourth, private debt proxied by a ratio of total credit to the private non-financial sector to GDP is included to provide information on lending financial institutions' ability to provide financial intermediation (Karanovic and Karanovic 2015). Private debt contributes to macroeconomic and financial stability by allowing households and corporates to smooth consumption and investment in the face of temporary income and revenue shocks. However, the destabilising effects of excessive private sector debt build-up can hamper this ability and weaken economic and financial stability (Röhn et al. 2015; Drehmann and Juselius 2014).

Furthermore, when a more significant part of the private sector is overindebted and overextended, this might trigger a rise in defaults and bankruptcies, which may, in turn, consequently and potentially result in a full-scale banking crisis (Drehmann and Juselius 2014). This is further affirmed by Arcand et al. (2015) and Sahay et al. (2015b) that the private sector debt, upon reaching a certain threshold, its benefits begin to decline per capita growth, which is partly due to rising financial stability risks when the economy becomes highly leveraged. Therefore, private credit to GDP serves as a good indicator for the build-up of vulnerabilities caused by private sector indebtedness, and private credit growth is also a robust predictor of banking and financial crisis (Röhn et al. 2015). Thus, private debt is expected to relate to financial stability negatively or positively.

Fifth, the flow of loans or credit to domestic bank credit to the private sector (*DBCPS*) expressed as a share of GDP is included as an alternative measure of interconnectedness[23] to capture any direct effect that credit availability might have on economic growth and development (Röhn et al. 2015). Higher growth rates of credit provision or securities issues are assumed to signal looser financial conditions (Angelopoulou et al. 2014). As the name suggests, this reflects the supply of funds channelled to the private sector by domestic banks. Also, it provides information related to the level of financial intermediation, thus capturing the level of interconnectedness of the financial system. The higher proportions of domestic credit supplied to the private sector, the more financial resources are given to the private sector or more resources are concentrated on a particular sector (Diallo and Al-Mansour 2017). This, in turn, leads to an increased probability of financial instability (Siddik and Kabiraj 2018*;* Morgan & Pontines 2014; Tan and Anchor 2017). Therefore, *DBCPS* is expected to relate to financial stability negatively or positively.

Sixth, total credit to the government sector as a percentage of GDP is used as a proxy for government debt (Kakes and Nijskens 2018). The relationship between government debt and economic growth is mixed. Most studies follow a conventional view of debt that suggest a "crowding-out effect" on private investment when the economy is facing a high debt problem (Chudik et al. 2017; De Vita et al. 2018). Others hold that government debt can also contribute to higher economic growth, for instance, in European countries (Gómez-Puig and Sosvilla-Rivero 2018). However, others document a non-linear relationship between EU countries (Gómez-Puig and Sosvilla-Rivero 2017) and emerging economies (Shkolnyk and Koilo 2018). Last, total credit to the government sector as a percentage of GDP is used as a proxy for government debt. Again, the outcome is expected to be mixed

[23] Other commonly used variables to measure of interconnectedness are intra-financial sector assets and liabilities and securities outstanding (Basel Committee 2011; 2014; 2018; Berry et al. 2015; Office of Financial Research 2020).

5.2.1.3. Financial conditions index (FCI)

The term "financial conditions", according to Hatzius et al. (2010), refers to a mix of a broad set of financial variables that influence economic behaviour and, thereby, the future of the economy. *FCIs* have long been used to assess the state of financial conditions and the evolution of economic activity. They guide monetary policy formulation and are an effective tool for macro-prudential regulation and financial stability (Zheng and Yu 2014). Traditionally, macro-econometric models have depicted financial conditions only through the interest rate. However, since the crisis, interest rates alone may not sufficiently capture all the interactions between the financial system and the real economy. An increase in the aggregate *FCI* would therefore signal higher risk (IMF 2017).

Relevant volatility measures are incorporated. Market volatility in financial markets and spreads between various asset classes convey further information on financial conditions, consequently influencing the economy (Angelopoulou et al. 2014). The IMF (2017) subdivides the index into three subindices which include the domestic price of risk (risk spreads, asset returns, and price volatility), credit aggregates (presented under the FDI in this study), and external conditions (global risk sentiment, commodity prices, and exchange rates). Angelopoulou et al. (2014) constructed *FCI* using a wide variety of indicators, including monetary policy variables (interest rates and quantities), market volatility, interest rate spreads, credit quantities and the volume of activity in debt securities markets. Zheng and Yu (2014) follow a similar trend and include five variables, money supply (*M2*), asset prices (stock price index (*SPI*) and house price index (*HPI*)), interest rates and exchange rates.

The selection of *FCI* broad range of indicators is based on the theoretical literature and the theory that market imperfections go beyond simple prices (interest rates) as measures of financial market conditions (Angelopoulou et al. 2014). Zabai (2018) argues that *FCIs* are sensitive to volatile variables and include short- and long-term interest rates, exchange rates, corporate credit spreads and stock market valuations. The IMF (2017) asserts that a period of tightening financial conditions is also reflected in increasing asset price volatility, prolonged low volatility and decompression in spreads, enabling additional risk-taking and further raising financial vulnerabilities.

Various studies have investigated the financial conditions index (Angelopoulou et al. 2014; Zheng and Yu 2014; Zabai 2018). Following empirical literature to capture macroeconomic and financial conditions, *FCI* is constructed using five indicators: money supply (*M2*), stock price index (*SPI*), house price index (*HPI*), interest rate spread (*IS*), real effective exchange rate (*REER*), short and long-term interest rates (Zheng and Yu 2014). The *FCI* indicators are divided by their standard deviation for the sample period to capture volatility.

Market volatility is commonly used as a proxy variable for stability in financial markets (World Bank 2016a). The literature associate higher volatility with tighter financial conditions; hence, measures of price volatility reflect heightened tension in financial markets (Angelopoulou et al. 2014). Similarly, the skewness of stock returns is a good indicator of financial markets with a more negative skewed distribution of stock returns that are likely to deliver significant negative returns and become prone to instability (World Bank 2016a). According to IMF (2017), domestic asset prices are valuable indicators of recessions or financial crises. They are the leading drivers of growth risks in the short term, and hence asset price shocks tend to be more important in driving changes in *FCI*s (than credit aggregates). Asset price volatility reflects the impact of movements in asset prices. The stock price volatility and housing price indices are used to capture the volatility of assets and housing prices, respectively. The volatility of the stock price index (*SPI*) captures facets of stress related to the stock market (Holopainen and Sarlin 2017; Koong et al. 2017). Borio and Lowe (2002) also suggest that the combination of sharp increases in asset prices and excessive credit growth is a good indicator of ensuing episodes of financial instability. Therefore, *SPI* is expected to relate to financial stability positively.

Another *FCI* indicator is the ratio of broad money to GDP (*M2*). This indicator is widely used in the empirical literature (see. Koong et al. 2017; Zheng and Yu 2014) to show the actual size of the country's financial sector (Koong et al. 2017). A higher value of *M2* signifies growth in the economy; hence, it is expected to influence financial stability positively. Furthermore, the core area of interest in financial stability is identifying potential vulnerabilities arising from overvaluations of real estate. Therefore, the housing price index (*HPI*) identifies valuation pressures in the real estate sector (Lepers and Serrano 2020). An increase in *HPI* often leads to an expansion in bank credit, which may enhance financial stability (Davis and Zhu 2011). Therefore, *HPI* is expected to correlate positively with financial stability (Holopainen and Sarlin 2017; Koong et al. 2017; Angelopoulou et al. 2014).

Interest rate spread (*IS*) is calculated as the difference between the average lending rate and the average borrowing rate (Babar et al. 2019; Angelopoulou et al. 2014). *IS* is a key indicator of banking system efficiency (Apergis and Cooray 2018), reflecting competition and efficiency in the banking sector (Karanovic and Karanovic 2015). An increase in interest rate signals periods of financial instability, especially when the credit institutions undertake additional protection measures against potential risks; hence an inverse relationship is expected (Karanovic and Karanovic 2015). Therefore, interest spread is expected to negatively affect financial stability.

FCI overcomes the shortcomings of the monetary conditions index (MCI), constituting a monetary policy stance by including interest rates and exchange rates. *FCI* incorporates these additional variables to capture the financial side to shed more light on the state of the economy (Zheng and Yu 2014; Matkovskyy et al. 2016). Therefore, a short-interest rate is included to capture money market (*MM*) volatility (Zabai 2018; Zheng and Yu 2014; Angelopoulou et al. 2014). *MM* plays a central role in modern term structure theory, and it is a key determinant of financial stability (Chaibi and Ftiti 2015; Fang et al. 2014); the financial soundness of the country (Koong et al. 2017) and controls for economic stability (Fang et al. 2014). It is also an indicator of the monetary and banking conditions used to guide appropriate central bank policies. For instance, policy rate cuts represent a loosening of financial conditions (Angelopoulou et al. 2014).

Real exchange volatility is proxied by the real effective exchange rate (*REER*), which is important in explaining an economy’s financial stability (Koong et al. 2017). Foreign exchange is one indicator of increased financial crisis risk (Csonto et al. 2020; Agénor et al. 2020). Literature explores how movements in *REER* affect financial conditions and credit developments (Nier et al. 2020; Hofmann et al. 2020; Carstens 2019), which may, in turn, spill over into the financial and macroeconomic outlook (Nier et al. 2020). Financial stability problems are, therefore, often connected to internal and external shocks enhanced by globalisation (Agénor et al. 2020).

An appreciation of the domestic *REER* can fuel the build-up in credit rough various channels that simultaneously reinforce each other (Carstens 2019). The common scenario is that a currency appreciation would tend to ease domestic financial conditions, consequently boosting the demand and supply of domestic credit (Nier et al. 2020). However, when such appreciation leads to the expansion of domestic provision credit, it may give rise to a build-up of systemic risk (Nier et al. 2020; Baskaya et al. 2017; IMF 2017). While this appreciation may potentially be expansionary, there is also a common contrasting notion in the earlier literature that held an appreciation to be contractionary. Moreover, exchange rate volatility due to a financial channel may exacerbate the effect of currency fluctuations induced by external shocks (Agénor et al. 2020). Some evidence also reveals that foreign exchange intervention can be expansionary through the bank portfolio effect, consequently magnifying macroeconomic fluctuations and increasing volatility and financial stability risks (Agénor et al. 2020). Literature reveals that *REER* may be expansionary or contractionary. Therefore, *REER* is expected to either be negatively or positively related to financial stability. Therefore, a positive value indicates that the currency is depreciating against the US dollar.

The 10-year government bonds (*GovBY*) proxied by long-term interest rate (*LIR*) is included to control economic stability (Fang et al. 2014). Lower interest rates enable credit expansion which may enhance financial stability (Siddik and Kabiraj 2018). Higher interest rates tighten credit, thus hindering access to financing. Also, *LIR* increases the funding cost and weakens lending standards leading to credit risk (Zabai 2018). Therefore, a negative association is expected. *Table 5.1* presents financial stability indicators, their description and expected signs.

Table 5.1: Financial stability indicators, their description and expected signs

Subindex	Indicator	Description	Impact*	Literature source
FDI	Market capitalisation	The market capitalisation of listed domestic companies to GDP	positive	Svirydzenka 2016; Karanovic and Karanovic 2015
	Market concentration	The HHI is calculated as the sum of the square of each bank's share in the banking sector.	positive	Karanovic and Karanovic 2015
	Domestic bank credit	Bank credit to the private sector (% of GDP)	positive	Röhn et al. 2015
	Private debt	Total credit to the private sector (% of GDP)	positive	Svirydzenka 2016; Karanovic and Karanovic 2015
	Household debt	Total credit to households (% of GDP)	positive	Kakes and Nijskens 2018
	Corporate debt	Total credit to corporations (% of GDP)	positive	Svirydzenka 2016
	Government debt	Total credit to the government sector (% of GDP)	positive	Svirydzenka 2016; Kakes and Nijskens 2018; Chudik et al. 2017; De Vita et al. 2018; Shkolnyk and Koilo 2018
BSI	Insolvency (Z-score)	Calculated as: Ln [1 + ($ROA_{i,t}$ + $A_{i,t}$)/σ$(ROA)_{i,t}$].	positive	Danisman and Demirel 2019; de-Ramon et al. 2018; Degl'Innocenti et al. 2018; Noman et al. 2018; Davis and Karim 2019; Davis et al. 2020
	Credit	Calculated as: Ln [$NPL_{i.t}$/(100-$NPL_{i.t}$)].	negative	Davis et al. 2020; Tan and Anchor 2017; Kočišová and Stavárek 2018
	Liquidity	Calculated as: Ln (Liquid assets to total assets).	positive	Danisman and Demirel 2019; Kočišová and Stavárek 2018
	Portfolio	Calculated as: Ln [$ROA_{i,t}$/σ$(ROA)_{i,t}$)]	positive	Lepetit et al. 2008; Barry et al. 2011; Al-Shboul et al. 2020
	Leverage	Calculated as: Ln [Equity to assets ratio/σ$(ROA)_{i,t}$]	positive	Kočišová and Stavárek 2018
FCI	M2	The volatility of the money supply	positive	Koong et al. 2017; Zheng and Yu 2014; Holopainen and Sarlin 2017
	SPI	The volatility of the stock price index	positive	Holopainen and Sarlin 2017; Koong et al. 2017;
	HPI	The volatility of the housing price index	positive	Zheng and Yu 2014; Koong et al. 2017).
	REER	The volatility of the real effective exchange rate	positive	Hofmann et al. 2020; Nier et al. 2020; Agénor et al. 2020.
	GovBY	Long term interest rates capture the volatility of Government bond yield.	negative	Siddik and Kabiraj 2018; Matkovskyy et.al 2016
	MM	The volatility of the money market captured by short term interest rate	negative	Zabai 2018; Koong et al. 2017; Zheng and Yu 2014
	IS	Interest rate spread computed as lending rate minus deposit rate, (%)	negative	Babar et al. 2019; Karanovic and Karanovic 2015

Source: Developed by author. FDI: Financial development index; BSI: Bank stability index; FCI: Financial conditions index; ROA: return on assets; EA: equity to assets ratio; σ(ROA): standard deviation of ROA. NPL: ratio of non-performing loans to gross loans. * Impact on respective subindex

5.2.1.4. Aggregate financial stability index

After selecting the indicators for the sub-indices as presented in *Table 4.3*, following similar studies, the *FSI* is constructed using the weighted-sum approach (Kočišová and Stavárek 2015; Morales and Estrada 2010). Several decisions are made to achieve this process. These include unifying scales of measurement (normalisation), weight allocation and finally, deriving the aggregate index (Matkovskyy et al. 2016). The normalisation procedure is undertaken to allow for comparability across indicators and assign the values of the indicators to the same scale and ensure that the development of adjusted indicators has the same effect on the development of the index. The literature proposes two main normalisation methods: statistical and empirical normalisation (Petrovska and Mihajlovska 2013). For this study, the empirical normalisation technique, commonly used in the literature, is employed (Petrovska and Mihajlovska 2013). The process entails placing all indicators on the same scale in the interval ranging from zero to one [0;1]; that is $I_{it} \in [0,1]$. The value "1" is equal to the best-recorded value of each indicator, thus indicating a stable situation, whilst the value "0" reflects a case of instability. The formula for the normalisation process is expressed as follows:

$$I_{it}^{n} = \frac{I_{it} - min(I_i)}{max(I_i) - min(I_i)} \tag{5.1}$$

where I_{it} is the value of indicator *i* in period *t*; $max(I_i)$ and $min(I_i)$ are the maximum and minimum values of the indicator in the analysed period, respectively.

The first step toward constructing the *FSI* is the computation of the three sub-indices corresponding to each of the three sets of variables presented in *Table 5.1*. Each sub-index is calculated as the simple arithmetic average of normalised values of indicators in that sub-index for each country *j* at time *t*. The values of variables with expected negative signs are multiplied by a coefficient (-1) prior to aggregation so that a positive value of those variables will signal a heightened financial instability. Thus, equations 5.2, 5.3 and 5.4 present *BSI*, *FDI* and *FCI*, respectively.

$$BSI_t^j = \frac{1}{5}\sum_{i=1}^{5} I_t^j \tag{5.2}$$

$$FDI_t^j = \frac{1}{7}\sum_{i=1}^{7} I_t^j \tag{5.3}$$

$$FCI_t^j = \frac{1}{7}\sum_{i=1}^{7} I_t^j \tag{5.4}$$

where *i* is the number of indicators in each sub-index and I_t^j is the normalised indicator for country *j* at time *t*.

After computing the sub-indices, the aggregate *FSI* is constructed as a weighted average of the composite indicators of *BSI*, *FDI* and *FCI*. First, the issue of the weighting of the sub-indices is considered. The two widely used methods in the empirical literature are the principal component approach (PCA) (e.g., Arzamasov and Penikas 2014; Brave and Butters 2011; Dumičić 2016; Svirydzenka 2016) and the weighted-sum approach (e.g., Kočišová and Stavárek 2015; Morales and Estrada 2010).[24] However, the PCA estimates the weights of each indicator by systemic and individual importance, and its applicability becomes limited when dealing with various countries. In this study, the weighted-sum approach is adopted to allow for comparability and standardisation of weights across countries.

Several methods have been employed to derive weights in the empirical literature (Maliszewski 2009; OECD 2008). These include: (i) statistical methods such as factor analysis; (ii) participatory methods such as analytical hierarchy process or expert judgement (Morales and Estrada 2010; Petrovska and Mihajlovska 2013); (ii) regression models (Arzamasov and Penikas 2014). Following other studies, an equal weighting approach across sub-indices is employed (Kočišová and Stavárek 2015). The sub-indexes are assumed to be equally important dimensions of financial stability. The three sub-indexes of financial stability are each assigned a weight of one-third (1/3), so the sum of weights equals one. The overall financial stability index is the sum of weighted normalised indicators for individual specific dimensions. It is calculated as follows:

$$FSI_t^j = \varphi_i \sum_{i=1}^{n} I_{it,BSI}^j + \omega_i \sum_{i=1}^{n} I_{it,FDI}^j + \delta_i \sum_{i=1}^{n} I_{it,FCI}^j \tag{5.5}$$

[24]Other methodologies include dynamic factor model (DFM) (Koong et al. 2017), Reduced Aggregate Demand Equation models (Zheng and Yu 2014), cumulative distribution functions and others are used to estimate the weight of individual indicator.

where FSI_t^j is the *FSI* for country *j* at time *t*; φ, ω and δ represent weights for *BSI*, *FDI* and *FCI* (respectively). The weights are assumed equal across the three sub-indices, each weighing one-third (1/3). The assumption is that the three indices are equally important dimensions of overall financial stability. To check whether the index is valid, differential weights with *BSI* and *FDI* having higher weights of 0.4 each and *FCI* with a weight of 0.2 is used. It is, however, important to avoid direct comparisons across the indexes as they are invalid. Instead, the comparison should be made concerning how they each capture financial conditions over time (Brave and Butters 2011).

5.2.2. Independent variables

5.2.2.1. Main independent variable (FinTech credit)

The focus on credit as an indicator of financial (in)stability is consistent with the literature that underscores the contribution of excessive credit growth to banking crises (e.g., Kim and Mehrotra 2018; Schularick and Taylor 2012). The emphasis on credit aggregates (leverage and credit growth) is also justified by the empirical regularity that strong credit growth is directly associated with boom-bust financial cycles and typically preceded crises (Alessi and Detken 2018; Jordà et al. 2013; Schularick and Taylor 2012). Strong domestic credit growth has been identified as one of the most robust and significant predictors of banking and financial crises (e.g., Röhn et al. 2015; Aikman et al. 2014) and a major source of financial instability in the past, particularly during periods of economic downturns (e.g., Kim and Mehrotra 2018; Schularick and Taylor 2012). If sustained over long periods, excessive credit growth tends to promote the build-up of vulnerabilities that may threaten the stability of the financial sector (Boh et al. 2017).

On the contrary, the literature suggests that credit growth promotes economic growth and represents an increase in demand for finance for households and businesses (Adrian and Liang 2018). Moreover, broadening credit access may lessen the impact of real shocks and provide an alternative source of credit when banks are under stress (Jagtiani and Lemieux 2018; Carney 2017; de Roure et al. 2022). The contrasting views on the potential impact of FinTech credit on bank risk-taking and overall financial stability are expected to yield a positive or negative relationship. Hence a quadratic term of FinTech credit share is included to capture the possible existence of a non-linear relationship. This study uses FinTech credit share *(FIN_S)* as a core explanatory variable. Following Frost et al. (2019), FinTech credit is measured as a share of the total volumes of loans originated by FinTech platforms to total credit to the private non-financial sector *(FIN_S)*. *FIN_S* is thus computed as the sum of loans originated by FinTech platforms divided by the sum of domestic credit (credit to the private non-financial sector). *FIN_S* is then converted into the natural log of FinTech credit share (*lnFIN_S*).

5.2.2.2. Bank-level control variables

Following various literature, the modelling approach used is based on selecting banking sector independent variables that feature the characteristics of banks' business models and balance sheet items that contribute to financial stability (Beck et al. 2013; Mirzaei and Aguir 2020; Davis et al. 2020; Davis and Karim 2019). These variables have been extensively used in the empirical literature and are instrumental in explaining bank and financial stability (Davis et al. 2020; Mirzaei and Aguir 2020). A total of six bank variables (bank balance-sheet characteristics) are included in the empirical models as control variables.

First, to control for the potential side effect of banks on financial stability, a proxy for bank size (*SIZE*) measured as the natural logarithm of total bank assets is included (Ahamed and Mallick 2019; Yusgiantoro et al. 2019; Noman et al. 2018). Banks of different sizes have different degrees of financial stability (Mirzaei and Aguir 2020). Therefore, the relationship between bank size and financial stability is relatively mixed. The opposing views about the link between bank size and financial stability can be viewed from the viewpoint of the concentration-stability and concentration-fragility hypotheses (Uhde and Heimeshoff 2009).

According to the concentration-stability hypothesis proposed by Keeley (1990), larger banks in concentrated banking sectors reduce financial fragility. Hence a positive relationship exists between bank size and financial stability. Their vast profits and built up high "capital buffers" enable them to be less susceptible to liquidity or macroeconomic shocks. Moreover, larger banks tend to benefit from higher economies of scale and scope, enabling them to diversify their loan portfolio risks efficiently, thus improving their performance with an overall positive effect on financial stability (Hu et al. 2004; Boot and Thakor 2000). They also have more capital (Fang et al. 2014), are more technologically advanced and have better access to liquidity than smaller banks (Mirzaei and Aguir 2020), which enhances overall financial stability. Laeven et al. (2016) also hold that larger banks may have a competitive advantage in market-based activities, which generally require high fixed costs and enjoy economies of scale. Adusei (2015) also indicates that bank size supports bank stability.

The concentration-fragility view suggests a negative relationship between bank size and financial stability. This view submits that larger banks in a concentrated market reduce stability by exacerbating moral hazard problems resulting from the 'too big to fail' hypothesis, which has been proven to destabilise the financial system (Ahamed and Mallick 2019; Yusgiantoro et al. 2019). In response to the 'too-big-to-fail' bailouts, larger banks tend to take excessive risks by increasing their leverage too much to increase lending, which might lower the quality of assets (Laeven et al. 2016). Other empirical evidence suggests that large or oversized financial systems are associated with financial instability due to their tendency to generate financial shocks in the first place (Bush et al. 2015). Köhler (2015) and Laeven et al. (2016) show that systemic risk increases with bank size. Altaee et al. (2013), on the other hand, find no statistically significant impact. Therefore, *SIZE* can either be negatively or positively related to financial stability.

Second, the non-interest income to total income (*NITI*) is included as a proxy for bank revenue diversification (Sharma and Gounder 2012; Ahamed and Mallick 2019; Kim et al. 2020; Mirzaei and Aguir 2020). Diversified banks generate more profit and are resilient to financial instability (Elsas et al. 2010). Therefore, *NITI* is expected to relate to financial stability positively. Third, overhead costs to total assets (*OVERHH*) is included to capture bank inefficiency (Athanasoglou et al. 2008; Mirzaei and Aguir 2020). Inefficient banks are more prone to financial fragility (Mirzaei and Aguir 2020) and expose their operation to higher risk (Boyd and De Nicoló 2005; Fiordelisi and Mare 2014). Thus, *OVERHH* is expected to negatively relate to financial stability because inefficient institutions are more likely to be less profitable.

Fourth, the regulatory capital/risk-adjusted adequacy ratio (*RCAR*) is included as a proxy for bank leverage (Davis et al. 2020). Leverage or capitalisation is perhaps the most widely used measure of bank risk and resilience to shocks. A highly leveraged financial system is prone to vulnerabilities; hence excessive leverage is one of the leading key drivers of the recent global financial crisis and many past crises (Acosta-Smith et al. 2020; Schularick and Taylor 2012). However, a well-capitalised bank tends to take a lesser risk, hence the need to test and control for capital risk (Ahamed and Mallick 2019; de-Ramon et al. 2018; Yusgiantoro et al. 2019). The interaction of a bank's capital adequacy to risk is somewhat mixed but mainly presented by two opposing viewpoints, which specify a positive relationship between capital and risk ("the regulatory hypothesis") or that capital and risk are inversely related ("skin in the game") (Bitar et al. 2018). The "skin in the game" suggests that a higher capital ratio would be consistent with lower risk (Lee and Hsieh 2013; Anginer and Demirgüç-Kunt 2014). The alternative "regulatory hypothesis" holds that a higher *RCAR* suggests a higher capital/assets ratio (Bitar et al. 2018). Bush et al. (2015) also find that leverage is associated with financial instability. (*RCAR*) is expected to be positively or negatively related to financial stability.

Fifth, the deposit to asset ratio (*DEPASS*) is included (Sharma and Gounder 2012; Fang et al. 2014; Davis et al. 2020). Institutions with higher levels of assets financed by deposit liabilities are likely to be more profitable (Sharma and Gounder 2012). The relationship between *DEPASS* and financial stability has yielded inconclusive results in the empirical literature. Muriu (2011) found a significant positive relationship between *DEPASS* and financial stability, while Bogan (2012) found a negative relationship between *DEPASS* and financial stability. Therefore, the results are expected to be either negative or positive.

Sixth, to account for individual banks' liquidity risk, the net loans to total assets ratio (*LOANASS*) is included (Fang et al. 2014; Noman et al. 2018; Ahamed and Mallick 2019; Davis et al. 2020). *LOANASS* captures banks' lending behaviour (Noman et al. 2018), and it indicates the percentage of the bank assets tied up in loans. The higher the ratio, the higher the banks' credit risk, thus negatively impacting overall financial stability (Heffernan and Fu 2010; Kasman and Kasman 2015). Also, Bourke (1989) and Molyneux and Thornton (1992), among others, find a negative and significant relationship between *LOANASS* and financial stability. On the other hand, Freixas (2005) postulates that a higher ratio provides informational advantages, lessens intermediation costs, and enhances profitability. Thus, the impact of *LOANASS* on financial stability may either be positive or negative.

5.2.2.3. Country-level control variables

Several macroeconomic variables which could contain relevant country-specific information are included to account for the influence of observable individual economic and market characteristics, which may influence financial stability (Bretschger et al. 2012). Furthermore, market-based information such as macroeconomic determinants augments the financial sector information by conveying perceptions of market wellbeing and the stability of the financial system (Koong et al. 2017). To capture key characteristics of respective economies, three key macroeconomic variables, namely: real GDP growth rate (*GDPGR*), inflation proxied by consumer price index (*CPI*) and trade openness (*TRADE*), are included. Financial stability studies have extensively used these three macroeconomic variables as control variables.

Economic growth and development seldom coincide with domestic credit expansion, including for households and small businesses. Therefore, the real GDP growth rate controls for economic growth (Saif-Alyousfi et al. 2020; Ahamed and Mallick 2019; Alessi and Detken 2018; Noman et al. 2018). *GDPGR* also implies fluctuation of economic activities or a business cycle movement (Noman et al. 2018). Financial stability is expected to be positively related to *GDPGR* and its components (Morgan and Pontines 2014).

Inflation is proxied by the consumer price index (*CPI*) (see. Noman et al. 2018; Tan and Anchor 2017; Saif-Alyousfi et al. 2020) to capture macroeconomic instability due to its inverse effect on the real economy (Noman et al. 2018; Fang et al. 2014). Empirical studies on inflation–financial stability relationship is still scarce and ambiguous. High inflation is identified as one of the causes of the global financial crisis. High inflation hurts the economy as it erodes competition. Unstable and high inflation erodes purchasing power and makes credit access more expensive, thus increasing the probability of default and increasing the level of NPLs, leading to financial instability.

On the contrary, Phan et al. (2020) and Fazio et al. (2015;2018) demonstrate that inflation targeting is positively related to the stability of a country's banking system. Other studies suggest that a higher inflation rate supports higher bank profitability (Batsinda and Shukla 2019; Guru et al. 2002). Guru et al. (2002) claim that when core inflation is fully anticipated and interest rates are adjusted; accordingly, this may positively impact bank profitability. Therefore, inflation can either be negative or positive.

Trade openness (*TRADE*) is included to capture the effect of international trade proxied by the ratio of total trade (exports and imports) to a country's GDP (Ashraf 2018; Hossain et al. 2020; Rahman et al. 2020; Mirzaei and Aguir 2020). However, the relationship between trade openness and economic growth is still scarce and has yielded inconclusive results (Keho 2017). Literature provides two mainstream literature strands on trade openness and economic development. Zhang et al. (2015) suggest that trade openness is a positive determinant of financial efficiency and competition but negatively impacts financial development. Ashraf et al. (2017) also provide mixed results arguing that trade openness can negatively and positively affect bank risk-taking.

The “diversification-stability” effect explains the positive relationship between trade openness and financial stability (Berger et al. 2017b). Higher trade openness promotes bank development by decreasing the cost, risk of bank credit, and banks’ risk-taking (Ashraf et al. 2017; Ashraf 2018; Bui and Bui 2019; 2020; Rahman et al. 2020). It also fosters the reforms that liberate the domestic financial sector (Hauner et al. 2013). Bui and Bui (2020) find a positive linear relationship between trade openness and bank stability. Similarly, Hossain et al. (2020) also document that higher trade openness may increase loan diversification opportunities between international and domestic trading firms. Hou et al. (2016) and Fu et al. (2020) show that trade openness promotes internet finance development, leading to market-driven financial liberalisation. The opposing view argues that the destabilising effects of trade openness are based on the ‘volatility-fragility effect’. Ashraf et al. (2017) posit that trade openness might increase bank risk-taking due to higher competition and volatility. Moreover, trade openness is negatively related to bank risk-taking (Hossain et al. 2020; Ashraf et al. 2017). Thus, trade openness is expected to be negatively or positively related to financial stability. The variable definitions are presented in *Table 5.2*.

Table 5.2: Description of variables used for regression estimations†

Variable name	Acronym	Variable description	Data sources
Measures of financial stability			
Financial stability index	*FSI*	FSI is calculated as the weighted average of BSI, FDI and FCI.	BIS; GFDD; OECD; WBI; Author's calculations
FinTech variables			
FinTech credit	*FIN_S*	*FIN_S* is Measured as the ratio of total volumes of loans originated (by FinTech platforms) to total credit to the private non-financial sector (see. Frost et al. 2019; Rau 2020).	Various FinTech Platforms, UK P2PFA; AFSAL; Korea P2PFA; SMLA; US S&P GMI 2018; Sweden RiksBank survey; CBIRC; Brismo; WDZJ.
Bank-specific variables			
Size	*SIZE*	Bank size is measured as the natural log of total bank assets	FSI
Non-interest income to total income	*NITI*	Bank non-interest income divided by total income	GFDD
Overheads to total assets (%)	*OVERHH*	The ratio of overhead costs to total assets of a bank	GFDD
Regulatory capital adequacy ratio	*RCAR*	The ratio of bank regulatory capital to risk-weighted assets	GFDD; FSI
Deposit to assets ratio	*DEPASS*	Constructed as the ratio of deposit money bank/GDP to deposit money banks' assets/GDP	BIS; GFDD
Loan to assets ratio	*LOANASS*	Constructed as the ratio of private credit by deposit money banks/GDP to deposit money banks' assets/GDP	BIS; GFDD;
Country-level control variables			
Real GDP growth	*DGPGR*	The growth rate of GDP	OECD
Inflation	*CPI*	Proxied by consumer price index (percentage change in CPI)	BIS
Trade openness	*TRADE*	Sum of exports and imports of goods and services measured as a share of GDP	OECD

Source: Developed by the author.

Notes: †FSI: Financial Soundness Indicator; BSI: Banking Stability Index, FDI: Financial Development Index; FCI: Financial Conditions Index; GFDD: Global Financial Development Database; BIS: Bank for International Settlements; OECD: Organisation for Economic Co-operation and Development; WBI: World Bank Institute; CBIRC: China Banking and Insurance Regulatory Commission; US S&P GMI 2018: US Standard & Poor's (S&P) Global Market Intelligence; Brismo (formerly known as AltFi data); UK P2PFA: UK Peer-to-Peer Finance Association; AFSAL: Alternative Financial Services Association of Latvia, Korea P2PFA: Korea P2P Finance Association, SMLA: Swiss Marketplace Lending Association; WDZJ: Wang Dai Zhi Jia

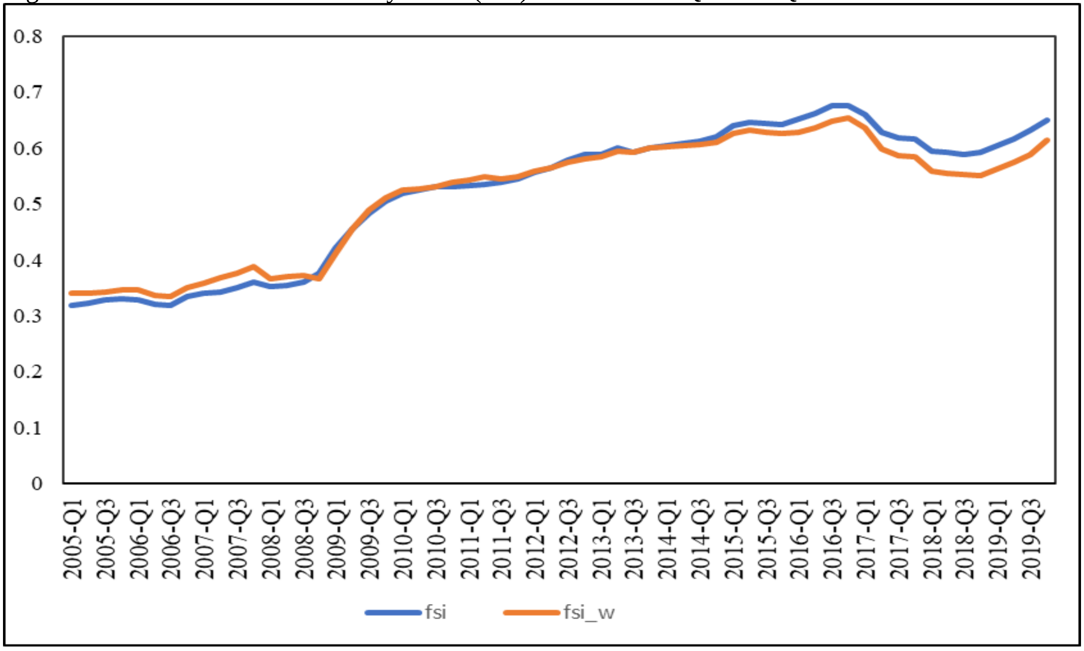
5.3. Descriptive statistics

5.3.1. Aggregate FSI

The results for the aggregate *FSI* are presented in *Figure 5.1*. The aggregate FSI is presented by an equal-weighted FSI and a differentiated-weighted FSI comprising *0.4 BSI, 0.4 FDI* and *0.2 FCI*. Based on the empirical normalisation, the approximation of the FSI value to 1, means higher levels of financial stability, while movement towards 0 means low levels of financial stability. The overall financial stability exhibited a period of relative growth and economic activity over time. This may be attributed to regulatory reforms, improving financial conditions and financial innovation developments in banking and finance. It may also mean that the state of the overall financial stability has been improving over time. There is an increasing trend from 2005 until 2007, after which a downward trend is observed. The *FSI* lower values or spikes during the period 2007 to 2009 are reflective of the global financial crisis as expected. This dent is more pronounced in *Figure 5.2,* showing individual sub-indexes. In particular, the *BSI* sub-index reveals a deeper dive, followed by the *FCI* sub-index (sometimes called the volatility index). As expected, the banking system was the most affected by the global financial crisis. This is also reflective of the *FCI* sub-index, which largely captures market volatilities.

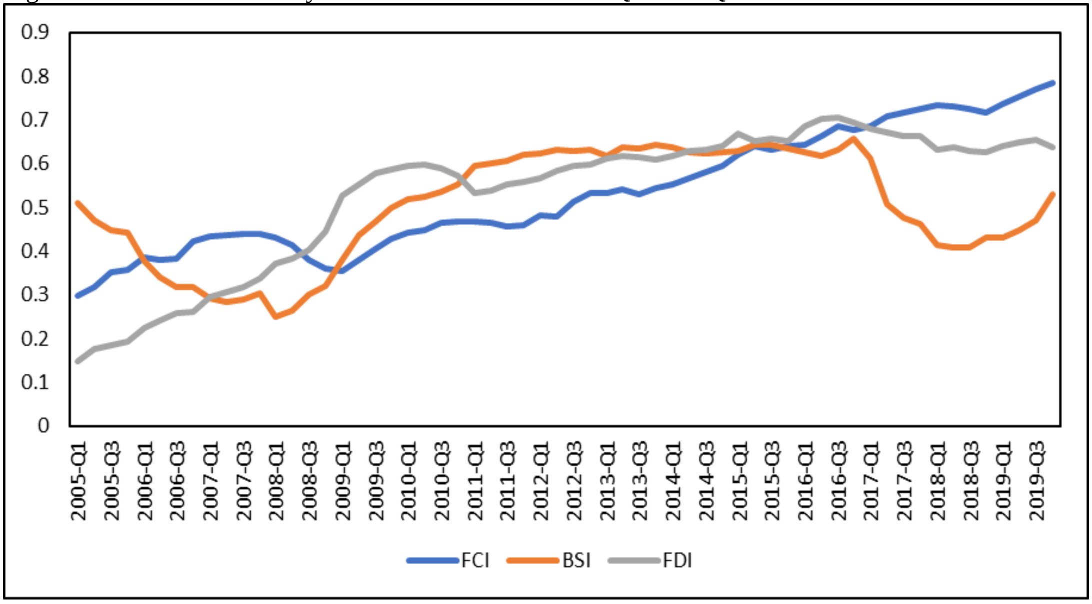
Thereafter, there is evidence of recovery in the index and a period of steady growth, which surpassed the prior years' levels until 2016Q1. Another spike is noticeable (more evidently on the *BSI* sub-index) from 2016Q2 to 2018Q4. This has been captured by various stress test indexes such as Bloomberg Financial Conditions Index (*BFCI*) and the Chicago Board Options Exchange (*CBOE*) Volatility Index (*VIX*). The 2017 financial stability report by the Office of Financial Research (*OFR*) noted a real-time measure of their financial stress index, highlighting a fall in 2017Q1 and nearing its lows since the financial crisis. This occurred during the period when several events occurred, such as the crude oil burst, the Brexit vote and the US election "Trump Win" in 2016. In 2017 there was a rise in shadow banking, and Bitcoin and other cryptocurrencies went mainstream, as well as the first UK interest rate hike in a decade.

Figure 5.1: Overall financial stability index (FSI) over the 2005Q1-2019Q4



Source: Author's calculations

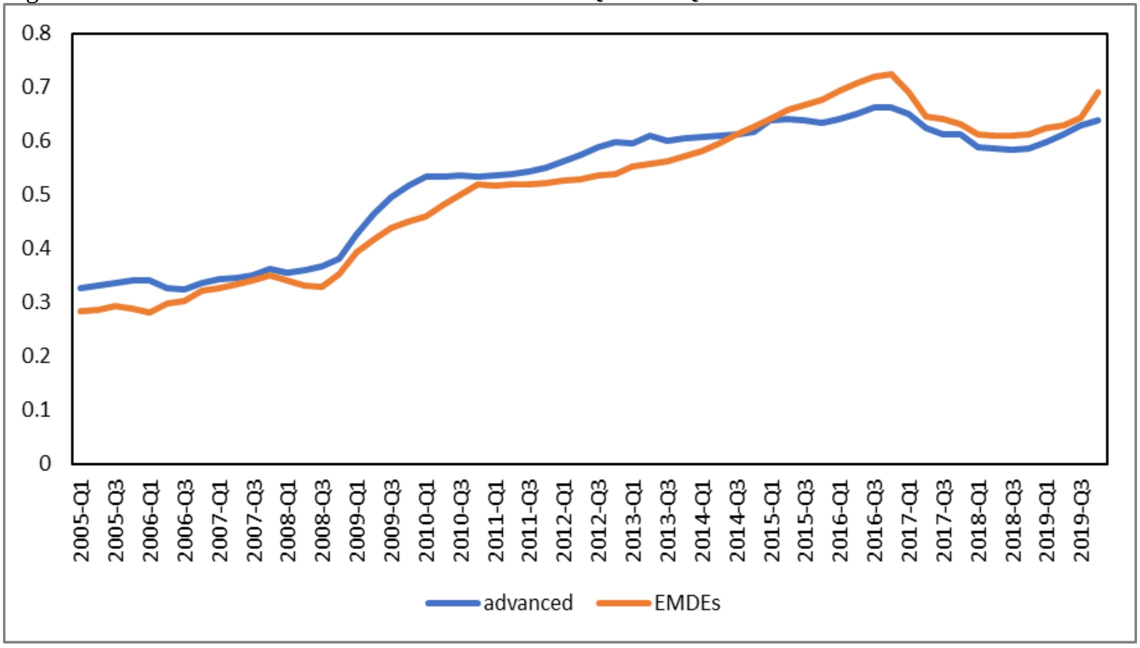
Figure 5.2: Financial stability Sub-indexes over the 2005Q1-2019Q4



Source: Author's calculations

Table 5.3 presents the average *FSI*, *FCI*, *FDI* and *BSI* for the period 2005Q1–2019Q4 across the 25 countries. The table confirms the heterogeneity of the countries in terms of financial stability. In addition, trends in overall *FSI* by advanced countries and EMDEs are presented in *Figure 5.3*. The results are consistent with the trends exhibited by the overall financial stability index. On average, it should be noted that financial stability for advanced economies had been consistently higher than that of EMDEs until 2016. Both economies revealed declining trends during the financial crisis.

Figure 5.3: FSI: advanced economies vs EMDEs 2005Q1-2019Q4



Source: Author's calculations

Table 5.3: Average FSI, FCI, FDI and BSI over 2005Q1-2019Q4

Country	Code	FSI	FCI	FDI	BSI
Australia	AUS	0.7688	0.5346	0.5736	0.4594
Belgium	BEL	0.6313	0.5371	0.5380	0.5172
Bulgaria	BGR	0.6438	0.4254	0.5139	0.5089
Canada	CAN	0.6701	0.5610	0.5243	0.4034
China	CHN	0.8191	0.5252	0.4602	0.4616
Estonia	EST	0.6517	0.5315	0.4791	0.4971
Finland	FIN	0.8138	0.6113	0.6510	0.4828
France	FRA	0.6785	0.5461	0.5345	0.4798
Germany	DEU	0.4660	0.4880	0.5090	0.6052
Indonesia	IDN	0.6084	0.5051	0.5304	0.4340
Ireland	IRL	0.5860	0.5556	0.4770	0.5438
Italy	ITA	0.6710	0.5254	0.5669	0.4462
Korea	KOR	0.6898	0.5723	0.5509	0.4769
Latvia	LVA	0.6419	0.5488	0.4139	0.5616
Lithuania	LTU	0.5705	0.5258	0.5112	0.5503
Mexico	MEX	0.6771	0.5311	0.5316	0.4497
Netherlands	NLD	0.5256	0.5632	0.5139	0.4321
New Zealand	NZL	0.6220	0.4866	0.5684	0.5497
Poland	POL	0.7084	0.5979	0.6056	0.5005
Slovakia	SVK	0.6966	0.4795	0.4738	0.5271
Spain	ESP	0.5405	0.5384	0.5291	0.5672
Sweden	SWE	0.7257	0.4831	0.6261	0.5301
Switzerland	CHE	0.7042	0.5227	0.5005	0.4800
United Kingdom	GBR	0.4790	0.6120	0.5002	0.5619
United States	USA	0.6671	0.4911	0.5369	0.5229

Source: Calculations by author.
FSI: Financial stability index; FCI: Financial conditions index; FDI: Financial development index. BSI: Bank stability index.

5.3.2. Summary statistics

Table 5.4 presents the summary statistics of the variables used in the first empirical estimations. The table shows that the financial stability index (*FSI*) averaged 0.519 and varied from 0.136 to 0.819 for the period analysed, indicating that *FSI* exhibited a high degree of heterogeneity across countries. Across economies, *FSI* is higher in advanced economies compared to EMDEs. The mean value for *FIN* averaged 5.2%, indicating that FinTech still has the potential to grow to higher levels over time. *FIN* values ranged from 0.0001% to 4.07% over the period analysed, signifying a high degree of heterogeneity. *FIN* levels are higher in advanced economies than in EMDEs. Generally, descriptive statistics present a high degree of heterogeneity, as shown by disparities in most variables' range values. Country control macroeconomic variables also show a level of variations (see *Table 4.8*). For example, *GDPGR* averaged 0.623 and ranged from -12.702 to 23.246.

5.3.3. Correlation analysis

The correlation, in essence, depicts the pairwise association between variables (not in the causality sense). *Table 5.5* presents the pairwise correlations between the variables based on the Pearson correlation matrix. The correlation highlights possible associations that can be further interrogated using econometric analysis. Generally, most of the variables are weakly associated with each other. For example, *FSI* has a weak and positive correlation with *FIN*. The results also reveal a weak and negative association between *FSI* and *OVERHH* and *FSI* and *LOANASS*. *FSI* further demonstrate a significant and weak positive correlation with *SIZE, NITI, RCAR* and *DEPASS.* The correlation for bank-related variables ranged between 0.0432 and 0.1006. FSI is positively associated with all country-control variables in terms of country-level control variables. The highest correlation is 0.621 between *FSI* and *CPI*. However, the remaining country control variables (*GDPGR* and *TRADE*) recorded weak positive correlations with *FSI*. The weak correlations between variables indicate that multicollinearity is not a problem. Kennedy (2008) and Gujarati (2009) both indicate that correlation coefficients above 0.8 indicate that multicollinearity is a critical problem. Thus, in this case, most variables are weakly correlated, suggesting the non-existence of multicollinearity issues.

Table 5.4: Summary statistics for variables used in the empirical estimations

	Overall					Advanced economies					EMDEs				
Variable	N	Mean	S.D.	Min	Max	N	Mean	S.D.	Min	Max	N	Mean	S.D.	Min	Max
FSI	1500	0.519	0.131	0.136	0.819	1200	0.521	0.127	0.136	0.819	300	0.509	0.147	0.196	0.792
FIN	673	0.052	0.300	0.000	4.075	549	0.051	0.328	0.000	4.075	124	0.056	0.115	0.000	0.440
SIZE	1500	13.981	1.991	9.354	17.498	1200	13.985	1.966	9.354	16.750	300	13.967	2.093	9.814	17.498
NITI	1500	39.547	13.892	10.639	79.661	1200	42.380	13.591	13.752	79.661	300	28.215	8.107	10.639	47.335
OVERHH	1500	1.799	0.915	0.109	5.341	1200	1.566	0.701	0.109	4.399	300	2.729	1.070	0.839	5.341
RCAR	1500	15.692	4.165	2.500	36.082	1200	15.626	4.250	9.728	36.082	300	15.956	3.802	2.500	23.318
DEPASS	1500	0.771	0.234	0.293	1.399	1200	0.774	0.233	0.369	1.399	300	0.760	0.238	0.293	1.113
LOANASS	1500	0.848	0.166	0.366	1.331	1200	0.860	0.155	0.433	1.331	300	0.800	0.199	0.366	1.123
GDPGR	1500	0.623	1.327	-12.702	23.246	1200	0.524	1.401	-12.702	23.246	300	1.020	0.873	-5.096	4.493
CPI	1500	103.547	10.811	64.540	151.920	1200	102.966	8.444	70.140	123.060	300	105.871	17.124	64.540	151.920
TRADE	1500	91.792	44.718	24.642	239.215	1200	96.184	46.835	24.642	239.215	300	74.226	29.019	35.680	130.632

Source: Author's calculations. FSI: Financial stability index; FIN: FinTech credit; SIZE: natural logarithm of total assets; NITI: Non-interest income to total income; OVERHH: Overhead costs to total asset ratio; RCAR: Regulatory capital asset ratio; DEPASS: Deposit to asset ratio; LOANASS: Loan to assets ratio; GDPGR: GDP growth rate; CPI: Inflation.

Table 5.5: Correlation coefficients

	FSI	FIN	SIZE	NITI	OVERHH	RCAR	DEPASS	LOANASS	GDPGR	CPI	TRADE
FSI	1.0000										
FIN	0.0101	1.0000									
SIZE	0.1006***	-0.2054***	1.0000								
NITI	0.0836***	0.0635	0.1139***	1.0000							
OVERHH	-0.1372***	0.0683	-0.1288***	-0.0919***	1.0000						
RCAR	0.4089***	0.1245***	-0.2725***	0.2351***	0.1356***	1.0000					
DEPASS	0.0432*	-0.0233	-0.0035	0.1195***	0.3427***	0.3633***	1.0000				
LOANASS	-0.0796***	0.0612	-0.2986***	-0.1872***	-0.3417***	-0.0412	-0.2227*	1.0000			
GDPGR	0.0190	0.0561	-0.0499*	-0.0708***	0.0907***	0.0369	0.0237	0.1007***	1.0000		
CPI	0.6217***	0.1439***	0.1410***	-0.0592**	-0.0149	0.4642*	0.1170*	-0.1214*	-0.0545*	1.0000	
TRADE	0.0431*	0.0528	-0.5286***	0.2000***	-0.0808***	0.3927***	0.1948***	0.1071***	0.0549**	-0.0097***	1.0000

Source: Author's calculations. FSI: Financial stability index; FIN: FinTech credit; SIZE: natural logarithm of total assets; NITI: Non-interest income to total income; OVERHH: Overhead costs to total asset ratio; RCAR: Regulatory capital asset ratio; DEPASS: Deposit to asset ratio; LOANASS: Loan to assets ratio; GDPGR: GDP growth rate; CPI: Inflation. * Statistically significant at 10%; ** Statistically significant at 5%; *** Statistically significant at 1%.

5.4. Empirical approach

This empirical chapter examines the effect of FinTech credit on financial stability. Due to the inconclusive arguments on whether FinTech credit enhances or disrupts financial stability, this chapter conducts the empirical estimations in two parts. First, a simple linear specification examines a linear relationship between FinTech and financial stability.[25] To present the model, let $j \in \{1,2,\cdots,N\}$ and $t \in \{1,2,\cdots,T\}$ stands for country and period indices, correspondingly. The baseline model is specified as follows:

$$FS_t^j = \alpha_0 + \delta FIN_t^j + \theta \boldsymbol{S}_t^j + \varphi \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \tag{5.6}$$

Second, the non-linear relationship between FinTech and financial stability is examined. To investigate the possibility of a non-linear relationship between FinTech credit and overall financial stability, Equation 5.6 is transformed to formulate the following specification by introducing a quadratic term for the FinTech credit variable (FIN_t^{2j}):

$$FS_t^j = \alpha_0 + \delta_1 FIN_t^j + \delta_2 FIN_t^{2j} + \theta \boldsymbol{S}_t^j + \varphi \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \tag{5.7}$$

where FS_t^j is a measure of financial stability in country *j* at time *t*, FIN_t^j is the measure of FinTech credit in country *j* at time *t*, $\boldsymbol{S}_t^j$ and $\boldsymbol{X}_t^j$ denote the vectors of observable bank-specific and country-level control variables for country *j* at time *t*, c_j is a country-specific fixed effect capturing the effect of country-level variation; h_t captures time fixed effect, which controls for possible cross-sectional dependence, and ε_{jt} captures stochastic error term; α_0 is a constant, and δ, θ and φ are vectors of parameters to be estimated.

5.5. Results and discussions

This section provides the findings and discussions of the results. For the econometric estimations, a regression analysis is conducted in two parts. First, a linear relationship between FinTech credit and financial stability is considered. The study theorised a linear relationship outcome which suggested either a positive, negative or insignificant relationship between FinTech credit and financial stability. The second part examines whether there exists a non-linear relationship between FinTech credit and financial stability. To achieve this, the quadratic term of FinTech credit is included. Finally, several robustness tests are conducted to check for the stability of the main results.

[25] A more traditional linear equation before estimating a nonlinear model.

5.5.1. Baseline results

For the baseline empirical estimations and following other studies (e.g., de Mendonca and Nascimento 2020; Noman et al. 2018), this study employs the fixed effects (FE) model. In this study, the number of time series data (*T*) is larger than the number of cross-sectional units (*N*). According to Gujarati (2004), in this case there is likely to be minimal difference in the values of the parameters estimated by both models. However, it is very important to identify the appropriate or fitted model. Therefore, the Hausman test (Hausman 1978; Wooldridge 2010) was run to select the appropriate model between FE and RE models. The null hypothesis of the Hausman test is that the preferred model is RE versus the alternative FE model (Green 2008). This means that if the null hypothesis is rejected, the results are in favour of the FE model (p<0.0001), indicating that the FE model is more suitable (Bollen and Brand 2010). The advantage of FE is that it removes the unobserved heterogeneity and alleviates endogeneity problems arising from omitted variables (Ketokivi and McIntosh 2017). The FE results are presented as the baseline results in *Table 5.6*. Overall, the results reveal a non-linear (inverted U-shaped) relationship between FinTech credit and financial stability.

The linear specification reveals a positive but statistically insignificant relationship between FinTech credit and financial stability. The second part was to examine whether there exists a non-linear relationship between FinTech credit and overall financial stability. The results reveal a statistically significant non-linear (inverted U-shaped) relationship between FinTech credit and financial stability, as evidenced by the highly significant negative coefficient of FinTech credit squared. This finding indicates that increased FinTech credit enhances financial stability to a certain threshold at lower levels, after which it would lead to declining levels of financial stability. Therefore, the study accepts the null hypothesis of a non-linear (inverted U-shaped) relationship between FinTech credit and financial stability. The findings are consistent with the views of Zhang et al. (2019), who suggest that FinTech credit may initially complement bank lending when FinTech lending balances are still low, subsequently substituting bank credit when FinTech lending increases.

Table 5.6: Financial stability and FinTech credit: Fixed effects regression model

	Linear specification	Non-linear specification
FinTech variables		
FinTech credit	0.0030	0.0361^{***}
	(0.0046)	(0.0119)
FinTech credit squared		-0.0021^{***}
		(0.0007)
Bank-level control variables		
Bank size	0.3141^{***}	0.3073^{***}
	(0.0451)	(0.0448)
Noninterest income to total income	0.1332^{***}	0.1105^{***}
	(0.0350)	(0.0356)
Overheads to total assets	-0.1693^{***}	-0.1548^{***}
	(0.0207)	(0.0212)
Regulatory capital adequacy ratio	0.3813^{***}	0.3839^{***}
	(0.0563)	(0.0560)
Deposit to assets ratio	0.1395	0.1651^{*}
	(0.0894)	(0.0893)
Loan to assets ratio	-0.3640^{***}	-0.3953^{***}
	(0.1031)	(0.1029)
Country control variables		
GDP growth rate	0.0042	0.0056
	(0.0069)	(0.0069)
Inflation	1.0037^{***}	1.1222^{***}
	(0.2063)	(0.2088)
Trade openness	-0.3821^{***}	-0.4985^{***}
	(0.0857)	(0.0935)
Intercept	-9.6598^{***}	-9.6594^{***}
	(0.7947)	(0.7897)
Time fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Clusters by country	Yes	Yes
Observations	673	673
R-squared	0.4708	0.4782
Number of countries	25	25
Wooldridge test	42.6283^{***}	42.6274^{***}
Modified Wald test	3046.3912^{***}	2799.2145^{***}
Pesaran CD test	17.0532^{***}	15.1913^{***}
Hausman test	149.6922^{***}	132.4532^{***}

Source: Author's calculations.
***, ** and * indicate statistically significance at 1%, 5% and 10% levels, respectively.
Robust standard errors are reported in brackets. Intercept is included in the model.
Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models.

Regarding the explanatory and control variables, the results reveal varying relationships. The results reveal a positive relationship between financial stability and bank size (proxied by the natural logarithm of total assets). This finding is consistent with the concentration-stability theory (Beck et al. 2013; Boot and Thakor 2000; Hu et al. 2004; Uhde and Heimeshoff 2009), which submits that increased bank size improves financial stability. The existing empirical literature supports the positive relationship between bank size and financial stability (see., Mirzaei and Aguir 2020; Fang et al. 2014; Laeven et al. 2016; Adusei 2015). Generally, large-sized banks tend to be more diversified, have more capital and better access to liquidity, and benefit from high economies, thus enabling them to diversify their loan portfolio risks efficiently better than smaller banks (Mirzaei and

Aguir 2020; Fang et al. 2014). Laeven et al. (2016) also hold that larger banks may have a competitive advantage in market-based activities, which normally require high fixed costs and enjoy economies of scale.

The results of non-interest income to total assets reveal a positive and significant relationship with financial stability. This result is expected since diversified banks generate more profit and are more resilient to financial instability (Mirzaei and Aguir 2020; Elsas et al. 2010), thus enhancing financial stability. Overhead costs to total assets are used to capture inefficiency. This variable negatively impacts financial stability, as shown by the negative and significant coefficient. Mirzaei and Aguir (2020) argue that inefficient banks are expected to be more prone to financial fragility.

The regulatory capital adequacy ratio is highly significant and positive, meaning that higher leverage ratios enhance financial stability. Similar findings exist in the literature (e.g., Ahamed and Mallick 2019; Davis et al. 2020). The deposit to asset ratio is positive and significant. This finding is consistent with Fang et al. (2014). The loan asset ratio is used to assess the impact of the size of loan composition or level of intermediation (Liu and Wilson 2013; Noman et al. 2018). A higher loan to assets ratio negatively impacts financial stability. This finding is consistent with Davis et al. (2020) but contrasts with Davis and Karim (2019), who found a positive relationship. Similar studies (e.g., Ahamed and Mallick 2019; Noman et al. 2018) also found a negative relationship between financial stability and loan to assets ratio.

Concerning country control macroeconomic variables, the GDP growth rate is non-significant. The inflation rate enhances financial stability. However, several studies link inflation to financial instability. Boyd et al. (2001) suggest that the relationship between inflation and financial stability is non-linear. In other words, it may even enhance stability which is consistent with the results of this study and that of Phan et al. (2020) and Fazio et al. (2015; 2018). Fazio et al. (2015) further add that systemically important banks in inflation-targeting countries appear less susceptible to risk-taking. This may be due to the effects of the transition policy towards a more credible and effective monetary policy. Most countries implementing inflation targeting faced high inflation levels in the period prior to inflation targeting implementation (Fazio et al. 2015). Other studies reveal that a higher inflation rate supports higher bank profitability (Batsinda and Shukla 2019; Guru et al. 2002), thus enhancing financial stability.

Trade openness is negative and highly significant. However, the empirical findings confirm that the existence and effect of a trade-openness relationship are still scarce and ambiguous (Keho 2017). These findings are consistent with the 'diversification-stability hypothesis' (Berger et al. 2017b). The hypothesis suggests that higher trade openness provides diversification opportunities, enriches resource allocation, lowers bank risk-taking and leads to more efficient production and economic growth (Bui and Bui 2019; 2020; Hossain et al. 2020; Rahman et al. 2020; Fu et al. 2020; Ashraf 2018).

5.5.2. Robustness checks

To establish whether the core (baseline) results are robust, the study conducts several robustness checks to explore further the relationship between FinTech credit and financial stability using other alternative regression models. First, to address heteroskedasticity, serial correlation and cross-dependence issues associated with FE models, the Feasible Generalised Least Squares (FGLS) is employed (e.g., de Mendonca and Nascimento 2020). The FGLS follows $AR(1)$ and generates robust standard errors in the presence of heteroskedasticity, serial correlation and cross-dependence (Reed and Ye 2011). The FGLS is also justified since the number of the time period (T) is higher than the cross-section entities (N) of this study. The study precedes the estimations by checking for the data characteristics to avoid estimating spurious regression (Wooldridge 2010). The FGLS model corrects for cross-section dependence, heteroscedasticity, and autocorrelation (Moundigbaye et al. 2018; Sarafidis and Wansbeek 2012; Reed and Ye 2011). The FGLS estimator is adopted mainly because it enhances the efficiency of the estimates (Reed and Ye 2011).

Table 5.6 presents the FGLS results. The results based on the FGLS model confirm a non-linear (inverted U-shaped) relationship between FinTech and financial stability. Concerning bank-level control variables, bank size, overhead costs to total assets, non-interest income to total income, regulatory capital adequacy results remain the same as those under the FE model and are all significant. Only two bank-level control variables changed signs (loan to asset ratio and deposit to asset ratio). However, these two variables have been shown by empirical literature that they can either negatively or positively influence financial stability. Regarding country control variables, the GDP growth rate remains non-significant. The trade openness variable has an opposite sign compared to the baseline model is highly significant.

Second, one might argue that different periods of observations across countries can affect the estimated association between financial stability and FinTech credit. The weighted least squares (WLS) regression is used. The results still reveal a non-linear relationship between financial stability and FinTech credit (*Table 5.7*). The signs and significance levels of all other control variables remain unchanged. In addition, the results are decomposed by each individual subindex. *Table 5.8* presents the results. The main results for BSI and FDI follow those of the overall FSI, while for FCI, the opposite is observed. The opposite results revealed by FCI could mean that relying on a single measure (unidimensional) as a proxy for the overall FSI could be misleading. For further robustness checks and to examine whether the aggregate FSI is stable, this study employed alternative FSI measures using differential weighting. *Table 5.9* presents the results. Overall, the results across the three alternative measures of FSI reveal a significant non-linear (inverted U-shaped) relationship between FinTech credit and financial stability. This finding suggests that the aggregate FSI is stable and that the main results are robust.

Table 5.7: Financial stability and FinTech credit: Robustness checks

	FGLS		WLS	
	Linear	Non-linear	Linear	Non-linear
FinTech variables				
FinTech credit	0.0049*	0.0488***	0.0018	0.0514***
	(0.0026)	(0.0075)	(0.0035)	(0.0085)
FinTech credit squared		-0.0036***		-0.0040***
		(0.0005)		(0.0006)
Bank-level control variables				
Bank size	0.0228***	0.0162***	0.0227***	0.0158***
	(0.0033)	(0.0037)	(0.0054)	(0.0053)
Noninterest income to total income	0.0698***	0.0513**	0.0603*	0.0674**
	(0.0196)	(0.0203)	(0.0302)	(0.0294)
Overheads to total assets	-0.0982***	-0.0872***	-0.1128***	-0.0965***
	(0.0140)	(0.0136)	(0.0163)	(0.0161)
Regulatory capital adequacy ratio	0.0649*	0.0899*	-0.0127	-0.0170
	(0.0374)	(0.0373)	(0.0486)	(0.0475)
Deposit to assets ratio	-0.0441**	-0.0857***	-0.0358	-0.0684**
	(0.0210)	(0.0201)	(0.0246)	(0.0244)
Loan to assets ratio	0.0714**	0.0676**	0.0431	0.0245
	(0.0330)	(0.0328)	(0.0392)	(0.0381)
Country control variables				
GDP growth rate	-0.0012	-0.0002	0.0017	0.0026
	(0.0040)	(0.0046)	(0.0089)	(0.0086)
Inflation	1.2189***	1.1354***	1.2892***	1.2488***
	(0.1136)	(0.1103)	(0.1334)	(0.1301)
Trade openness	0.0431**	0.0177***	0.0856***	0.0567**
	(0.0171)	(0.0172)	(0.0219)	(0.0220)
Intercept	-7.1783***	-6.7109***	-7.4295***	-7.1749***
	(0.5653)	(0.5519)	(0.6391	(0.6234)
Time fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes	Yes
Observations	673	673	673	673
R-squared†	-	-	0.3343	0.2935
Number of countries	25	25	25	25

Source: Authors' calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels, respectively. Robust standard errors are reported in brackets. Intercept is included in the model. †R-squared for FGLS is not reported.

Table 5.8: Financial stability indices and FinTech credit: Fixed effects regression model

	BSI	FDI	FCI
FinTech variables			
FinTech credit	0.1568***	0.0095	-0.0513***
	(0.0483)	(0.0145)	(0.0121)
FinTech credit squared	-0.0066**	-0.0019**	0.0015***
	(0.0028)	(0.0009)	(0.0007)
Bank-level control variables			
Bank size	0.6099***	0.6031***	0.2049***
	(0.1822)	(0.0549)	(0.0456)
Noninterest income to total income	0.1536	0.1040**	0.0394
	(0.1445)	(0.0435)	(0.0362)
Overheads to total assets	-0.2097**	-0.2360***	-0.1431***
	(0.0860)	(0.0259)	(0.0215)
Regulatory capital adequacy ratio	0.1696	0.3343***	0.4890***
	(0.2275)	(0.0685)	(0.0569)
Deposit to assets ratio	1.9872***	-1.2466***	0.5332***
	(0.3628)	(0.1092)	(0.0908)
Loan to assets ratio	-3.9233***	1.5080***	0.2680***
	(0.4183)	(0.1259)	(0.1047)
Country control variables			
GDP growth rate	0.0476*	-0.0159*	0.0107
	(0.0281)	(0.0085)	(0.0070)
Inflation	1.5222*	-0.6985***	1.1263***
	(0.8483)	(0.2554)	(0.2123)
Trade openness	-2.1323***	-0.0720	0.1645*
	(0.3799)	(0.1144)	(0.0951)
Intercept	-9.4721***	-6.7681***	-10.4334***
	(3.2090)	(0.9663)	(0.8032)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes
Observations	673	673	673
R-squared	0.2382	0.6092	0.7421
Number of countries	25	25	25
Wooldridge test	24.054***	77.235***	131.348***
Modified Wald test	15545.81***	6485.84***	3957.98***
Pesaran CD test	19.925***	14.983***	1.549***

Source: Author’s calculations.

***, ** and * indicate statistically significance at 1%, 5% and 10% levels, respectively.

Robust standard errors are reported in brackets. Intercept is included in the model.

BSI: Bank stability index; FDI: Financial development index; FCI: Financial conditions index.

Table 5.9: Financial stability indices and FinTech credit: Fixed effects regression model

	$FSIw_1$	$FSIw_2$	$FSIw_3$
FinTech variables			
FinTech credit	0.0533***	0.0881***	0.0935***
	(0.0140)	(0.0211)	(0.0224)
FinTech credit squared	-0.0028***	-0.0040***	-0.0042***
	(0.0008)	(0.0012)	(0.0013)
Bank-level control variables			
Bank size	0.3442***	0.3653***	0.4141***
	(0.0527)	(0.0797)	(0.0846)
Noninterest income to total income	0.1348***	0.1657***	0.1929***
	(0.0418)	(0.0632)	(0.0671)
Overheads to total assets	-0.1702***	-0.1895***	-0.2053***
	(0.0249)	(0.0376)	(0.0399)
Regulatory capital adequacy ratio	0.3508***	0.2994***	0.2790***
	(0.0658)	(0.0995)	(0.1056)
Deposit to assets ratio	0.1248	0.5426***	0.3761**
	(0.1049)	(0.1587)	(0.1684)
Loan to assets ratio	-0.5399***	-1.3352***	-1.2610***
	(0.1209)	(0.1829)	(0.1942)
Country control variables			
GDP growth rate	0.0065	0.0161	0.0153
	(0.0081)	(0.0123)	(0.0130)
Inflation	1.0456***	1.3107***	1.0789***
	(0.2453)	(0.3710)	(0.3938)
Trade openness	-0.6202***	-0.9728***	-0.9838***
	(0.1098)	(0.1661)	(0.1763)
Intercept	-9.4282***	-9.6972***	-9.3558***
	(0.9277)	(1.4033)	(1.4898)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes
Observations	673	673	673
R-squared	0.3823	0.2931	0.2707
Number of countries	25	25	25
Wooldridge test	43.020***	28.355***	39.251***
Modified Wald test	3362.79***	4463.25***	5332.80***
Pesaran CD test	15.875***	18.090***	17.422***

Source: Author's calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model. Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models.
$FSIw_1$: FSI with differential weighting: 0.4, 0.4 and 0.2 for BSI, FDI and FCI, respectively.
$FSIw_2$: FSI with differential weighting: 0.6, 0.3 and 0.1 for BSI, FDI and FCI, respectively.
$FSIw_3$: FSI with differential weighting: 0.6 and 0.4 for BSI and FDI, respectively.

5.6. Conclusions

The main purpose of this empirical chapter was to investigate the impact of FinTech credit on overall financial stability. The empirical results have indicated a strong relationship between FinTech credit and financial stability. Specifically, the results reveal a non-linear (inverted U-shaped) relationship, suggesting that FinTech credit may be beneficial to overall financial stability in the short run, but in the long run or beyond a certain threshold may disrupt the financial stability.

These results are consistent with empirical and theoretical literature. Specifically, the non-linear relationship corresponds with more recent empirical work suggesting the ‘vanishing positive effects’ (Gründler 2019). The results are also consonant with the threshold effect, where FinTech credit is beneficial to financial stability only up to a certain threshold, beyond which further credit expansion adversely affects financial stability (Law and Singh 2014). Indeed, extensive banking crisis literature reveals that rapid credit growth can potentially escalate into financial crises and identify credit growth as one of the most robust crisis predictors (Aikman et al. 2014; Röhn et al. 2015).

The study also validates the theories of the “good and bad” side of financial innovation and that ‘too much finance’ can hurt the stability of a financial system (Zhu et al. 2020a; Arcand et al. 2015). Indeed, the expansion of FinTech credit may cause financial instability, particularly in events of excessive levels of credit. Furthermore, it is consistent with the ‘cross-sector substitution’ that suggests that the substitution effects may enhance financial stability yet engendering new risks to financial stability (Cizel et al. 2019). This becomes stronger, especially when credit growth shifts away from banks, but household and corporate debts continue to accumulate in the nonbank sector, creating new problems for MaPP and raising vulnerabilities in the financial system (Cizel et al. 2019).

CHAPTER 6: DOES FINTECH CREDIT INCREASE OR DECREASE BANK RISK-TAKING? A BANK STABILITY PERSPECTIVE.

6.1. Introduction

The post-financial crisis has marked a dramatic shift toward credit disintermediation through FinTech credit platforms and imposing disruption on established traditional financial intermediaries (Agarwal and Chua 2020; Palmié et al. 2020; Hikida and Perry 2020). Within the context of banking, the structure and nature of financial services, markets, and traditional institutions have increasingly transformed due to emerging disruptive and innovative technological practices following the latest financial crisis (Gomber et al. 2017). Such disruptive innovations have potential implications not only for consumers but pose distinct challenges for incumbent financial service providers and the regulatory and supervisory frameworks, which are even more important as the financial services industry evolves (Anagnostopoulos 2018).

The FinTech credit transformation has further sparked debates regarding its ability to disrupt the traditional banking system (Phillipon 2019; Foottit et al. 2016). The rise of FinTech credit today coincides with the contraction of traditional bank credit to consumer and small business lending (Buch 2019). Amid the extended slow economic growth, rising nonperforming loans, increasing regulatory, competitive forces and operating costs, evidence show a global decline of traditional bank market share since the financial crisis (FSB 2020b; Wójcik 2021; Buch 2019; Pereira da Silva 2018). The latest available quantitative evidence confirms that the NBFI has grown faster than the traditional banking sector over the past decade, now currently estimated to be about 50% of global financing activities (FSB 2020b).

The boundaries between FinTech innovation and traditional banking are rapidly blurring as they become increasingly interconnected (Gray and Leibrock 2017) and drawing banks and nonbanks even closer, posing risks for both (Sahay et al. 2020). Such risks could further become more aggravated when non-bank activities have stronger links to the traditional banking system and even worsen the rise in the systemic importance of non-traditional players (FSB 2019a; Aikman et al. 2019). The link between FinTech credit and traditional bank credit has been explored, particularly on whether they compete or supplement each other (see., Cornelli et al. 2021; Hornuf et al. 2021; Ali et al. 2019;

Zhang et al. 2019). However, the extant literature is still embryonic in empirically exploring the interaction between FinTech credit and the traditional banking system, particularly how its growth may affect bank risk-taking.

Relevant exposures of traditional banks to new market players (FinTech credit) are inherently (directly or indirectly) linked to traditional financial institutions (Hornuf et al. 2021; Li et al. 2020a; Bertsch and Rosenvinge 2019. Bank risk exposure to FinTech credit may materialise should there be a strong direct link or exposure between FinTech credit and the banking sector. This could be through interconnectedness as the margins between the FinTech and traditional banking sectors rapidly diminish. As a result, FinTech credit may trigger bank and financial instability both directly and through their own account and through various channels and interconnectedness to the traditional banking system (Buch 2019; European Systemic Risk Board (ESRB) 2016). Moreover, a significant increase in empirical findings underscores the adverse effects of capital regulation on risk-taking behaviour, and those excessive risks inhibit bank stability (Dias 2021; Mohsni and Otchere 2018; Zheng and Moudud-Ul-Huq 2017; Laeven and Levine 2009). FinTech credit platforms are believed to benefit from capital regulatory advantage as they are currently not subjected to stringent regulation (Frost et al. 2019; Claessens et al. 2018).

The notion of "disruptive innovation" is often used in a broader context to designate any innovation that revolutionises an industry and significantly alters its competitive patterns (Kumaraswamy et al. 2018; Christensen et al. 2015). FinTech credit presents a potentially existential threat to traditional financial intermediation (Delabarre 2021; Foottit et al. 2016) but is largely associated with the concepts of revolutionary, innovative (Chishti and Barberis 2016), decentralised, disintermediated (Ehrentraud et al. 2020b; Minto et al. 2017). Existing studies, therefore, present different views about the impact of FinTech credit on bank risk-taking. On the one hand, FinTech credit creates new market competition for several banking business segments to compete with banks in their core lending function (Stulz 2019; Vives 2019a).

Increased competition may generate a larger impact on banks by eroding or putting pressure on the bank profit margins, thus increasing competition and contestability of banking markets and perhaps leading to increased bank risk-taking (Vives 2019a; Foottit et al. 2016). Several empirical findings have supported the substitution or competition view on the link between FinTech credit and bank credit (e.g., Havrylchyk et al. 2020;

Vives 2019a; Tang 2019; de Roure et al. 2022). The proliferation of FinTech credit may affect characteristics of traditional banks, including growth, profitability, liquidity and security, thus impacting the overall performance of banks (Dong et al. 2020). FinTech innovation, therefore, affects the fragility of traditional financial institutions through the channel of profitability (Fung et al. 2020). However, the literature also suggests that FinTech credit may have favourable effects under certain conditions, i.e., supplementary or complementary view (Cornelli et al. 2020; Tang 2019; de Roure et al. 2022). FinTech credit may have beneficial effects in the long run by reducing bank risk-taking as banks adapt to new competition. They may thus enhance efficiency and foster healthy competition in the banking sector (Fuster et al. 2019; Bertsch and Rosenvinge 2019; Mnohoghitnei et al. 2019; Navaretti et al. 2018).

The scholarly foundation for the present views of FinTech credit is weak, with mixed views on the potential effects of FinTech credit on bank risk-taking. Some views underscore the negative effects of FinTech developments that increase incentives for bank risk-taking (e.g., Phan et al. 2021; Haddad and Hornuf 2021; Guo and Shen 2019). Others claim that well-capitalised banks are less inclined to increase risk-taking or improve financial stability (Noman et al. 2018). Fung et al. (2020) suggest that FinTech enhances bank stability in emerging markets but undermines it in developed markets. Another strand of literature claims that FinTech credit may substitute bank credit (Havrylchyk et al. 2020; de Roure et al. 2022; Ziegler et al. 2021), while the other vouch for a complementary viewpoint (Cornelli et al. 2021; 2020; Zhang et al. 2019).

Despite the recent progress in banking and finance literature on bank risk-taking, there still remains a question on whether or not the emergence of FinTech credit reduces incentives for bank risk-taking. The limited research in this area may also reflect the limited data and a general understanding of the implications of nonbank credit intermediation for the banks' general equilibrium of risk-taking incentives. The seemingly ambiguous views on this interaction validate the question of this study. Against this backdrop, this study explores the relationship between FinTech credit and bank risk-taking using five main bank risks: credit, liquidity, insolvency, leverage, and portfolio risks. The remainder of the chapter is structured as follows. *Section 6.2* presents variable definitions and descriptions, followed by *Section 6.3*, presenting descriptive statistics. *Section 6.4* presents an empirical approach, while *Section 6.5* presents results and discussions. Last, *Section 6.6* provides summary and conclusions.

6.2. Variable definitions and description

6.2.1. Bank risk-taking measures (dependent variables)

Measures of bank (in)stability, profitability, and performance are the most commonly used dimensions in the empirical banking literature to measure bank risk-taking (Ahamed and Mallick 2019; Scott et al. 2017). To evaluate bank risk-taking, the present study employs five specific risk-taking measures as dependent variables. Most bank risk and stability literature usually employ a one-dimensional risk indicator, such as the Z-score, capital ratios or the share of non-performing loans (NPL), to mention but a few. However, there are some uncertainties about whether these indicators fully capture bank risk, suggesting that bank risk is multidimensional in nature (Klomp and de Haan 2014). Zhao et al. (2009) also suggest that most balance-sheet-based indicators may contain some measurement error due to differences in calculation methods or on- and off-balance issues. Agoraki et al. (2011) even suggest that leverage, asset quality indicators, and market structure are more informative indicators of bank risk than indicators of efficiency, profitability, and management qualities. If there exists a relationship between FinTech credit and bank risk-taking, the study can further distinguish the impact of FinTech credit on various bank risk-taking measures.

A substantial body of literature explores the risk-taking behaviour of traditional banks (Dias 2021; Bitar et al. 2018; Mohsni and Otchere 2018; Bhagat et al. 2015; Laeven and Levine 2009). Literature thus identifies several risk indicators for banks that are believed to influence banks' risk-taking (Ashraf et al. 2016). These are varying various types of bank risks and their basic characteristics (Zhu et al. 2020b; Begley et al. 2017). These measures are of macroprudential relevance (Davis et al. 2020); hence this study uses different bank risks as opposed to bank risk aggregation. These are typically standard bank risk variables aggregated to the banking sector level and represent various aspects of bank risk. Based on empirical literature that captures bank risk behaviour, five variables are used to capture key bank risk factors: insolvency, credit, liquidity, portfolio and leverage risks, in line with Al-Shboul et al. (2020). Decomposing bank risk into various banks' risk-taking measures helps identify the various channels through which FinTech credit may affect bank risk-taking. Except for the credit risk represented by NPL, the remaining four measures are derived from the additive components of the Z-score. Below each of the mentioned risk variables used is discussed.

6.2.1.1. Insolvency risk

First, the insolvency risk is proxied by the *Z*-score measured *as ((ROA+Equity/Total Assets)/Std. of ROA)*. The Z-score is a widely used accounting-based risk measure used in the banking and financial stability-related literature but less so in macroprudential policy circles (Davis et al. 2020; Siddik and Kabiraj 2018). Despite the criticism of it being based on accounting data, Chiaramonte et al. 2016 demonstrate that the Z-score can, in fact, predict about 76% of bank failures in the US; hence, it is a well-accepted measure of risk-taking (Beck et al. 2013, Laeven and Levine 2009). The Z-score, therefore, measures the probability of default of a country's domestic banking system (see Davis et al. 2020; Abdelsalam et al. 2020; Al-Shboul et al. 2020; Trinh et al. 2020; Davis and Karim 2019; de-Ramon et al. 2018).

A higher *Z*-score indicates a lower probability of a country's banking system becoming financially distressed or unstable, that is, a lesser distance from default and vice versa. Conversely, a lower Z-score means a higher probability of failure or insolvency, thus, greater financial instability (Degl'Innocenti et al. 2018; Li et al. 2017; Fang et al. 2014; Beck et al. 2012; Boyd and Runkle 1993). The Z-score is computed as follows:

$$Z - score \ = Ln\left[\frac{\left(ROA_{jt} + EA_{jt}\right)}{\sigma(ROA)_{jt}}\right] \tag{6.1}$$

where ROA_{jt} and EA_{it} are return on assets and equity-to-assets ratio (respectively) for country *j* at time *t*. The standard deviation of *ROA* specified as $\sigma(ROA)_{jt}$, and is computed over twelve quarters (3 years) for the sample period.

Z-score is equal to the number of standard deviations by which returns (*ROA*) would decrease below the predictable mean value to deplete all equity in the bank (Beck et al. 2013; 2016; Fang et al. 2014), causing the bank to be insolvent (De Nicoló 2000).[26] To address the high skewness of the Z-score, the natural logarithm of the *Z*-score is used to normalise the distribution (e.g., Ahamed and Mallick 2019; Noman et al. 2018; Fang et al. 2014). Lepetit and Strobel (2015) posit that a natural log-transformed Z-score is proportional to the log odds of insolvency, making it a good bankruptcy or insolvency risk measure. To facilitate comparability with other bank risk measures, the Z-score is

[26] The inverse Z-score can be used to approximate the bank's probability of default (Fang et al. 2014; Ahamed and Mallick 2019), assuming bank profits are normally distributed (Roy 1952).

multiplied by (−1), so that higher values in the analysis indicate higher bank risk-taking (Danisman and Demirel 2019).

6.2.1.2. Credit risk

Second, the ratio of non-performing (defaulting) loans (NPL) to gross loans is used to measure the asset quality in the loan portfolio across the whole banking sector (credit risk) (Al-Shboul et al. 2020; Trinh et al. 2020; Abdelsalam et al. 2020) and bank risk-taking behaviour (Kasman and Kasman 2015; Ashraf et al. 2016; Saif-Alyousfi et al. 2020). This measure has been widely used in the empirical literature (Al-Shboul et al. 2020; Chaibi and Ftiti 2015) as a macroprudential indicator used by policymakers to monitor the stability of banking systems. Kasman and Kasman (2015) suggest that credit risk is the main source of banking risk and that their inability to control the rise in NPL may result in banking failures. A higher value of NPL indicates higher bank credit risk and low asset quality. Following empirical literature (Al-Shboul et al. 2020; Chaibi and Ftiti 2015), the credit risk is expressed as follows:

$$CR_{jt} = Ln\left[\frac{NPL_{jt}}{\left(100 - NPL_{jt}\right)}\right] \tag{6.2}$$

where CR_{jt} is the credit risk for country *j* at time *t*, NPL_{jt} is the ratio of non-performing loans to gross loans for country *j* at time *t*. The rate of non-performing loans to total loans is the key indicator to measure the level of credit risk. This is because it identifies problems with the loan portfolio quality, whereas it captures the value of loans for which the bank expects it to have difficulty collecting.

6.2.1.3. Liquidity risk

Third, the ratio of liquid assets over total assets is used to measure bank liquidity (Al-Shboul et al. 2020; Singh and Sharma 2016). The level of liquidity influences the ability of a banking system to withstand shocks. Banks require liquidity to carry out daily operations (Singh and Sharma 2016). It facilitates the availability of funds in the event of expected or unexpected cash demands by customers. This indicator also reflects the maturity structure of the asset portfolio and can highlight excessive maturity mismatches and a need for more careful liquidity management (Sundararajan et al. 2002).

Taking the natural logarithm of the ratio of liquid assets over total assets, the liquidity risk is expressed as follows:

$$LQ_{jt} = Ln\left(\frac{LA_{jt}}{TA_{jt}}\right) \tag{6.3}$$

where LQ_{jt} is liquidity risk for country *j* at time *t*; LA_{jt} is liquid assets, and TA_{jt} is total assets. To facilitate comparability with other bank risk measures, the LQ_{jt} is multiplied by (−1), so higher values in the analysis indicate higher bank risk-taking (Al-Shboul et al. 2020). Moreover, a higher value indicates higher bank liquidity risk and vice versa (Bourgain et al. 2012; Danisman and Demirel 2019).

6.2.1.4. Portfolio risk

Fourth, the first additive component of Z-Score, the ratio of *ROA* to the standard deviation of *ROA,* as in Barry et al. (2011), is used to measure portfolio risk. The Z-Score is not only used as a bank stability indicator but allows this study to further decompose it into other components. Other studies use this decomposition process of Z-score's additive components in the empirical literature (Fung et al. 2020; Al-Shboul et al. 2020; Lepetit et al. 2008; Barry et al. 2011). Therefore, the portfolio risk is computed as follows:

$$PR_{jt} = Ln\left(\frac{ROA_{jt}}{\sigma(ROA)_{jt}}\right) \tag{6.4}$$

where PR_{jt} is the portfolio risk for country *j* at time *t*, ROA_{jt} represents *ROA*, and $\sigma(ROA)_{jt}$ denotes the standard deviation of *ROA*. The *ROA* part considers both the level of returns and the volatility of returns as a measure of banks' portfolio risk. A higher value indicates lower bank portfolio risk and vice versa. The analysis multiplies this measure by (−1) so that higher values indicate greater bank portfolio risk.

6.2.1.5. Leverage risk

Finally, the additive component of the Z-score, the ratio of equity capital to assets ratio divided by the standard deviation of *ROA*, is used to compute bank leverage risk. Taking the natural logarithm, the formula is expressed as follows:

$$LR_{jt} = Ln\left(\frac{EA_{jt}}{\sigma(ROA)_{jt}}\right) \tag{6.5}$$

where LR_{jt} is the leverage risk for country j at time t; EA_{jt} represents equity capital to assets ratio for country j at time t, and $\sigma(ROA)_{jt}$ denotes the standard deviation of ROA. To facilitate comparability with other bank risk measures, this study uses the natural logarithm of the liquidity ratio multiplied by (-1), so that higher values in the analysis indicate higher bank risk-taking (Al-Shboul et al. 2020).

6.2.2. Independent variables

6.2.2.1. Main independent variable (FinTech credit)

The FinTech credit share (*FIN_S*) is used as the main independent variable. Following Frost et al. (2019), FinTech credit is measured as a share of the total volumes of loans originated by FinTech platforms to total credit to the private non-financial sector. *FIN_S* is then converted into the natural log of FinTech credit share.

6.2.2.2. Bank-specific control variables

Bank-specific variables were selected following other studies (Beck et al. 2013). Based on these studies, a total of seven bank-specific variables are included to control for an array of common bank-specific characteristics in the model (Laeven and Levine 2009). First, the study captures market concentration to measure the degree of bank concentration using the Herfindal-Hirschmann Index (*HHI*). The *HHI* is widely used in the banking literature and by supervisory regulators, calculated as the sum of the square of each bank's share (or market share of the largest banks) in a banking sector. The competition (or the market power) impacts traditional banks' financial results and functioning, such as lending activity (Badarau and Lapteacru 2020). Moreover, certain bank competitive behaviours or market power can influence bank risk-taking behaviour (Badarau and Lapteacru 2020). Therefore, bank concentration controls for bank competition and cross-country variation in the banking sector structure (Srairi 2019).

Literature on the relationship between concentration and bank risk provides contrasting views. The traditional concentration/competition-fragility paradigm holds that concentration increases fragility. According to this view, a high-competition environment tends to cause banks to seek for alternative revenue and adopt more aggressive risk-taking behaviours by investing in riskier assets or engaging in activities that promise higher returns to compensate losses (Badarau and Lapteacru 2020). Furthermore, a decrease in market concentration level can aggravate the 'too big to fail' or 'too-important-to-fail' moral hazard and further induce bank risk-taking, consequently causing financial fragility (Beck et al. 2010; Demirgüç-Kunt and Huizinga 2013).

Moreover, systemic risk also becomes more significant in highly competitive or concentrated markets due to correlations between banks' risk-taking decisions and since a single bank's probability may become potentially large enough to impact the overall system (Badarau and Lapteacru 2020; Nier et al. 2007). Several empirical works of literature confirm the "concentration-fragility" view (see Saif-Alyousfi et al. 2020; Pawlowska 2016; Kasman and Kasman 2015). Pawlowska (2016), using the Z-score, *HHI*, and loan risk (measured by NPL), finds evidence for the existence of a "too-big-to-fail" effect. Saif-Alyousfi et al. (2020) prove that lower banking market concentration increases the risk-taking of low-capitalised, low-liquid and small banks. Weiß et al. (2014) find a significant increase in the idiosyncratic default and the systemic risk of acquirers following a bank merger. Similarly, previous empirical literature also reveals evidence of a negative correlation indicating that a concentrated market could destabilise bank stability, which could emanate from increased bank risk-taking. Some studies hold that greater concentration has a negative impact on the Z-score (Uhde and Heimeshoff 2009; Kasman and Kasman 2015).

A contrasting view follows the concentration/competition-stability view widely supported by theoretical and empirical evidence (Fiordelisi and Mare 2014). The arguments in support of this postulate that a concentrated banking system tends to be more stable over time and is less likely to engage in excessively risky lending behaviour (Allen and Gale 2004; Repullo 2004; Beck et al. 2006). Furthermore, highly concentrated banking systems are resilient to higher risk absorption (Shijaku 2017) and less prone to contagion (Sáez and Shi 2004). Banks in more concentrated markets are more informed about larger proportions of their borrowers, thus lessening their credit risk exposure (Marquez 2002). This is supported by various empirical literature. For instance, Haq and Heaney (2012) found market concentration is negatively related to European banks' credit risk. De Haan and Poghosyan (2012) support the risk-shifting effect as bank earnings volatility decreases with market concentration. Kick and Prieto (2015) suggested varying relationships between bank competition and bank risk. However, Berger et al. (2017b) suggest the existence of a non-linear relationship between concentration and bank stability. Berger et al. (2017b) and Liu et al. (2012) assert that market concentration may encourage stability and fragility concurrently. Liu et al. (2013) add that higher competition enhances stability in a highly concentrated market but may lead to fragility in a competitive banking sector.

Second, the study controls for bank size measured as the natural logarithm of total assets (*SIZE*) (Ahamed and Mallick 2019; Yusgiantoro et al. 2019; Noman et al. 2018). Bank's risk-taking varies with their size and market share (Kim et al. 2016). The relationship between bank size and bank risk-taking is somewhat mixed, as explained by the concentration-stability and concentration-fragility hypotheses (Mirzaei and Aguir 2020; Uhde & Heimeshoff 2009). The concentration-stability hypothesis suggests that larger banks tend to support bank stability (Adusei 2015). Larger banks tend to have larger capital (Fang et al. 2014), are more technologically advanced, and have better access to liquidity (Ali and Iness 2020; Mirzaei and Aguir 2020). The high economies of scale and scope enable banks to be more diversified, with a greater capacity to effectively manage risk compared to smaller banks (Al-Shboul et al. 2020; Maji and Hazarika 2018; Fang et al. 2014; Laeven et al. 2016).

On the contrary, the concentration-fragility view submits that larger banks in a concentrated market reduce stability by exacerbating moral hazard problems resulting from the "too big to fail" hypothesis (Ahamed and Mallick 2019; Yusgiantoro et al. 2019; Beck et al. 2013). Under the "too big to fail" presumption, large banks tend to have incentives to take on more risks when anticipating government bailouts (Zardkoohi et al. 2018) which might lower the quality of assets (Laeven et al. 2016). However, Carlson and Rose (2019) find that institutional creditors with large exposures tend to withdraw funds from systemically important financial institutions during periods of bank runs despite guaranteed government support. Moreover, large or oversized financial systems are associated with financial instability due to their tendency to generate financial shocks in the first place (Bush et al. 2015), significantly contributing to systemic losses under severe shocks (de Souza 2016). Large banks also tend to have lower capital ratios, less stable funding, and more exposure to potentially risky market-based activities (Laeven et al. 2016). Therefore, bank size can either be negatively or positively related to bank risk-taking.

Third, following Demirgüç-Kunt and Huizinga (2010) and Köhler (2014), I include the non-interest income ratio, calculated as non-interest income divided by the total income

(*NITI*), to measure the degree of the bank's revenue diversification. Non-traditional banking activities have been widely used in literature in the form of non-interest revenues (see. Williams 2016; Köhler 2014). Therefore, *NITI* is an important indicator that reflects the bank's non-interest-generating activities (Demirgüç-Kunt & Huizinga 2010) and the proportion of income from non-traditional activities toward the bank's total income generation (Chen et al. 2020).

The literature on the effect of bank diversification has provided conflicting results on the impact of bank diversification on bank risk. The traditional view holds that revenue from non-interest activities may improve the bank's total income and stability via the diversification channel (as banks can expand their income source). Banks tend to be more stable than traditional interest income, more profitable and resilient to bank risk (Ali and Iness 2020; Elsas et al. 2010). Thus, the bank's risk is reduced through diversification (Laeven and Levine 2007; Stiroh and Rumble 2006). The studies indicate that bank diversification is associated with lower bank risk (Hamdi et al. 2017; Lee et al. 2014). Moreover, diversification within non-interest activities reduces bank insolvency or default risk (Cheng et al. 2020).

However, several studies do not support the banks' diversification strategy and argue that shifting to non-interest activities increases bank risk and even reduces profits. Higher non-interest income shares are associated with increased bank risk (Chen et al. 2020; Nguyen 2019; Hamdi et al. 2017). Higher non-interest income shares also positively affect bank returns volatility (Stiroh and Rumble 2006). Studies also demonstrate that the shift toward non-traditional banking activities significantly impacts the probability of a bank failure (DeYoung and Torna 2013). An increased share of *NITI* increases systemic banking risk (tail betas) and reduces bank stability (Brunnermeier et al. 2020a; Bostandzic and Weiß 2018; Köhler 2015), thus increasing bank risk. Engle et al. (2014) show that income diversification is positively related to systemic risk and does not reduce the volatility of profitability in the US, Germany, and the UK. Others found no convincing evidence that suggests that noninterest-generating activities impair bank profitability or increase bank failure, insolvency, or systematic risks during both crisis and no-crisis periods (Saunders et al. 2020; 2016; Weiß et al. 2014; Zhou 2014).

Fourth, the ratio of overhead costs to total assets (*OVERHH*) is used as a bank control variable to capture bank inefficiency. Bank efficiency plays a crucial role in determining the riskiness of banks. However, the relationship between bank inefficiency and bank risk yields mixed results. Bank efficiency tends to decrease due to higher monitoring costs or the problem of being “too complex to manage”. The “bad management (*BM*)” hypothesis holds that increased bank inefficiency induces stronger risk-taking incentives and that lower-cost efficiency may signal poor-risk monitoring and management practices. As such, bank inefficiency may exaggerate agency problems. As such, it may attempt to boost their returns by lowering their lending standards and risk management techniques, or relaxing their monitoring efforts, consequently leading to increased bank risk (Fiordelisi et al. 2011; Berger and DeYoung 1997). Operational inefficiency negatively affects bank profitability (Yao et al. 2018b; Sun et al. 2017; Tan 2016) and lowers stability levels (Polizzi et al. 2020; Wu et al. 2020). Wu et al. (2020) find that the Z-scores (in the stability sense) and banks’ efficiency are positively correlated. The literature concurs that banks with higher efficiency would have a lower chance of failure.

Conversely, the “risk-averse management (*RAM*)” hypothesis by Hughes (1999) maintains that an increase in bank inefficiency (low efficiency) reduces bank default risk. Other things held equal; risk-averse managers may refrain from participation in risky profit-generating activities, resulting in reduced default risk, suggesting a risk-averse strategy that might be deemed inefficient. Athanasoglou et al. (2008) also argue that well-managed banks have the ability to reduce operating costs and increase bank profitability. Saeed and Izzeldin (2016) find that decreased default risk is associated with lower efficiency levels (or high inefficiency). The “moral hazard hypothesis *(MH)”* (see Gorton and Rosen 1995) holds that a reduction in bank inefficiency (or high efficiency) increases bank default risk. The “moral hazard hypothesis” is based on the classical problem of excessive risk-taking as such well-established ‘risk-loving managers of an efficient bank may be enticed to follow an expansionary strategy, which may turn out to be excessively risky. Similarly, the “skimping” hypothesis (see Berger and DeYoung 1997) suggests that banks can become more efficient by opting to cut their operating costs, either by increasing their balance sheets' size or rolling over bad loans.

Fifth, following Beck et al. (2013), the regulatory capital to risk-weighted assets ratio (*RCAR*) is included as a proxy for bank leverage or capitalisation and to control for capital risk (see. Davis et al. 2020; Abdelsalam et al. 2020; Ahamed and Mallick 2019; de-Ramon et al. 2018; Yusgiantoro et al. 2019). Previous studies on the interaction of the bank’s capital adequacy and bank risk are somewhat mixed. The traditional theory suggests that capital regulation and constraints can inhibit banks' risk-taking behaviours or moral hazards by restraining bank risk assets' overexpansion. Therefore, *RCAR* reflects the regulatory requirements for bank capitalisation (Buch and Prieto 2014; Fonseca and González 2010) that ensure their robustness and resilience to shocks to their balance sheets. It also prevents possible bank runs, crises and bankruptcy. Increasing the banks' capital strength and their ability to resist risks influences banks' ability to optimize both their costs and profits (Abdelsalam et al. 2020) and influences risk levels (Hunjra et al. 2020), thus enhancing the banking systems' stability (Bouheni et al. 2014).

The "skin in the game" theory suggests that a higher capital ratio would be consistent with lower risk (Bitar et al. 2018; Bouheni and Rachdi 2015; Pereira and Saito 2015). Bougatef and Korbi (2019) and Daher et al. (2015) found a negative two-way relationship between changes in the capital buffer and credit risk. Le (2019) also finds a negative relationship between bank risk (ratio of loan loss reserves to total assets) and capital, suggesting that credit risk and financial leverage reinforce each other. Chiaramonte and Casu (2017) revealed that the default risk of banks decreases whenever capital increases.

A contrasting viewpoint specifies a positive relationship between capital and risk level ("the regulatory hypothesis"), suggesting that capital acts as a buffer; hence, banks increase their capital ratios or buffers in response to an increase in risk exposure (Davis et al. 2020; Bitar et al. 2018). Moreover, banks tend to take more risks in response to capital regulation. The theory also holds that a higher *RCAR* suggests a higher capital/assets ratio (Bitar et al. 2018). Furthermore, a highly leveraged financial system is prone to vulnerabilities (Acosta-Smith et al. 2020; Schularick and Taylor 2012). Bush et al. (2015) also find that leverage is associated with financial instability. Abou-El-Sood (2016) also found that regulatory capital led to fragility for banks that own below 6% capital. Others suggest no relationship (Nguyen et al. 2019; Bougatef and Mgadmi 2016). The *RCAR* is therefore expected to relate to bank risk positively or negatively.

Sixth, deposit to asset ratio (*DEPASS*) is included (Sharma and Gounder 2012; Fang et al. 2014; Davis et al. 2020) to measure the degree of bank's reliance on deposit funding (Laeven et al. 2016) and to control for banks' funding structure linked to liquidity risk (Davis et al. 2020; Köhler 2014; 2015). The relationship between bank risk-taking and *DEPASS* yields mixed results. Institutions with higher levels of assets financed by deposit liabilities are likely to be more profitable (Sharma and Gounder 2012), hence less risky.

Amador et al. (2013) and Srairi (2016) found a positive relationship between *DEPASS* and bank risk. On the other hand, other studies found a negative relationship between *DEPASS* and bank risk (Davis et al. 2020), while others found no significant relationship (Laeven et al. 2016; Köhler 2014). Therefore, *DEPASS* is expected to be either positively or negatively related to bank risk.

Last, consistent with Beck et al. (2013), the net loans to total assets (*LOANASS*) ratio is incorporated to control for banks' lending activities (Köhler 2014); and as a proxy for measuring bank liquidity management (Davis et al. 2020; Abdelsalam et al. 2020). *LOANASS* indicates the percentage of the bank assets tied up in loans and suggests lower liquidity management (Abdelsalam et al. 2020). Moreover, the asset structure and the size of loan composition or level of intermediation (Liu and Wilson 2013; Noman et al. 2018) matter for bank risk. A higher loan to assets ratio reduces the banks' risk-taking. For instance, banks holding more liquid assets can lower their liquidity risk, thus reducing the likelihood of bank failure (DeYoung and Torna 2013). A contrasting view by Heffernan and Fu (2010) suggests that very high ratios may reduce liquidity and increase the bank's risk of higher defaults. Thus, the impact of the net loans to total assets ratio may be positive or negative.

6.2.2.3. Market-based variables

This study includes six market-based variables (stock price index (*SPI*), housing price index (*HPI*), government bond yield (*GovBY*), money market rate (*MMR*), and domestic credit to the private sector (*DCPS*). Makri et al. (2014) and Nkusu (2011) posit that market-based variables such as changes in the *HPI*, equity price index, inflation, nominal effective exchange rate, *MMR* and *DCPS* are determinants of loan portfolio quality. First, asset prices are included (stock price and real estate price indexes) to capture asset price growth (Altunbas et al. 2014; Pouvelle 2012; Makri et al. 2014).

The relationship between asset prices and banking distress generates a natural characterisation of banking distress and financial instability as an unstable credit contraction coupled with plummeting asset prices and escalating loan losses (Von Peter 2009). Asset price bubbles (in stock and real estate markets) are potential sources of financial fragility and are associated with heightened systemic risk at the bank level (Brunnermeier et al. 2020b). Moreover, credit-fuelled bubbles tend to be followed by more severe crises (Jordà et al. 2015; Brunnermeier and Schnabel 2016). As such, a (systemic) banking crisis may be amplified by depressed asset prices, which may consequently decrease banks' assets' value, leading to insolvency (World Bank 2016a). Such systemic risk significantly expands during real estate busts, particularly for banks with unfavourable balance sheet characteristics (bank size, loan growth, leverage, maturity mismatch) (Brunnermeier et al. 2020b).

Nkusu (2011) reveals that decreasing asset prices could be associated with increasing NPLs in advanced economies. Falato and Scharfstein (2016) also argue that stock market pressure generates earnings and induces financial institutions (particularly publicly held banks) to take more risk. Stock market developments impact the demand for banking services (Bahri and Hamza 2019), thus urging banks to compete with capital markets to maintain their market power (Schaeck and Cihák 2012). Conversely, asset prices may positively affect bank lending via the supply and demand side by lowering the bank's cost of funding and raising the bank's ability to extend loans (Pouvelle 2012). However, a decline in asset prices may be large enough to threaten financial stability (Mishkin and White 2003). On the other hand, Von Peter (2009) reveals that the impact of decreasing asset prices on the banking system is rather indirect (through borrower default and balance sheet effects) and non-linear.

Second, interest rates are included to control for economic stability (Fang et al. 2014). Interest rates play a vital role in the country's financial soundness (Koong et al. 2017) and affect bank intermediation margins (Borio et al. 2017; Claessens et al. 2016). Therefore, this study accounts for bank risk-taking's differential responses to changes in short-term and long-term interest rates. The government bond yield proxied by long-term interest rate (*LTIR*) is included to find whether risk-taking changes as *LTIR* decline. Bolt et al. (2012) and Borio et al. (2017) observe that a positive effect of the yield curve slope for loan loss provisions is positive. The *LTIR* also positively affects net interest income (Bolt et al. 2012; Borio et al. 2017). However, Hanson and Stein (2015) show that *LTIR* negatively affects bank risk-taking.

The money market rate, measured as the short-term interest rate (*STIR*), examines the dynamic impact of monetary policy on bank risk-taking. An expansionary monetary policy, such as an interest rate cut, can impact financial stability through bank risk-taking (Buch et al. 2014). This follows the 'too low for too long' theory that maintains that a protracted period of low-interest rates could induce financial imbalances and help fuel asset price booms, spurring banks to increase leverage and take on excessive risks (Altunbas et al. 2014; Borio and Zhu 2012; Adrian and Shin 2010). Very low-interest rates may affect bank risk-taking through the "risk-taking channel" (Borio and Zhu 2012; Adrian and Shin 2010) by eroding the profits and net-interest margin of banks, accentuating the risk-taking channel (Badarau and Lapteacru 2020). Several empirical studies provide compelling evidence consistent with the "risk-taking channel" of monetary policy (see Brei et al. 2020a; Adrian et al. 2019; Dell'Ariccia et al. 2017). Geng et al. (2016) claim that *STIR* led to NPLs (credit risk). However, Bolt et al. (2012) and Borio et al. (2017) find that a positive effect of *STIR* on loan loss provisions is positive. However, some studies conclude that lower interest rates increase bank risk, and a higher interest rate prevents the accumulation of bank risk (Ioannidou et al. 2015; Angeloni et al. 2015).

Third, a proportion of domestic bank credit presented by domestic credit to the private non-financial sector by banks (*DCPSB*) (percentage of GDP) is incorporated. Domestic bank credit remains the prominent form of private-sector borrowing in most advanced economies (Bauer and Granziera 2017; Jordà et al. 2016). Therefore, it is an important indicator of financial intermediation that reflects the extent to which funds are channelled into the private sector by domestic banks. Credit risk is related to the country's GDP; hence excessive bank credit to the private sector beyond the optimal level, coupled with lower credit standards, tends to accumulate higher financial sector risks such as bank risks (Hossain et al. 2020; Ductor and Grechyna 2015). However, Adachi-Sato and Vithessonthi (2021) found no relationship between *DCPSB* and three bank risk-taking measures (Z-score, NPL ratio and NIM).

Last, a share of domestic credit to the private sector (*DCPS*) over GDP reflects the depth of financial sector development and captures any direct effect that credit availability might have on economic growth and development (Lensink et al. 2008). The effect of *DCPS* on bank risk can be ambiguous (Delis and Kouretas 2011). An increased share of private credit to GDP may increase the probability of financial instability and bank risks (Siddik and Kabiraj 2018; Morgan and Pontines 2014). Several studies conclude that DCPS is strongly procyclical (Bauer and Granziera 2017; Jordà et al. 2016). Bauer and Granziera (2017) emphasise private-sector leverage (measured as the ratio of nominal private debt to nominal output), citing that excessively leveraged economies tend to be less resilient to shocks and have lower loss-absorption capacities. Moreover, a financial crisis is likely to occur in a country where the private credit to GDP ratio is larger (Ashraf et al. 2017; Zheng et al. 2017; Zheng and Moudud-Ul-Huq 2017). Brei et al. (2020b) and Chen et al. (2017) also find a negative relationship between credit risk and *DCPS*. However, Jordà et al. (2016) posit that a lower credit-to-GDP ratio decreases the probability of a financial crisis.

6.2.2.4. Country-specific control variables

In this study, four macroeconomic control variables are included. First, to control for economic growth, real GDP growth (*GDPGR*) is used (Ahamed and Mallick 2019; Alessi and Detken 2018; Noman et al. 2018). *GDPGR* can lower bank risk-taking, which is concordant with previous literature (Chen et al. 2015; Fang et al. 2014; Agoraki et al. 2011). Moreover, such economic expansions may increase banks' profitability, consequently boosting bank equity and reducing risk-taking (Bui and Bui 2019). For instance, Sobarsyah et al. (2020) find a negative relationship between *GDPGR* and three bank credit risk measures (ratios of loan loss provisions to total assets, loan loss reserves to total assets and NPLs to total loan). Conversely, *GDPGR* positively impacts banking stability (Ghenimi et al. 2017), thus negatively relating to bank risk. However, Tan and Floros (2012) investigate the association between *GDPGR* and bank profitability in China and find a negative association between both variables, suggesting a positive association with bank risk. However, Bui and Bui (2019) also find a positive association between *GDPGR* and bank risk (Z-scores).

Second, inflation is captured using the consumer price index (*CPI)* to control for variation in macroeconomic conditions (Ashraf et al. 2017; Chaibi and Ftiti 2015; Bouvatier et al. 2014). Empirical literature yielded mixed results on the relationship between inflation and bank risk. Higher inflation is positively correlated with bank risk, suggesting that bank risk tends to be higher in inflationary economies (Ashraf et al. 2017; Kauko 2014). Hussain and Hassan (2005) also find a positive association between inflation and bank risk. On the other hand, Guru et al. (2002) and Jiang et al. (2015) found a negative relationship between inflation and bank risk. Lassoued (2018) finds no significant impact between *z*-scores and inflation. Therefore, the relationship between inflation and bank risk can be positive or negative.

Third, the real exchange rate (*REER*) is included (Chaibi and Ftiti 2015). Exchange rate fluctuations can influence economic activity through various channels (Carstens 2019), such as the financial channel, which functions through its impact on banks' risk-taking capacity (Avdjiev et al. 2019). Domestic appreciation may raise market participants' collateral values and net worth, boost borrowers' capacity to accumulate debt, and ease lenders' constraints to provide it (Bruno and Shin, 2015). It can encourage market participants (both borrowers and lenders) to take more risks, thereby increasing the demand and supply of credit (Nier et al. 2020; Hofmann et al. 2020). Some literature has since referred to these mechanisms as the "risk-taking channel" (Hofmann et al. 2020; Borio and Zhu 2012). Furthermore, currency appreciation is often associated with reducing credit spreads (Hofmann et al. 2020). Hofmann et al. (2017) show that currency appreciation is associated with greater bank risk-taking and cross-border bank lending reduction. On the other hand, Druck et al. (2018) document a negative relationship between *REER* and bank risk.

Last, trade openness (*TRADE*) is included to capture the effect of international trade represented by the ratio of total trade (exports and imports) to a country's GDP (Ashraf 2018; Hossain et al. 2020; Rahman et al. 2020; Mirzaei and Aguir 2020). Trade openness allows foreign competition and limits the incumbents' ability to oppose financial development (Bui and Bui 2020). However, it also generates incentives to support and promote financial development (Rahman et al. 2020). Recent studies have examined the impact of trade openness on bank risk-taking and found inconclusive results (Ashraf et al. 2017). Two mainstream literature strands on trade openness and economic development explain the relationship between trade openness and bank risk.

The "diversification-stability effect" may explain the negative relationship between trade openness and bank risk-taking (Berger et al. 2017a). Higher trade openness may decrease bank risk-taking through diversification opportunities (Bui and Bui 2019; 2020; Rahman et al. 2020; Ashraf 2018). Rahman et al. (2020) observe that higher trade openness reduces bank risk-taking in both the short and long run. Bui and Bui (2020) observe that trade openness can help discipline banks' risk-taking, consequently increasing their stability. The opposing view demonstrates the destabilising effects of trade openness, as explained by the 'volatility-fragility effect'. Trade openness may increase bank risk-taking due to higher competition and volatility (Ashraf et al. 2017). In essence, trade openness is positively correlated to bank risk-taking and volatility (Hossain et al. 2020; Ashraf et al. 2017). The variable definitions are presented in *Table 6.1*.

Table 6.1: Description of variables used for regression estimations†

Variable name	Acronym	Variable description	Data sources
Measures of bank risk (dependent variables)			
Insolvency risk (Z-score)	*Z*	Calculated as: Ln [1 + ($ROA_{i,t}$ + $EA_{i,t}$)/σ$(ROA)_{i,t}$].	BankScope; Author's calculations
Credit risk	*CR*	Calculated as: Ln [$NPL_{i.t}$/(100-$NPL_{i.t}$)].	BankScope; Author's calculations
Liquidity risk	*LQ*	Calculated as: Ln (Liquid assets to total assets).	BankScope; Author's calculations
Portfolio risk	*PR*	Calculated as: Ln [$ROA_{i,t}$/σ$(ROA)_{i,t}$)]	BankScope; Author's calculations
Leverage risk	*LR*	Calculated as: Ln [Equity to assets ratio/σ$(ROA)_{i,t}$]	BankScope; Author's calculations
Main independent Variables			
FinTech credit share	*FIN_S*	Measured as the ratio of total volumes of loans originated (by FinTech platforms) to total credit to the private non-financial sector (Frost et al. 2019; Rau 2020).	Various FinTech Platforms, UK P2PFA; AFSAL; Korea P2PFA; SMLA; US S&P GMI 2018; Sweden RiksBank survey; CBIRC; Brismo; WDZJ
Bank-specific variables			
Market concentration	*HHI*	Calculated as the market share (assets) of the top five largest banks in a country	BankScope; Author's calculations
Bank Size	*SIZE*	Bank size measured as the natural log of total bank assets	FSI
Diversification	*NITI*	Bank non-interest income divided by total income	BankScope; Author's calculations
Inefficiency	*OVERHH*	The ratio of overhead costs to total assets of a bank	GFDD
Regulatory capital adequacy	*RCAR*	The ratio of bank regulatory capital to risk-weighted assets	GFDD; FSI
Deposit to assets ratio	*DEPASS*	Constructed as the ratio of deposit money bank/GDP to deposit money banks' assets/GDP (Davis et al. 2020)	BIS; GFDD
Loan to assets ratio	*LOANASS*	Constructed as the ratio of private credit by deposit money banks/GDP to deposit money banks' assets/GDP (see. Davis et al. 2020)	BIS; GFDD
Market-based variables			
Stock price index	*SPI*	Stock price index	BIS
Housing price index	*HPI*	Housing price index	BIS
GovBY	*LTIR*	Government bond yield captured by long term interest rate	BIS
Money market	*STIR*	The money market is captured by short term interest rate	BIS
Domestic Credit	*DCPS*	Total domestic credit to the private sector as a percentage of GDP	BIS
Bank credit	*DCPSB*	Domestic credit to the private sector by banks as a percentage of GDP	BIS
Country-level control variables			
Real GDP growth	*RGPGR*	The growth rate of GDP	OECD
Inflation	*CPI*	Percentage change in consumer price index	BIS
Real effective exchange rate	*REER*	The volatility of real effective exchange rate	OECD
Trade openness	*TRADE*	Sum of exports and imports of goods and services measured as a share of GDP	OECD

Source: Developed by the author.

Notes: †GFDD: Global Financial Development Database; BIS: Bank for International Settlements; OECD: Organisation for Economic Cooperation and Development; CBIRC: China Banking and Insurance Regulatory Commission; US S&P GMI 2018: US Standard & Poor's (S&P) Global Market Intelligence; Brismo (formerly known as AltFi data); UK P2PFA: UK Peer-to-Peer Finance Association; AFSAL: Alternative Financial Services Association of Latvia, Korea P2P Finance Association, SMLA: Swiss Marketplace Lending Association; WDZJ: Wang Dai Zhi Jia.

6.3. Descriptive statistics

6.3.1. Summary statistics

Table 6.2 presents descriptive statistics for all the variables used in the econometric estimations. Concerning bank risk-taking measures, liquidity risk has the highest positive mean value of 1.7039 with a standard deviation of 0.5937, followed by leverage risk with a positive value of 0.899 and a standard deviation of 1.0889. the other three bank taking-risk variables had negative mean values. Credit risk had the lowest negative mean value of -3.7707 with a standard deviation of 1.1395, followed by insolvency risk with a negative mean value of -2.3657 and standard deviation of 1.0802 and last, portfolio risk with a negative mean value of -1.5007 with a standard deviation of 1.1138.

Table 6.2: Summary statistics of variables used for empirical estimations

Variable	Observations	Mean	Std. Dev.	Min	Max
Credit risk	1,500	-3.7707	1.1395	-7.1322	-1.0612
Liquidity risk	1,500	1.7039	0.5937	0.5463	4.0212
Insolvency risk	1,478	-2.3657	1.0802	-6.2493	5.2182
Leverage risk	1,492	0.8990	1.0889	-3.6901	4.7365
Portfolio risk	1,422	-1.5007	1.1138	-4.9318	5.4436
FinTech credit	673	0.0517	0.3002	0.0000	4.0752
Market competition	1,500	4.3561	0.2084	3.6715	4.6052
Bank size	1,500	13.9810	1.9913	9.3540	17.4980
Diversification	1,500	39.5466	13.8917	10.6394	79.6610
Inefficiency	1,500	1.7990	0.9155	0.1087	5.3413
Regulatory capital adequacy	1,500	15.6917	4.1649	2.5000	36.0815
Deposit to assets ratio	1,500	0.7715	0.2340	0.2930	1.3989
Loan to assets ratio	1,500	0.8479	0.1665	0.3663	1.3314
Stock price index	1,500	96.4447	37.3194	21.7600	510.4700
Housing price index	1,500	102.9290	17.7231	55.0600	171.7000
Long-term interest rate	1,500	3.5086	2.3805	-0.7800	15.0000
Short-term interest rate	1,500	2.3766	2.6110	-0.8400	15.7000
Domestic bank credit	1,500	87.2534	39.9393	8.8000	173.1000
Domestic credit	1,500	158.3500	64.7657	23.5000	401.2000
GDP growth rate	1,500	0.6229	1.3269	-12.7023	23.2460
Inflation	1,500	103.5470	10.8107	64.5400	151.9200
Real effective exchange rate	1,500	99.8089	8.3874	75.5900	131.7000
Trade openness	1,500	91.7925	44.7179	24.6416	239.2150

Source: Author’s calculations.

6.3.2. Correlation analysis

Table 6.3 presents the Pearson correlation matrix for all variables used in the empirical estimations. Overall, independent variables are weakly correlated with dependent variables (bank risk-taking). There is also a weak and negative correlation between FinTech credit and four risk-taking measures (liquidity, insolvency, leverage and portfolio risks) but a positive correlation with credit risk. A low correlation implies that there are no serious multicollinearity issues in the study. As expected, the insolvency risk is positive and highly correlated with its additive components– leverage and portfolio risks. The insolvency risk is, however, weak and negatively correlated to credit risk and positively correlated to liquidity risks. Credit risk is negatively correlated to all four risk-taking measures.

Table 6.3: Correlation matrix

	CR	LQ	Z	LR	PR	FIN	HHI	SIZE	NITI	OHH	RCAR
LQ	-0.275***	1.000									
Z	-0.112***	0.253***	1.000								
LR	-0.175***	0.145***	0.949***	1.000							
PR	-0.082***	0.311***	0.930***	0.851***	1.000						
FIN	0.034***	-0.116***	-0.014***	-0.046***	-0.047***	1.000					
HHI	-0.192***	-0.162	0.391***	0.468***	0.305***	-0.041***	1.000				
SIZE	-0.149***	0.103***	-0.341***	-0.287***	-0.154***	-0.211***	-0.518***	1.000			
NITI	0.074*	-0.073	-0.143***	-0.106	0.044***	0.060***	0.152***	0.068***	1.000		
OHH	0.195***	-0.070***	-0.014***	-0.154***	-0.037***	0.072***	-0.415***	-0.014***	-0.074	1.000	
RCAR	-0.036***	-0.317***	0.173	0.127***	0.121***	0.129***	0.450***	-0.547***	0.284***	0.044***	1.000
DEP	0.057***	-0.037***	-0.180***	-0.288***	-0.089***	-0.038	-0.175***	-0.051***	0.226***	0.461***	0.177***
LOAN	-0.136***	0.282***	0.166***	0.079***	0.160***	0.064***	0.148***	-0.342***	-0.079***	-0.267***	0.216***
SPI	-0.055*	-0.041	0.220	0.166	0.108***	0.349***	0.314	-0.503***	0.005***	0.135***	0.463***
HPI	-0.114**	0.164***	0.149***	0.121***	0.105***	0.208***	-0.071***	0.042	-0.110***	0.101	0.018***
LTIR	0.136***	-0.021***	0.047***	0.096***	-0.052***	-0.088***	-0.477***	0.236***	-0.475***	0.217***	-0.506***
STIR	-0.107***	0.018	0.033***	0.124***	-0.094***	-0.039***	-0.481***	0.322	-0.452***	0.183***	-0.511***
DCB	-0.371***	0.315***	0.111***	0.173***	0.205***	-0.107***	0.282***	0.238***	0.099***	-0.635***	-0.182***
DCP	-0.293***	0.313***	-0.007***	-0.007***	0.101	-0.118	0.290***	0.086***	0.208***	-0.470***	0.063***
GDPR	-0.001***	-0.067***	-0.002***	-0.020***	-0.100***	0.053***	-0.046***	-0.127***	-0.173***	0.049***	0.124***
CPI	-0.145***	-0.201***	0.166***	0.149**	0.017***	0.145	0.070***	-0.109***	-0.418	0.170	0.284***
REER	-0.151***	0.043***	-0.119	-0.130*	-0.084***	0.115***	-0.211*	0.049***	-0.098***	-0.151***	-0.199**
TR	0.242***	-0.401***	0.243***	0.242***	0.126***	0.061***	0.607***	-0.711***	0.205***	0.108***	0.642***

	DEP	LOAN	SPI	HPI	LTIR	STIR	DCB	DCP	GDPR	CPI	REER
DEP	1.000										
LOAN	-0.109***	1.000									
SPI	0.162***	0.124***	1.000								
HPI	-0.147	0.050**	0.378***	1.000							
LTIR	-0.172***	-0.369***	-0.362***	-0.153**	1.000						
STIR	-0.234***	-0.291	-0.278**	0.037***	0.860***	1.000					
DCB	-0.424***	0.406***	-0.175***	0.086***	-0.334***	-0.230***	1.000				
DCP	-0.044***	0.417***	-0.052***	0.149***	-0.567***	-0.477***	0.777***	1.000			
GDPR	-0.125***	0.151***	0.111***	0.052***	0.034***	0.088***	-0.040***	-0.045***	1.000***		
CPI	-0.114***	-0.079***	0.393**	0.169***	0.099***	0.170***	-0.262	-0.343***	0.140***	1.000	
REER	-0.035***	0.292***	-0.090***	0.017	0.020	0.137	0.239***	0.231***	0.117***	-0.266	1.000
TR	0.080***	0.074***	0.346***	0.041**	-0.385***	-0.415***	-0.220**	-0.019***	0.085	0.056	-0.213***

Source: Author's calculations. CR: Credit risk; LQ: Liquidity risk; Z: Insolvency risk (Z-score); PR: Portfolio risk; LR: Leverage risk; FIN: FinTech credit; HHI: Market competition; SIZE: Bank Size; NITI: Diversification; OHH: Inefficiency; RCAR: Regulatory capital adequacy; DEP: Deposit to assets ratio; LOAN: Loan to assets ratio; SPI: Stock price index; HPI: Housing price index; LTIR: Long-term interest rate; STIR: short-term interest rate; DCB: Domestic Credit; DCP: Domestic Bank Credit; GDP: Real GDP growth rate; CPI: Inflation; REER: Real effective exchange rate; TR: Trade. * Statistically significant at 10%; ** Statistically significant at 5%; *** Statistically significant at 1%.

6.4. Empirical approach

The second empirical chapter (Chapter 6) examines the effect of FinTech credit on bank risk-taking measures. Because of inconclusive arguments on whether FinTech credit reduces or increases bank risk-taking, the study examines whether there exists a non-linear between FinTech credit and bank risk-taking. To present the model, let $j \in \{1,2,\cdots,N\}$ and $t \in \{1,2,\cdots,T\}$ stands for country and period indices, correspondingly. The econometric models are specified as follows:

$$LnCR_{jt} = \alpha_0 + \delta_1 FIN_t^j + \delta_2 FIN_t^{2j} + \theta \boldsymbol{S}_t^j + \tau \boldsymbol{M}_t^j + \varphi \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \quad (6.6)$$

$$LnLQ_{jt} = \alpha_0 + \delta_1 FIN_t^j + \delta_2 FIN_t^{2j} + \theta \boldsymbol{S}_t^j + \tau \boldsymbol{M}_t^j + \varphi \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \quad (6.7)$$

$$LnZ_{jt} = \alpha_0 + \delta_1 FIN_t^j + \delta_2 FIN_t^{2j} + \theta \boldsymbol{S}_t^j + \tau \boldsymbol{M}_t^j + \varphi \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \quad (6.8)$$

$$LnPR_{jt} = \alpha_0 + \delta_1 FIN_t^j + \delta_2 FIN_t^{2j} + \theta \boldsymbol{S}_t^j + \tau \boldsymbol{M}_t^j + \varphi \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \quad (6.9)$$

$$LnLR_{jt} = \alpha_0 + \delta_1 FIN_t^j + \delta_2 FIN_t^{2j} + \theta \boldsymbol{S}_t^j + \tau \boldsymbol{M}_t^j + \varphi \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \quad (6.10)$$

where CR_{jt}, LQ_{jt}, Z_{jt}, PR_{jt} and LR_{jt} are the five bank risk-taking measures (credit, liquidity, insolvency, leverage risk and portfolio risk, respectively) in country *j* at time *t*, FIN_t^j and FIN_t^{2j} are, respectively, the measure of FinTech credit and the squared term of FinTech credit in country *j* at time *t*, $\boldsymbol{S}_t^j$, $\boldsymbol{M}_t^j$ and $\boldsymbol{X}_t^j$ denote the vectors of observable bank-specific, market-based and country-level control variables for country *j* at time *t*, c_j is a country-specific fixed effect capturing the effect of country-level variation; h_t captures time fixed effect, which controls for possible cross-sectional dependence, and ε_{jt} corresponds to the stochastic error term; α_0 is a constant, and δ, θ, τ, and φ are vectors of parameters to be estimated.

6.5. Results and discussions

6.5.1. Baseline results

The econometric equations in this chapter are based on equations (*6.6*) to (*6.10*). To test the relationship between FinTech credit and bank risk-taking, the study addresses an important issue of determining the appropriate model, which is to examine whether individual effects are fixed or random. For the baseline empirical estimations and following other previous studies (see. de Mendonca and Nascimento 2020; Noman et al. 2018; Ketokivi and McIntosh 2017), this study employs the FE models instead of the alternative RE model. The Hausman (1978) test is used to select the appropriate method between fixed and random effects models. The Hausman test statistic is asymptotically distributed as a chi-square with k (number of explanatory variables) degree of freedom under the null hypothesis that the preferred model is RE vs the alternative FE model (Green 2008). The null hypothesis is since rejected, and the alternate hypothesis, i.e., the FE model ($p<0.0001$), is suitable for the given data set in this study (Bollen and Brand 2010). The FE model removes the unobserved heterogeneity and alleviates endogeneity from omitted variables (Ketokivi and McIntosh 2017). Finally, the heteroskedasticity-robust standard errors are used to calculate t-statistics (Beck et al. 2013; Houston et al. 2010).

Table 6.4 presents the baseline results on the impact of FinTech credit on bank risk-taking. The study examines the relationship between FinTech credit and bank risk-taking proxied by five bank-risk measures credit, liquidity, insolvency, leverage and portfolio risks. Overall, the results reveal significant evidence of a non-linear (inverted U-shaped) relationship between FinTech credit and risk-taking. Based on the individual risk-taking measures, the impact of increased FinTech credit on risk-taking is particularly pronounced and significant among credit and liquidity risks. However, the other measures (portfolio, insolvency and leverage) reveal an insignificant but inverted U-shaped relationship.

Overall, the findings of this study may indicate that FinTech credit initially disrupts bank risk-taking in the short run, thus inducing banks to engage in risk-taking. However, in the long run, the opposite ensues. The incumbents may initially perceive the growth of FinTech credit as a threat or hostile competitor in the short run and engage in risk-taking behaviour. They may eventually adjust their business models to stay abreast with changes in the financial system, thus reducing bank risk-taking. For instance, they may improve their technologies, actively participate in digitalisation and even partner with FinTech entities. The results are consistent with several related studies which found a non-linear (inverted U-shaped) relationship between internet finance or FinTech developments on traditional bank risk-taking (Wang et al. 2021).[27] The results harmonise and complement existing literature that suggests that FinTech credit can act as both complements and substitutes for traditional bank credit (Hodula 2021; Zhang et al. 2019). They also harmonise the consumer theory, which is based on the substitution (de Roure et al. 2022; Ziegler et al. 2021; Havrylchyk et al. 2020; Kohardinata et al. 2020) and complementary theories (Cornelli et al. 2021; 2020; Zhang et al. 2019; Demertzis et al. 2018).

It is rather not surprising to find the baseline results for credit and liquidity risks revealing a significant non-linear (U-shaped) relationship when looking at the individual bank-risk measures. According to Imbierowicz and Rauch (2014), credit and liquidity risks are two major bank default risk sources. Kasman and Kasman (2015) also assert that the credit risk channel, especially through bank exposures, appears to be the leading source of bank risk. These findings may thus imply that the expansion of FinTech credit largely affects banks' risk-taking through credit and liquidity channels. To some extent, the findings may confirm a possible self-reinforcing or reciprocal relationship between credit and liquidity risks. Moreover, several studies have shown that credit and liquidity risks may individually and or jointly interact and influence bank stability (Vazquez and Federico 2015; Imbierowicz and Rauch 2014). Vazquez and Federico (2015) assert that such simultaneous exposure to credit and liquidity risks intensifies bank distress during the crisis.

While bank risk-taking may constitute a useful indicator for financial stability consideration, the scope of the study does not extend to the exploration of the association between bank-risk taking and aggregate financial stability. However, it is worth noting an apparent contradiction between the findings in Chapters 5 and 6. This scenario could be explained by several reasons. For instance, naturally, banks globally have structurally enhanced their resilience to future risks by substantially building up capital and liquidity buffers (Buch and Dages 2018). Since the GFC, the traditional banking sector has adopted structural and regulatory changes that make banks more resilient. For instance, strengthened capital framework and liquidity requirements prescribed by the Basel III banking regulations serve to restrict the build-up of excessive leverage in the banking sector and to avoid destabilising deleveraging processes that can damage the broader

[27] However, these indicators do not specifically capture the FinTech credit market as they use internet finance as a proxy for FinTech development constructed as an index based on "text mining" or search engine.

financial system and the economy (BIS 2014). The capital regulatory framework thus ensures that banks do not operate with excessive leverage and, at the same time, have sufficient incentives for keeping risk-taking in check.

Acosta-Smith et al. (2020) suggest that the aggregate negative impact of the estimated increase in bank risk-taking is outweighed by the benefits of increasing loss-absorbing capacity, i.e., that a leverage ratio requirement could be beneficial for financial stability by significantly reducing the failure probability of highly leveraged banks. The authors thus suggest that there is a net effect of the potential trade-off between greater loss-absorbing capacity and higher bank risk-taking due to other economic factors, thereby leading to more stable banks. Kawamoto et al. (2020) also reveal that while the riskiness of credit allocation has increased in Japan's loan market, it does not seem to pose an immediate threat to financial stability. The contradiction of the results, in this case, may suggest that bank risk-taking may not always suggest instability in the financial system. However, a cautionary interpretation of the results is advised as excessive leverage has been identified as a key driver of the recent financial crisis and of many past crises (Schularick and Taylor 2012). Moreover, FinTech credit has not yet completed its full financial cycle (FSB 2017; 2019a), hence more room for further research. The findings add a new understanding of the interaction effects of the expansion of Fintech credit and banks' balance sheet soundness and how it drives the dynamics of aggregate risk-taking. It also highlights the limitations of single-based measures as a proxy of financial stability.

Table 6.4: Impact of FinTech on bank risk-taking: Fixed effect regression models

	Credit	Liquidity	Insolvency	Leverage	Portfolio
Fintech variables					
FinTech credit	0.1795***	0.0500*	0.0370	0.0094	0.1405
	(0.0259)	(0.0258)	(0.0813)	(0.0823)	(0.0878)
FinTech credit squared	-0.0082***	-0.0028*	-0.0042	-0.0026	-0.0091**
	(0.0015)	(0.0015)	(0.0046)	(0.0046)	(0.0049)
Bank-level variables					
Concentration	-0.6568***	0.0662	-1.1517	-0.9379	-1.7415**
	(0.2409)	(0.2400)	(0.7626)	(0.7662)	(0.8403)
Bank size	-0.0985	-1.2683***	-1.2766***	-1.0810***	-1.1130***
	(0.1034)	(0.1030)	(0.3245)	(0.3287)	(0.3474)
Noninterest income to total income	0.3581***	-0.1188*	-0.7838***	-0.6110***	-0.8515***
	(0.0679)	(0.0677)	(0.2143)	(0.2164)	(0.2331)
Overheads to total assets	0.1207***	0.1329***	0.8872***	0.5600***	0.9009***
	(0.0405)	(0.0403)	(0.1354)	(0.1288)	(0.1513)
Regulatory capital adequacy ratio	0.0090	-0.0689	0.7906**	0.2696	0.5748
	(0.1092)	(0.1088)	(0.3464)	(0.3474)	(0.3796)
Deposit to assets ratio	1.4019***	0.6730***	0.5428	1.1867	1.0658
	(0.2569)	(0.2559)	(0.8054)	(0.8175)	(0.8629)
Loan to assets ratio	-2.3709***	-1.5964***	-1.0116	-0.5346	-1.7294*
	(0.3054)	(0.3042)	(0.9677)	(0.9719)	(1.0489)
Market-based variables					
Stock price index	-0.1842**	0.2344***	-0.9208***	-0.7458***	-0.8535***
	(0.0823)	(0.0820)	(0.2605)	(0.2618)	(0.2888)
Housing price index	-2.2187***	0.7585***	3.1565***	3.1144***	3.5128***
	(0.1202)	(0.1197)	(0.3864)	(0.3827)	(0.4205)
Govt Bond yield	0.0661***	-0.0128	0.1817***	0.1508***	0.1341**
	(0.0160)	(0.0159)	(0.0502)	(0.0510)	(0.0557)
Money market	-0.1044***	0.0593***	0.0116	0.0968**	-0.0187
	(0.0124)	(0.0124)	(0.0400)	(0.0397)	(0.0447)
Domestic bank credit	3.0353***	2.2697***	3.6599***	3.4585***	3.8735***
	(0.3161)	(0.3149)	(1.0010)	(1.0058)	(1.0822)
Domestic credit to private sector	-0.8125***	0.5393***	0.6941	0.4357	0.5364
	(0.2045)	(0.2037)	(0.6424)	(0.6508)	(0.6957)
Country-control variables					
GDP growth rate	0.0295**	-0.0004	-0.0079	-0.0091	-0.0047
	(0.0129)	(0.0128)	(0.0409)	(0.0409)	(0.0440)
Inflation	0.3462	-0.1622	-2.5201**	-4.0513***	-2.5871*
	(0.3976)	(0.3960)	(1.2481)	(1.2655)	(1.3387)
Real effective exchange rate	0.1614	0.7984***	1.6841**	1.6477**	1.6420**
	(0.2407)	(0.2397)	(0.7579)	(0.7657)	(0.8121)
Trade openness	-0.1260	1.2894***	4.8254***	5.1193***	4.9609***
	(0.2053)	(0.2045)	(0.6654)	(0.6531)	(0.7273)
Constant	-1.5507	-5.8942**	-26.0505***	-17.6679**	-26.6041***
	(2.4024)	(2.3929)	(7.5454)	(7.6510)	(8.1000)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes	Yes	Yes
Observations	673	673	669	672	653
R-squared	0.7738	0.4475	0.3807	0.3851	0.3218
Number of countries	25	25	25	25	25
Hausman test	160.99***	190.14***	68.20***	128.10***	44.25***
Wooldridge test	123.82***	50.16***	288.64***	10.17***	54.08***
Modified Wald test	2853.42***	10540.02***	1366.20***	1255.12***	1163.20***
Pesaran CD test	1.53	2.43***	14.87***	12.87***	12.29***

Source: Author's calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model. Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models. Pesaran test of cross-sectional independence.

Concerning bank variables, concentration (proxied by *HHI*) is negative (for all bank risks) and statistically significant for two bank risk measures (credit and portfolio risks). This finding is consistent with the "concentration-stability" hypothesis. This result corroborates the argument that banks in more concentrated markets tend to be more stable and are less likely to engage in excessively risky lending (Beck et al. 2006; Allen and Gale 2004; Repullo 2004). Moreover, a highly concentrated banking system is resilient to higher risk absorption (Shijaku 2017) and less prone to contagion (Sáez and Shi 2004). Haq and Heaney (2012) find a negative relationship between concentration and credit risk in European banks. This finding is also supported partly by studies that suggest a non-linear relationship between concentration and stability (Berger et al. 2017b; Liu et al. 2012; 2013). This finding is in contrast with the "concentration-fragility" hypothesis (see Saif-Alyousfi et al. 2020; Pawlowska 2016; Kasman and Kasman 2015).

Bank size, measured as the natural logarithm of total assets (*SIZE*), is significant and negative for all bank-risk measures except for credit risk. Generally, a larger bank size is associated with lower risk levels. The results are consistent with the "concentration-stability" hypothesis, suggesting that larger banks enhance bank stability (Adusei 2015), thereby reducing financial fragility and bank risks. Larger banks have a greater ability to diversify, exploit economies of scale and have a greater capacity to manage risk than small banks (Al-Shboul et al. 2020; Maji and Hazarika 2018; Laeven et al. 2016). In addition, larger banks tend to have larger capital (Fang et al. 2014) and are more technologically advanced with better access to liquidity (Mirzaei and Aguir 2020; Ali and Iness 2020). The results somewhat contrast with the "concentration-fragility" view linking banks' size with increased bank risk (see Ahamed and Mallick 2019; Yusgiantoro et al. 2019; Laeven et al. 2016).

The results are mixed for different bank risks and bank revenue diversification or non-interest revenue, proxied by noninterest income to total income (*NITI*). The results highlight the existence of a negative and statistically significant relationship between a bank's revenue diversification and four bank risk measures (liquidity, insolvency, leverage, and portfolio) but positive and significant for credit risk. The negative association between the four risk measures follows the traditional view that holds that revenue from non-interest activities reduces bank risk through diversification (Bitar et al. 2018; Cheng et al. 2020; Davis et al. 2020; Hamdi et al. 2017; Lee et al. 2014; Stiroh and Rumble 2006).

The results also show that bank diversification positively relates to bank credit risk. This finding is in line with other studies that suggest the positive impact of bank diversification on bank risk (Chen et al. 2020; Nguyen 2019; Hamdi et al. 2017). It also shows that the shift toward non-traditional banking activities significantly impacts the probability of a bank failure (DeYoung and Torna 2013). Bank diversification increases systemic banking risk (tail betas) and reduces bank stability (Brunnermeier et al. 2020a; Bostandzic and Weiß 2018; Köhler 2015), thus increasing bank risk.

The results for bank inefficiency measured by the ratio of overhead costs to total assets (*OVERHH*) are positive and highly significant across all five risk measures. This finding is in line with the "bad management (BM)" hypothesis, which follows that an increase in bank inefficiency induces stronger incentives for risk-taking; hence bank inefficiency increases bank risk (Fiordelisi et al. 2011; Berger and DeYoung 1997). Moreover, operational inefficiency negatively affects bank profitability (Yao et al. 2018b; Sun et al. 2017; Tan 2016) and lowers levels of stability (Polizzi et al. 2020; Wu et al. 2020). Inefficient banks are generally riskier (Ali and Iness 2020), and inefficient banks are commonly riskier (Al-Shboul et al. 2020). The results are not consistent with the "risk-averse management", "moral hazard", and skimping" hypotheses.

The regulatory capital adequacy ratio (*RCAR*) is significant and positive for insolvency risk only. The positive relationship confirms 'the regulatory hypothesis' that suggests that banks tend to raise their capital buffers following an increase in risk exposure (Davis et al. 2020; Bitar et al. 2018). Furthermore, a highly leveraged financial system tends to be vulnerable (Acosta-Smith et al. 2020; Schularick and Taylor 2012) and fragile (Abou-El-Sood 2016; Bush et al. 2015). Furthermore, the overall findings are inconsistent with the "skin in the game" theory that associates higher capital ratio with lower risk levels (Lee and Hsieh 2013; Anginer and Demirgüç-Kunt 2014). Other studies also hold that capital and risk are inversely related (Bitar et al. 2018; Bouheni and Rachdi 2015; Pereira and Saito 2015). The other risk measures' findings are not significant but positive for credit, leverage, and portfolio risks and negative for liquidity risk. The variation in the results for liquidity risk may arise when using the Basel credit risk mitigation techniques, which reduces or transfers credit risk; it may also increase other risks to which a bank is exposed, such as liquidity and market risks (BIS 2021).

The deposit to asset ratio (*DEPASS*) is positive and significant for two bank risk measures (credit and liquidity). These findings are not surprising since banks depend on deposits for their credit and liquidity needs (Singh and Sharma 2016). These findings are consistent with Amador et al. (2013) and Srairi (2016) but in contrast with Davis et al. (2020), who found a negative relationship. Laeven et al. (2016) and Köhler (2014), on the other hand, found a non-significant relationship between *DEPASS* and bank risk.

Bank's lending behaviour, proxied by loan asset ratio (*LOANASS*), negatively relates to all the five risk measures but is only significant for credit, liquidity and portfolio risks. The results are consistent with Davis et al. (2020) and Laeven et al. (2016). Banks with higher *LOANASS* have high profitability, thus lower bank risk (Bourke 1989). This finding directly contrasts with Heffernan and Fu (2010), who found a negative impact of *LOANASS* on bank profitability. *LOANASS* is not significant, either. On the other hand, Köhler (2014) finds no significant relationship between bank risk and *LOANASS*.

The findings reveal interesting and varying results for asset prices (stock price index (*SPI*) and house price index (*HPI*)). The results are highly significant in all five risk-taking measures. The results show a negative relationship between asset prices and credit risk. This result implies that rising asset prices reduce bank credit risk, thus enhancing bank stability. This finding may be due to the diversification channel as risks are shifted from the banking system to capital markets. Asset prices may affect bank lending by lowering the bank's cost of funding and raising the bank's ability to extend credit (Pouvelle 2012), thus inhibiting bank risk-taking. However, deep declines in asset prices may be large enough to threaten financial stability (Mishkin and White 2003) and increase bank risk. The results are consistent with the literature, which reveal that depressed asset prices could be associated with NPLs (credit risk) (Nkusu 2011) and further amplify systemic banking crisis, consequently decreasing the value of banks' assets, leading to its insolvency (World Bank 2016a).

Contrary to credit risk, the findings depict a highly significant and positive relationship between asset prices and bank liquidity risk. Consistent with Pouvelle (2012) and Brunnermeier et al. (2020b), asset price bubbles are a potential source of financial fragility and are associated with increased systemic bank risk. Moreover, stock prices may impact banks through the competition channel (Bahri and Hamza 2019; Schaeck and Cihák 2012). Von Peter (2009) highlighted that the relationship between decreasing asset prices and the banking system is indirect and non-linear. Moreover, concerning insolvency, leverage and portfolio risks, the finding presents the opposite results for housing and stock price indexes. *SPI* and *HPI* show negative and positive associations with insolvency, leverage and portfolio risks, respectively.

The findings reveal a significant and positive relationship between long-term interest rates (*LTIR*) and bank risk measures (credit, insolvency, leverage, and portfolio risk). The findings reveal that lower long-term interest rates reduce bank risk-taking, as collaborated by previous literature (Borio et al. 2017; Bolt et al. 2012). The findings contrast with Hanson and Stein (2015). In addition, the coefficient for short-term interest rate (*STIR*) is significant and negative for credit risk, whereas positive for liquidity and leverage risks. The results for credit risk are consistent with the "risk-taking channel" of monetary policy, which suggests that low short-term interest rates can increase the risk-bearing capacity of banks through increased lending or the creation of 'excessive' bank risk-taking (Brei et al. 2020a; Adrian et al. 2019; Dell'Ariccia et al. 2017; Geng et al. 2016). The essence of the risk-taking channel is that variations in monetary policy affect the effective "risk appetite" of banks, thus shifting the supply curve for credit to the real economy (Adrian et al. 2019). However, the results for credit risk are in contrast with Bolt et al. (2012) and Borio et al. (2017). Contrary to the mainstream "risk-taking channel", the findings indicate that lower *STIR* decreases liquidity and leverage risks.

Domestic bank credit (measures by the share of credit to the private non-financial sector by banks (*DCPSB*) to GDP) is highly significant and positively associated with all five bank-risk measures. This finding indicates that an increased share of domestic bank credit fuels bank risk-taking and disrupts bank stability. The results align with several studies (e.g., Hossain et al. 2020; Siddik and Kabiraj 2018; Ductor and Grechyna 2015). In addition, while credit growth promotes economic growth, studies have shown that rapid or excessive domestic bank credit growth relative to GDP increases beyond its optimal level propels financial sector risks such as bank risks (Cecchetti and Kharroubi 2012). However, the results are inconsistent with the findings by Adachi-Sato and Vithessonthi (2021). They found no relationship between domestic bank credit and three bank risk-taking measures (Z-score, *NPL* ratio and Net interest margin (*NIM*)).

The findings for domestic credit to the private sector are proxied by domestic credit to the private sector (*DCPS*) to GDP. *DCPS* shows a highly significant and negative relationship to credit risk and a positive relationship to liquidity risk. *DCPS* encapsulate total domestic credit to the private sector, and as expected, credit growth promotes economic growth, thereby reducing credit risk. The findings are consistent with previous empirical studies (e.g., Brei et al. 2020b; Chen et al. 2017). Moreover, the non-linear nature of the 'growth-finance' relationship, as recorded in various empirical studies (see. Zhu et al. 2020a; Arcand et al. 2015; Sahay et al. 2015b), suggest that credit growth can promote economic growth, which is beneficial to the banking sector.

The findings also present a positive relationship between *DCPS* and liquidity risk. This finding is confirmed by Jordà et al. (2016), that lower credit to GDP ratio decreases the probability of a financial crisis. Inversely, an increased share of *DCPS* is likely to increase the probability of financial instability, thus increasing bank risks (Siddik and Kabiraj 2018; Morgan and Pontines 2014). Moreover, due to the strong procyclical nature of *DCPS* (Bauer and Granziera 2017; Jordà et al. 2016), several studies associate a country with a higher *DCPS* with a high probability of encountering a financial crisis (Ashraf et al. 2017; Zheng et al. 2017; Zheng and Moudud-Ul-Huq 2017).

Concerning country control macroeconomic variables, the results show that GDP growth rate (*GDPGR*) significantly and positively relates to credit risk. This result may be explained by the fact that a reduction in economic activity may decrease the demand for loans and deposits decreases and negatively affects the profit margins (Sufian and Chong 2008), thus increasing bank risk. Moreover, the expansion of aggregate credits to GDP or (excessive) private credit to GDP beyond optimal levels, accompanied by lower credit standards, may further accumulate higher bank risks (Hossain et al. 2020; Ductor and Grechyna 2015). The findings align with the empirical literature by Bui and Bui (2019), who documents a positive association between *GDPGR* and bank risk (Z-scores). This finding contrasts with other researchers who argue that *GDPGR* can lower bank risk-taking (Chen et al. 2015; Fang et al. 2014; Agoraki et al. 2011). The results are insignificant and negative concerning the other four bank risk measures (liquidity, insolvency, leverage and portfolio).

The relationship between inflation proxied by the consumer price index (*CPI*) and bank risk is mixed in the empirical literature. This study reveals that inflation negatively affects three bank risk measures (insolvency leverage and portfolio risks). These results are not surprising since, in general, high inflation rates are associated with high loan interest rates and high income, leading to higher bank profitability (Guru et al. 2002; Jiang et al. 2015), which leads to lower bank risks. Furthermore, the findings contrast with studies that document a positive relationship between inflation and bank risk (Ashraf et al. 2017; Kauko 2014; Hussain and Hassan 2005), most of which are common in inflationary or emerging economies. On the other hand, the results find no significant relationship between credit and liquidity risks.

The results present a positive and significant relationship between *REER* and bank risks, except for credit risk. Consistent with other empirical evidence, Hofmann et al. (2017) show that currency appreciation is associated with greater bank risk-taking. Nevertheless, the results do not collaborate with the views of Druck et al. (2018), who document a negative relationship between exchange rate and bank risk. The results further reveal a positive and highly significant impact of trade openness (*TRADE*) on bank risk-taking. *TRADE* is statistically significant across the four bank risk-taking measures (liquidity, insolvency, leverage and portfolio risks), implying that higher trade openness increases bank risk-taking. This finding is in line with the 'volatility-fragility effect' that maintains that trade openness increases bank risk-taking and volatility (Hossain et al. 2020; Ashraf et al. 2017). The results are contrary to the 'diversification-stability effect' as documented by several authors (see. Rahman et al. 2020; Bui and Bui 2019; 2020; Ashraf 2018).

6.5.2. Robustness checks

Robustness checks are conducted to check the consistency in the results and to establish whether the core (baseline) results are stable. In order to confirm the consistency in the results, the study undertakes a set of robustness tests. First, the study re-estimates all equations by employing an alternative dependent variable of FinTech credit. Other alternative regression models are used to explore the relationship between FinTech credit and bank risk. The necessary model diagnostics were also conducted.

First, to address the issues of heteroskedasticity, serial correlation and cross-dependence, this study employs the Feasible Generalised Least Squares (FGLS) (e.g., de Mendonca and Nascimento 2020). The FGLS follows *AR*(1) and generates robust standard errors in the presence of heteroskedasticity, serial correlation and cross-dependence (Reed and Ye 2011). The FGLS is justified since the period (*T*) is higher than the cross-section entities (*N*). *Table 6.5* presents the FGLS results. The results based on FGLS confirm the baseline findings. The results reveal an inverted U-shaped relationship between FinTech credit and all bank risk-taking measures. The squared FinTech credit variable is negative and statistically significant for four bank risk-taking measures (liquidity, insolvency, leverage, and portfolio risks). The study further re-estimated all equations by employing an alternative measure of FinTech credit as a percentage of GDP (*FIN_GDP*). The robustness tests estimation results based on both fixed effects (*Table 6.6*) and FGLS (*Table 6.7)* confirm an inverted U-shaped non-linear relationship between FinTech credit and bank risk-taking measures.

Table 6.5: Robustness checks: Feasible generalized least squares models

	Credit	Liquidity	Insolvency	Leverage	Portfolio
FinTech variables					
FinTech credit	0.1186***	0.1381***	0.0799***	0.1090***	0.1007***
	(0.0316)	(0.0195)	(0.0306)	(0.0329)	(0.0327)
FinTech credit squared	-0.0028	-0.0079***	-0.0061***	-0.0048*	-0.0080***
	(0.0019)	(0.0013)	(0.0023)	(0.0025)	(0.0024)
Bank-level control variables					
Concentration	-2.9230***	-0.2200***	2.5649***	2.8157***	2.4066***
	(0.1326)	(0.0839)	(0.1904)	(0.1779)	(0.2075)
Bank size	-0.0841***	-0.1284***	-0.1268***	-0.1068***	-0.0091
	(0.0241)	(0.0099)	(0.0229)	(0.0218)	(0.0251)
Noninterest income to total income	0.5917***	0.1130***	0.0616	0.1957	0.3250**
	(0.0941)	(0.0435)	(0.1261)	(0.1252)	(0.1373)
Overheads to total assets	-0.4135***	0.2677***	0.7253***	0.4094***	0.5711***
	(0.0574)	(0.0295)	(0.0801)	(0.0796)	(0.0850)
Regulatory capital adequacy ratio	-1.1854***	-0.3563***	0.8873***	0.8148***	1.0313***
	(0.1521)	(0.0673)	(0.1979)	(0.2144)	(0.2258)
Deposit to assets ratio	-1.0009***	-0.1014**	-0.1131	0.0257	0.3088**
	(0.0780)	(0.0430)	(0.1076)	(0.1142)	(0.1225)
Loan to assets ratio	-0.3316**	0.2213***	0.7277***	0.3224**	0.9503***
	(0.1618)	(0.0739)	(0.1765)	(0.1608)	(0.1888)
Market-based control variables					
Stock price index	0.4539***	0.2819***	-0.0408	0.2985**	0.0352***
	(0.1028)	(0.0643)	(0.1360)	(0.1398)	(0.1469)
Housing price index	-1.4440***	0.4036***	2.2446***	1.8465***	2.5018
	(0.1918)	(0.1048)	(0.2627)	(0.2724)	(0.2766)
Govt Bond yield	0.1455***	-0.0227**	0.3107***	0.2228***	0.2773***
	(0.0257)	(0.0097)	(0.0313)	(0.0306)	(0.0349)
Money market	-0.2567***	0.0095	-0.0270	0.1127***	-0.0660***
	(0.0211)	(0.0078)	(0.0264)	(0.0254)	(0.0293)
Domestic bank credit	-0.4128***	0.1784***	0.8211***	1.1886***	0.9016**
	(0.0916)	(0.0453)	(0.1217)	(0.1140)	(0.1304)
Domestic credit to private sector	0.0375***	0.2870***	-0.3578***	-0.6959***	-0.6072***
	(0.0727)	(0.0482)	(0.1196)	(0.1126)	(0.1323)
Country-control variables					
GDPGR	-0.002	0.0034	-0.0597*	-0.6959	-0.0754**
	(0.0281)	(0.0121)	(0.0306)	(0.0271)	(0.0343)
Inflation	1.5941***	-0.2089	-0.5618	-0.0269	-1.4147**
	(0.4736)	(0.1971)	(0.5233)	(0.5597)	(0.5685)
Real effective exchange rate	-0.4130	-0.9186***	-0.4299	0.0324	-0.0634
	(0.2930)	(0.1328)	(0.3312)	(0.3289)	(0.3654)
Trade openness	0.8798***	-0.6479***	-0.2338**	0.1392	-0.2978***
	(0.0795)	(0.0386)	(0.0959)	(0.0987)	(0.1059)
Constant	7.3971**	7.1152***	-22.0367***	-26.4025***	-21.2817***
	(3.0092)	(1.4765)	(3.3774)	(3.5973)	(3.6080)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes	Yes	Yes
Observations	673	673	669	672	653

Source: Authors' calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model.

Table 6.6: Fixed effect models based on an alternative measure of FinTech credit

	Credit	Liquidity	Insolvency	Leverage	Portfolio
Fintech variables					
FinTech credit (*FIN_GDP*)	0.1664***	0.0384	0.0294	0.0217	0.1487*
	(0.0258)	(0.0256)	(0.0806)	(0.0816)	(0.0871)
FinTech credit (*FIN_GDP*) squared	-0.0079***	-0.0023	-0.0044	-0.0040	-0.0105**
	(0.0015)	(0.0015)	(0.0047)	(0.0048)	(0.0051)
Bank-level control variables					
Concentration	-0.6215***	0.0879	-1.1341	-0.9651	-1.7377**
	(0.2412)	(0.2393)	(0.7590)	(0.7624)	(0.8360)
Bank size	-0.0777	-1.2602***	-1.2660***	-1.0752***	-1.0940***
	(0.1037)	(0.1029)	(0.3236)	(0.3278)	(0.3465)
Noninterest income to total income	0.3701***	-0.1124*	-0.7803***	-0.6193***	-0.8518***
	(0.0678)	(0.0673)	(0.2128)	(0.2147)	(0.2313)
Overheads to total assets	0.1306***	0.1335***	0.8957***	0.5718***	0.9247***
	(0.0412)	(0.0409)	(0.1371)	(0.1304)	(0.1525)
Regulatory capital adequacy ratio	0.0457	-0.0584	0.8155**	0.2911	0.6321*
	(0.1102)	(0.1093)	(0.3475)	(0.3484)	(0.3799)
Deposit to assets ratio	1.2796***	0.6308**	0.4380	1.0754	0.8540
	(0.2607)	(0.2586)	(0.8127)	(0.8243)	(0.8705)
Loan to assets ratio	-2.3506***	-1.5761***	-0.9885	-0.5298	-1.7221
	(0.3068)	(0.3044)	(0.9667)	(0.9704)	(1.0471)
Market-based control variables					
Stock price index	-0.2019**	0.2177***	-0.9452***	-0.7497***	-0.8602***
	(0.0827)	(0.0820)	(0.2599)	(0.2613)	(0.2886)
Housing price index	-2.2523***	0.7461***	3.1376***	3.1115***	3.4766***
	(0.1205)	(0.1195)	(0.3850)	(0.3811)	(0.4183)
Govt Bond yield	0.0661***	-0.0132	0.1781***	0.1462***	0.1295**
	(0.0161)	(0.0160)	(0.0504)	(0.0512)	(0.0558)
Money market	-0.1101***	0.0577***	0.0096	0.0947**	-0.0252
	(0.0125)	(0.0124)	(0.0402)	(0.0398)	(0.0449)
Domestic bank credit	3.0533***	2.2738***	3.6485***	3.4294***	3.8577***
	(0.3177)	(0.3152)	(0.9999)	(1.0047)	(1.0802)
Domestic credit to private sector	-0.8700***	0.5218**	0.6532	0.3982	0.4431
	(0.2060)	(0.2044)	(0.6435)	(0.6517)	(0.6970)
Country-control variables					
GDPGR	0.0285**	-0.0004	-0.0077	-0.0092	-0.0058
	(0.0129)	(0.0128)	(0.0409)	(0.0409)	(0.0440)
Inflation	0.2436	-0.2449	-2.6814**	-4.1746***	-2.7498**
	(0.3982)	(0.3950)	(1.2428)	(1.2599)	(1.3317)
Real effective exchange rate	0.1847	0.7952***	1.6712**	1.6623**	1.6652**
	(0.2415)	(0.2396)	(0.7563)	(0.7637)	(0.8099)
Trade openness	-0.1499	1.3018***	4.8005***	5.0631***	4.8532***
	(0.2100)	(0.2083)	(0.6774)	(0.6640)	(0.7380)
Constant	-1.1623	-5.5512**	-24.9425***	-16.5950**	-25.2106***
	(2.4318)	(2.4125)	(7.5973)	(7.6984)	(8.1531)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes	Yes	Yes
Observations	673	673	669	672	653
R-squared	0.7715	0.4462	0.3813	0.3862	0.3220
Number of countries	25	25	25	25	25
Hausman test	182.12***	133.00***	22.01***	128.10***	80.13***
Wooldridge test	124.689***	50.592***	289.146***	10.158***	54.387***
Modified Wald test	2823.51***	11044.26***	1279.51***	1272.88***	1126.48***
Pesaran CD test	1.838*	2.710***	14.843***	12.920***	12.310***

Source: Authors' calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model. Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models. Pesaran test of cross-sectional independence.

Table 6.7: FGLS models using an alternative measure of FinTech credit

	Credit	Liquidity	Insolvency	Leverage	Portfolio
FinTech variables					
FinTech credit (*FIN_GDP*)	0.1318***	0.1112***	0.1093***	0.1550***	0.1489***
	(0.0299)	(0.0175)	(0.0298)	(0.0321)	(0.0314)
FinTech credit (*FIN_GDP*) squared	-0.0039**	-0.0071***	-0.0089***	-0.0093***	-0.0125***
	(0.0020)	(0.0012)	(0.0024)	(0.0026)	(0.0025)
Bank-level control variables					
Concentration	-2.9442***	-0.2649***	2.4549***	2.7607***	2.2359***
	(0.1311)	(0.0862)	(0.1884)	(0.1751)	(0.2036)
Bank size	-0.0714***	-0.1062***	-0.1193***	-0.0934***	0.0019
	(0.0228)	(0.0092)	(0.0219)	(0.0206)	(0.0239)
Noninterest income to total income	0.6024***	0.0700	0.0227	0.1316	0.2808**
	(0.0927)	(0.0442)	(0.1225)	(0.1229)	(0.1329)
Overheads to total assets	-0.4173***	0.2681***	0.7061***	0.4175***	0.5421***
	(0.0565)	(0.0304)	(0.0782)	(0.0780)	(0.0823)
Regulatory capital adequacy ratio	-1.1950***	-0.3594***	0.8776***	0.8422***	0.9930***
	(0.1509)	(0.0675)	(0.1967)	(0.2136)	(0.2233)
Deposit to assets ratio	-1.0572***	-0.2096***	-0.2540***	-0.1652	0.1090
	(0.0826)	(0.0495)	(0.1169)	(0.1269)	(0.1322)
Loan to assets ratio	-0.3340**	0.1842**	0.6460***	0.2470	0.8247***
	(0.1611)	(0.0731)	(0.1773)	(0.1621)	(0.1888)
Market-based control variables					
Stock price index	0.3888***	0.2689***	-0.0228	0.3143**	0.0829
	(0.1040)	(0.0635)	(0.1322)	(0.1361)	(0.1414)
Housing price index	-1.4287***	0.2869***	2.2197***	1.8436***	2.4716***
	(0.1922)	(0.1024)	(0.2510)	(0.2619)	(0.2621)
Govt Bond yield	0.1394***	-0.0285***	0.3083***	0.2134***	0.2758***
	(0.0256)	(0.0102)	(0.0307)	(0.0302)	(0.0341)
Money market	-0.2536***	0.0122	-0.0291	0.1163***	-0.0720**
	(0.0208)	(0.0084)	(0.0262)	(0.0253)	(0.0290)
Domestic bank credit	-0.4186***	0.1210***	0.7542***	1.1238***	0.8189***
	(0.0900)	(0.0468)	(0.1202)	(0.1125)	(0.1276)
Domestic credit to private sector	0.1365***	0.3345***	-0.3334***	-0.6329***	-0.5905***
	(0.0694)	(0.0497)	(0.1164)	(0.1107)	(0.1273)
Country-control variables					
GDPGR	0.0068	0.0110	-0.0525*	-0.0190	-0.0641*
	(0.0279)	(0.0124)	(0.0302)	(0.0265)	(0.0333)
Inflation	1.8461***	-0.5460***	-0.5669	-0.1781	-1.3545**
	(0.4917)	(0.2059)	(0.5134)	(0.5511)	(0.5546)
Real effective exchange rate	-0.1584	-0.9749***	-0.1858	0.4394	0.3256
	(0.3105)	(0.1557)	(0.3389)	(0.3368)	(0.3694)
Trade openness	0.8733***	-0.5936***	-0.2152**	-0.0684	-0.2602**
	(0.0775)	(0.0377)	(0.0953)	(0.0978)	(0.1050)
Constant	4.7005	9.4945***	-22.5612***	-26.7708***	-22.6189***
	(3.1862)	(1.5422)	(3.2663)	(3.5111)	(3.4670)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes	Yes	Yes
Observations	673	673	669	672	653

Source: Authors' calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model.

6.6. Conclusions

The recent financial crisis has raised a serious question about traditional banks' response to the emergence of new financial and technological innovations. In particular, debates surrounding the impact of FinTech innovation in banking and financial stability have become a green area of discussion within the policy and academia. The financial system naturally responds to new information, and its adjustments to such information may have positive and negative effects. Moreover, the emergence of FinTech credit in the credit market, directly and indirectly, impact the banking sector, some of which have had a significant bearing on bank risk-taking. As the debates on how the FinTech sector's development will affect the banking system, such questions have motivated this study to investigate how banks respond to the entrance of ‘new’ competitors.

Although a growing body of prior work examines the interaction between FinTech credit and the financial and banking system, these studies fail to reach a consensus. Furthermore, no prior work specifically assesses the impact of FinTech credit on banks’ risk-taking. Moreover, most previous studies conduct single-country analyses and lack careful consideration of the possibility of a non-linear relationship between bank risk and FinTech credit. Thus, this chapter contributes empirically to the well-documented literature on bank risk-taking and bank stability literature by focusing on the possibility of a non-linear relationship between bank risk and FinTech credit. It also contributes to the developing literature on FinTech and non-bank credit intermediation. In addition, this chapter provides a broader research scope that includes EMDEs and developed countries with active and or significant FinTech credit activities. Furthermore, this study’s framework allows for a non-linear relationship between FinTech credit and bank risk-taking, providing more insight into the banking system’s response to the emergence of FinTech innovation.

The study shows that FinTech credit has a non-linear (inverted U-shaped) relationship with bank risk-taking. Specifically, bank risk-taking increases at lower FinTech credit growth levels and later declines as FinTech credit develops. The results are particularly significant for two bank risk-taking measures (credit and liquidity risks). These findings show that a market can experience different impacts at different credit growth levels, thus raising monitoring issues. Further robustness checks confirm these results.

The increasing role of the nonbank sector in undertaking financial intermediation may have important implications for financial and bank stability, both directly and indirectly, through their linkages with the traditional banking system, given the limited current regulatory frameworks applicable to such entities (Durdu and Zhong 2022). Emerging risks from such entities can prove to be more challenging to monitor hence the need to develop macroprudential instruments beyond the banking perimeter. There is also a need to develop financial stability measures for NBFIs as well as develop and implement reporting requirements that fully capture nonbank credit activities. The intensity of the macroprudential oversight should be based on each sector's contribution to systemic risk. Despite the patchy knowledge base of FinTech credit, monitoring the resilience of financial institutions, particularly the relationship between non-bank finance and bank finance, is vital. Whether these evolving developments will ultimately endanger the financial system's stability crucially depends on the resilience of the overall financial system (Buch 2019).

CHAPTER 7: DO MACROPRUDENTIAL POLICIES INFLUENCE FINTECH CREDIT GROWTH?

7.1. Introduction

The 2007/09 global financial crisis (GFC) underscores the need for a dedicated macroprudential policy (MaPP) and system-wide surveillance that effectively detects the build-up of macroeconomic risks such as credit, liquidity and capital risks before they can undermine the overall stability of the financial system. MaPP has since been extensively and actively used in emerging and advanced economies following the financial crisis (Cizel et al. 2019). The main purpose of MaPP is to prevent financial instability, such as banking crises, which usually produce long-lasting and devastating economic effects (Nakatani 2020). Although MaPP has continued to evolve, macroprudential measures were mainly implemented exclusively in the traditional banking sector (IMF 2013), thereby creating regulatory and policy gaps for the NBFI sector. As NBFI assumes an active role in financial intermediation and alternative finance in the financial system, it remains an empirical question whether MaPP can influence its growth.

Prior to the crisis, the financial sector's share of overall economic activity grew exponentially due to the expansion of credit and growth of financial assets resulting from increased leverage in the banking sector and expansion of the non-bank financial sector (Constâncio et al. 2019). Despite the progress made in the regulatory reform process since the crisis, the macroprudential framework for the NBFI sector is still in its infancy (de Guindos 2019). The NBFI sector has grown significantly in size and relevance and accumulated more risks on its balance sheet (de Guindos 2019). In particular, the growing relevance of the non-bank credit market can create potential new vulnerabilities. Moreover, past experiences remind us that risks to financial stability can emerge outside the banking sector, hence a growing global call to extend beyond the banking sector (Buch 2020; Boh et al. 2019; Constâncio et al. 2019).

While a growing number of studies have tended to examine the effects of MaPP on credit growth (bank credit, household credit), until recently, studies have begun to dissect its effect on nonbank credit (Claessens et al. 2021; Irani et al. 2021; Hodula and Ngo 2021; Cizel et al. 2019). Specifically, a vast literature documents the effectiveness of MaPP measures in curbing credit, excessive growth in leverage and housing prices (e.g., De Schryder and Opitz 2021; Pochea and Niţoi 2021; Akinci and Olmstead-Rumsey 2018). Moreover, previous studies have, by and large, focused on the cross-country effect of MaPP on bank or total credit growth (Akinci and Olmstead-Rumsey 2018; Altunbas et al. 2018; Cerutti et al. 2017a). However, the literature has largely ignored the effects on the nonbank sector-related flows and perhaps underestimated total spillovers (Buch and Goldberg 2017).

Emerging empirical evidence suggests that MaPP may be subjected to "cross-sector substitution" and "boundary problems", which may trigger a migration of leveraged lending toward the nonbank financial system (Claessens et al. 2021; Irani et al. 2021; Hodula and Ngo 2021; Cizel et al. 2019). While this "spillage" effect may potentially enhance financial stability through the diversification channel, a trade-off with financial stability may ensue as the benefits of MaPP may be outweighed when credit spills to other parts of the markets (exempted from such regulation). In the worst case, emerging lending activities may further aggravate exposures that may even cause worst possible outcomes than the one regulation initially sought to circumvent and pose a question on the effectiveness of MaPP.

Despite the recent progress in banking and finance literature and the growing significance of prudential regulation, there remains a question on their effectiveness given the growth of FinTech credit. The analysis of this study is particularly important given the growing role of NBFIs in credit intermediation and their potential implication for financial stability. This study attempts to fill this gap by investigating how domestic MaPP affects the growth of FinTech credit. The study also examines if a tightening (easing) of MaPP is associated with an increase (decrease) in FinTech credit. The study points to the boundaries of MaPP, which mostly targets traditional financial intermediaries with limited engagement with a host of other non-banks, such as FinTech innovations (Claessens 2015). This study, therefore, provides the first attempt and fill this gap by examining whether there is a significant relationship between MaPP and FinTech credit. The main research question is whether MaPP influences FinTech credit growth. To answer this question, this study employs a quarterly cross-country panel dataset from 2005Q1 to 2018Q2. The remainder of the chapter is structured as follows. *Section 7.2* presents the MaPP data description, followed by *Section 7.3,* presenting variable definitions and descriptions. *Section 7.4* presents descriptive statistics, and *Section 7.5* presents an empirical approach. *Section 7.6* presents results and discussions, and *Section 7.7* provides conclusions.

7.2. MaPP data description

The iMaPP dataset captures MaPP implemented by central banks and supervisory authorities, containing information on whether the MaPP action is a tightening, loosening or no action (Alam et al. 2019; De Schryder and Opitz 2021). The respective policy actions for each tool are further presented as dummy-type indices, which specify the information on the introduction and removal of policy measures. The advantage of dummy coding is that it can capture the direction and intensity of a MaPP change while incorporating qualitative traits from the policy that cannot be captured by a unique numerical statistic (Cerutti and Zhou 2018). In addition, the use of dummy-type indices allows for analysis and comparability across countries. It also enables the characterisation and comparison of the relative effects of different MaPP instruments, such as grouping into loan-targeted tools sector-specific and general measures (Alam et al. 2019). They are, therefore, useful for assessing the effects of macroprudential instruments per policy action.

The iMaPP database is fairly detailed and covers 17 different MaPP instruments and their subcategories based on the latest IMF dataset covering 134 countries from January 1990 to December 2018. It provides more recent data and comprehensive coverage in terms of a vast range of policy instruments, countries, and time periods in higher frequencies (Alam et al. 2019). The iMaPP data is aggregated from monthly data to quarterly observations to align with the frequency of the dependent variables and other variables in the empirical analysis. The 17 specific MaPP tools include: Countercyclical Capital Buffers (*CCB*); Conservation Buffers (*CV)*; Capital requirements (*CR*); Leverage ratio (*LVR*); Loan loss provisions (*LLP*); Limits on credit growth (*LCG*); Loan restrictions (*LR*); Limits on foreign currency (*LFC*); Limits on the loan-to-value ratio (*LTV*); Limits on the debt-service-to-income ratio (*DSTI*); Tax measures (*TAX*); Liquidity requirements (*LQR*); Limits on the loan-to-deposit ratio (*LTD*); Limits on foreign exchange positions (*LFX*); Reserve requirements (*RR*); Systemically important financial institution (*SIFI*) and other macroprudential measures (*OT*). Individual and grouped MaPP instruments from the iMaPP dataset are defined in *Table 7.1*

Table 7.1: Definitions of MaPP instruments

Instrument/Group	Abbreviation	Definition
Instrument (0–1)		
Countercyclical Capital Buffers	*CCB*	A requirement for banks to maintain a countercyclical capital buffer.
Conservation	*CV*	Requirements for banks to maintain a capital conservation buffer, including the one established under Basel III.
Capital Requirements	*CR*	Capital requirements for banks include risk weights, systemic risk buffers, and minimum capital requirements.
Leverage ratio	*LVR*	A limit on leverage of banks calculated by dividing a measure of capital by the bank's non-risk-weighted exposures.
Loan Loss Provisions	*LLP*	LLP requirements for macroprudential purposes include dynamic provisioning and sectoral provisions (e.g., housing loans).
Limits on the debt-service-to-income ratio	*DSTI*	Limits to the debt-service-to-income ratio and the loan-to-income ratio which restrict the size of debt services or debt relative to income. They include those targeted at housing loans, consumer loans, and commercial real estate loans.
Limits on Credit Growth	*LCG*	Limits on growth or the volume of aggregate credit, the household-sector credit, or the corporate-sector credit by banks, and penalties for high credit growth.
Loan Restrictions	*LR*	Loan restrictions that are more tailored than those captured in "LCG". They include loan limits and prohibitions, which may be conditioned on loan characteristics (e.g., the maturity, the size, the LTV ratio and the type of interest rate of loans), bank characteristics (e.g., mortgage banks), and other factors.
Limits on Foreign Currency	*LFC*	Limits on foreign currency (FC) lending and rules or recommendations on FC loans.
Limits on The Loan-To-Value Ratio	*LTV*	Limits to the loan-to-value ratios, including those mostly targeted at housing loans, but also includes those targeted at automobile loans and commercial real estate loans.
Limits on The Debt-Service-To-Income Ratio	*DSTI*	Limits to the debt-service-to-income ratio and the loan-to-income ratio which restrict the size of debt services or debt relative to income. They include those targeted at housing loans, consumer loans, and commercial real estate loans.
Tax Measures	*TAX*	Taxes and levies applied to specified transactions, assets, or liabilities, which include stamp duties and capital gain taxes.
Liquidity Requirements	*LQR*	Measures taken to mitigate systemic liquidity and funding risks, including minimum requirements for liquidity coverage ratios, liquid asset ratios, net stable funding ratios, core funding ratios and external debt restrictions that do not distinguish currencies
Limits on the Loan-To-Deposit Ratio	*LTD*	Limits to the loan-to-deposit (LTD) ratio and penalties for high LTD ratios.
Limits on Foreign Exchange Positions	*LFX*	Limits on net or gross open foreign exchange (FX) positions, limits on FX exposures and FX funding, and currency mismatch regulations.
Reserve Requirements	*RR*	Reserve requirements (domestic or foreign currency) for macroprudential purposes.
Systemically Important Financial Institution	*SIFI*	Measures taken to mitigate risks from global and domestic SIFIs, which include capital and liquidity surcharges.
Other macroprudential measures	*OT*	Macroprudential measures not captured in the above categories—e.g., stress testing, restrictions on profit distribution, and structural measures (e.g., limits on exposures between financial institutions).
Groups		
Borrower-Targeted Instrument (0-2)	*BORROWER*	DSTI+LTV
Financial Institution-Targeted Instruments (0-12)	*LENDER*	LCG+LLP+LR+LFC+CR+CV+LVR+SIFI+CCB+RR+LQR+LFX

Source: Alam et al. (2019) and author's illustration

7.3. Variable definitions and description

7.3.1. Dependent variables

The dependent variable is FinTech credit. Several studies have used P2P loans, or loan origination data from FinTech platforms, as a proxy for FinTech credit variables (see., Braggion et al. 2021; Zhang et al. 2019; Jagtiani and Lemieux 2018). Following Frost et al. (2019), FinTech credit is measured as a share of total new loan originations of marketplace lending volumes (FinTech credit) to total private credit (*FIN_S*). *FIN_S* is thus computed as the sum of loan originated volumes (by FinTech platforms) divided by the sum of credit to the private non-financial sector. Further, following Frost et al. (2019) and Rau (2020), the FinTech credit values are normalised by being transformed into natural logarithms to minimise the effect of outliers. The study further includes additional dependent variables in the form of the logarithm of the FinTech credit as a percentage of GDP (*FIN_GDP*) (Bazarbash et al. 2020) and FinTech credit per capita (*FIN_PC*) in an economy (Cornelli et al. 2021; 2020; Rau 2020; Frost et al. 2019) for robustness analysis.

7.3.2. Independent variables

7.3.2.1. Main independent variable

The study uses seventeen (17) different MaPP indicators or instruments and their subcategories based on the latest IMF database developed by Alam et al. (2019) to develop MaPP variables. This study uses several categories of MaPP instruments to examine their impact on FinTech credit growth. The main independent variables used are three dummy variables: the overall MaPP policy stance (MaPP), MaPP tightening (MaPP^{T}), and MaPP loosening (MaPP^{L}). In addition, borrower-targeted measures (MaPP_Bw) and financial-institutions-targeted measures (MaPP_FI) are included. Using an overall MaPP policy stance variable is consistent with several studies (e.g., Kang et al. 2021; Claessens et al. 2021; Alam et al. 2019; Akinci and Olmstead-Rumsey 2018; Kim and Mehrotra 2018; 2019; Cerutti et al. 2017a). These studies argue that the overall MaPP variable can capture policy actions that may not be easy to measure using a single MaPP instrument.

The overall MaPP policy stance variable is derived from an aggregate measure of macroprudential policy stance, the MaPP index ($MaPP_{j,t}^{Index}$) by summing up individual MaPP instruments (dummies that take a value of 1 if the policy is activated and 0 otherwise). The $MaPP_{j,t}^{Index}$ is then transformed to a dummy variable taking a value of 1 if at least one policy is activated and 0 if no policy actions, denoted by $MaPP_{j,t}$. That is, $MaPP_{j,t} = 1 \; if \; MaPP_{j,t}^{Index} \geq 1$ and 0 otherwise. The $MaPP_{j,t}$ variable is used in the baseline regression model to examine the joint effect of the policy action on FinTech credit.

However, a common limitation of using the overall MaPP policy stance is that it treats all MaPP actions in the same way and symmetrically (Claessens et al. 2021). To address this, an alternative classification for MaPP that provides a distinction between MaPP actions is also included. Two dummy variables capturing MaPP policy stance based on MaPP tightening ($MaPP_{j,t}^{T}$) and MaPP loosening ($MaPP_{j,t}^{L}$) variables are used. The $MaPP_{j,t}^{T}$ ($MaPP_{j,t}^{L}$) is derived from an aggregate index obtained by cumulating the sum of the number of tightening actions (loosening actions) across all individual tools to proxy a country's MaPP stance. A value of 1 is assigned for at least one tightening (loosening) policy action and a value of zero for no policy action.

Further, MaPP alternative classifications are specific to the "loan-targeted" group, which consist of lenders or financial institutions (i.e., loan supply) and borrowers (i.e., loan demand) (see. Davis et al. 2022; Claessens et al. 2021; Cerutti et al. 2017b). Borrower-targeted measures include the debt-service-to-income (*DSTI*) ratio and limits to bank exposures to the housing sector as a loan-to-value (*LTV*) ratio. Financial institution-targeted measures cover the majority of the variables. These are supply-related measures which include supply loan (limits on credit growth (*LCG*), loan loss provisions (*LLP*), loan restrictions (*LR*), and limits on foreign currency loans (*LFC*)), supply capital (capital requirements (*CR*), conservation buffers (*CV*), the leverage ratio (*LVR*), capital surcharges for systemically important financial institutions (*SIFI*), and countercyclical capital buffers (*CCB*)) and supply general (reserve requirements (*RR*), liquidity requirements (*LQR*), and limits on foreign exchange positions (*LFX*)). Two dummy variables are derived; borrower-targeted instruments (MaPP_Bw) and financial institution-targeted measures (lenders) (MaPP_FI), to capture the group policy stance of these two instruments.

7.3.2.2. Control variables

Other explanatory variables are taken from the standard literature, using various macroeconomic aggregates and financial and market-based variables as control variables

(Nakatani 2020; Cerutti et al. 2017a). However, the control variables do not represent the focal point of the analysis but are very critical for taking into account different times and country-specific institutional characteristics. Specifically, the control variables include domestic credit to the private sector (*DCPS*), the real GDP growth rate (*RGDPG)*, real effective exchange rate (*REER*), crisis dummy *(Crisis)*, monetary policy rate (*MPR*), financial openness (*FINOP)* and regulation quality (*REGQ).*

The stock of total domestic credit to the private sector (*DCPS*) is employed as a target for MaPP (Alam et al. 2019; Kim and Mehrotra 2018). This may be explained by the "*substitution"* and "*complementary"* relationship between FinTech credit and domestic bank credit. Several studies suggest that FinTech credit may complement bank credit and other market-based finance (Cornelli et al. 2021; 2020; Tang 2019; de Roure et al. 2022). Cornelli et al. (2020) even suggest that FinTech credit may, in fact, complement other traditional forms of credit (rather than substitutes). Literature also suggests a substitution relationship between FinTech credit and bank credit (Havrylchyk et al. 2020; Vives 2019a; de Roure et al. 2022).

The real GDP growth (*RGDPG)* is included to measure overall economic activity (e.g., Cornelli et al. 2020; Nier et al. 2020; Alam et al. 2019; Kim and Mehrotra 2019). High GDP growth is associated with higher credit growth proxied by bank credit (Akinci and Olmstead-Rumsey 2018). Optimism with regard to short-run economic outcomes is expected to boost both credit demand and supply; hence a positive coefficient is expected (Nier et al. 2020). Other related studies document a positive association between total alternative credit activity (BigTech and FinTech credit) and income level (GDP per capita) (Cornelli et al. 2020; Frost et al. 2019; Claessens et al. 2018). Claessens et al. (2018) conducted a multivariate cross-country regression analysis of 63 economies and found a positive and non-linear relationship between GDP per capita and FinTech credit volume per capita. A similar study by Cornelli et al. (2021; 2020) observes that more developed economies with higher GDP per capita tend to have a higher demand for credit from firms and households, an opportunity for FinTech credit growth. However, further evidence reveals that this relationship diminishes for very high levels of development (Cornelli et al. 2021; Bazarbash et al. 2020; Claessens et al. 2018).

To adjust for the occurrence of systemic banking crises, a crisis dummy indicator *(Crisis)* following dates of banking crises developed by Laeven and Valencia (2020) is included as a control variable (Cornelli et al. 2020; Cizel et al. 2019; Alam et al. 2019; Cerutti et al. 2017a). The crisis dummy denotes whether a country had suffered a crisis during the period of study (Cornelli et al. 2020). Pre-crisis literature identifies credit growth as a reliable crisis predictor (Röhn et al. 2015; Aikman et al. 2014). Moreover, credit and liquidity risks tend to intensify bank distress during a crisis (Vazquez and Federico 2015). The banking crisis literature also reveals that the effect of rapid credit growth can potentially escalate into financial crises (Aikman et al. 2014). The "too much finance" and vanishing positive theories suggest that excessive credit may cause financial instability (see., Zhu et al. 2020a; Arcand et al. 2015; Gründler 2019).

A central bank policy rate proxied by the monetary policy rate (*MPR*) is included to capture the monetary policy stance (Nier et al. 2020; Alam et al. 2019; Cizel et al. 2019; Cerutti et al. 2017a). *MPR* is one of the most important monetary policy tools used by central banks to control bank lending. Several monetary policy proxies have been used in the literature to capture different types of information from the monetary policy stance. For instance, a US monetary policy surprise measure or an increase in the MPR may be viewed as a sign of an economic boom, promoting the creation of credit (Claessens et al. 2021). While several monetary policy proxies have been used in the literature, their impact may vary depending on the proxy employed and if the analysis is undertaken for the period of conventional or unconventional monetary policy (Claessens et al. 2021). Changing monetary policy affects aggregate demand and the level of economic activity by increasing or decreasing credit availability. As such, a policy tightening may strongly lower the credit supply. An increase in *MPR* is expected to lower the credit growth rate (Akinci and Olmstead-Rumsey 2018). Furthermore, as the tightening of *MPR* is generally viewed as reducing aggregate demand and increasing the cost of borrowing, a negative coefficient is expected (Nier et al. 2020).

The study includes *REER* to represent a real exchange rate appreciation (Nier et al. 2020; Alam et al. 2019). *REER* movements are associated with subsequent changes in domestic credit (Nier et al. 2020). Recent empirical literature also links currency appreciation to domestic credit developments (Nier et al. 2020; Hofmann et al. 2020; Carstens 2019; Baskaya et al. 2017). Contrary to the standard notion in the earlier literature, where a currency appreciation is viewed as contractionary through the reduction of net exports, REER may actually potentially be expansionary (Nier et al. 2020). An appreciating domestic *REER* can fuel the build-up in domestic credit through various channels that may simultaneously reinforce each other (Carstens 2019). Since *REER* may be expansionary or contractionary, a negative coefficient is expected. By convention, a positive value represents a real exchange rate depreciation against the US dollar.

The study uses two measures that benefit financial integration and other externalities of financial integration, such as developments in institutional and regulatory quality and improvement in private and public governance (Nagaraj and Zhang 2019). The study uses a financial openness (*FINOP)* indicator based on the KAOPEN[28] de-jure index (or the Chinn-Ito index) developed by Chinn and Ito (2006, 2008) to measure a country's degree of capital account openness (Alam et al. 2019). It captures capital account openness reforms such as liberalising exchange rates and easing international payments and receipts procedures. Prior literature has widely used the KAOPEN index measure, focusing on regulatory restrictions of capital account transactions (Gräbner et al. 2021; Nagaraj and Zhang 2019). The KAOPEN indicator is based on the IMF's AREAR database, which covers a large proportion of the global asset categories and broad country coverage. It is also publicly available, and also a preferred measure using a de-facto measure might cause the endogeneity problem in the model (Ashraf et al. 2021). The KAOPEN index is normalised to range between 0 and 1, i.e., it takes value 1 during periods classified as open and 0 otherwise. Thus, a higher value of the KAOPEN index indicates a higher level of capital account openness and lesser restrictions (Arif-Ur-Rahman and Inaba 2020).

Institutional characteristics, disclosure and the judicial system are also associated with higher alternative credit volumes, probably because they allow FinTech firms to enter the credit markets and grow (Cornelli et al. 2021). This study uses the World Governance Indicators (WGI)[29] developed by Kaufmann et al. (2011) to measure regulatory quality *(REGQ).* This indicator has been widely used in literature (e.g., Nagaraj and Zhang 2019; Jeanneret 2018). The *REGQ* captures perceptions of the ability of the government to develop and implement sound policies and regulations that permit and promote private sector development (Alam et al. 2019; Nagaraj and Zhang 2019). It, therefore, measures the presence and scope of regulations that ease doing business (Nagaraj and Zhang 2019).

[28] The KAOPEN index dataset and calculation is available at http://web.pdx.edu/~ito/Chinn-Ito_website.htm (updated to 2019).
[29] The WGI covers six (6) indicators that define institutional quality, one of which is regulatory quality. It also covers a wide range of regulations that include inter alia, price controls, presence of trade barriers, and effectiveness of anti-trust policy.

The values range from approximately -2.5 to 2.5, with higher values signalling better institutional quality. Some advantages of using the *REGQ* measure are that it is publicly available and covers longer time series that are comprehensive. *Table 7.2* shows the description of variables used for regression estimations.

Table 7.2: Description of variables used for regression estimations†

Variables	Abbreviation	Description	Source
Dependent variables			
FinTech credit share	*FIN_S*	Measured as the ratio of total volumes of loans originated (by FinTech platforms) to total credit to the private non-financial sector (see. Frost et al. 2019; Rau 2020).	Various FinTech Platforms, UK P2PFA; AFSAL; Korea P2PFA; SMLA; US S&P GMI 2018; Sweden RiksBank survey; CBIRC; Brismo; WDZJ.
FinTech credit to GDP	*FIN_GDP*	Measured as the ratio of total volumes of loans originated as a percentage of GDP (see. Rau 2020).	
FinTech credit per capita	*FIN_PC*	Measured as the ratio of total volumes of loans originated to population (see. Rau 2020).	
Independent variables			
MaPP overall policy stance	*MaPP*	MaPP activation variable taking value 1 if MaPP policy is activated and 0 otherwise.	iMaPP database by Alam et al. (2019).
MaPP tightening	$MaPP^{T}$	Dummy variable for tightening taking values 0 and 1.	iMaPP database by Alam et al. (2019).
MaPP loosening	$MaPP^{L}$	Dummy variable for loosening taking values 0 and 1.	iMaPP database by Alam et al. (2019).
MaPP groups			
MaPP borrower	*MaPP_Bw*	Borrower-targeted instrument (0-1)	iMaPP database by Alam et al. (2019).
MaPP lender	*MaPP_FI*	Financial institution-targeted instruments (0-1):	iMaPP database by Alam et al. (2019).
Control variables			
Domestic credit	*DCPS*	Share of domestic credit to the private sector to GDP	BIS
GDP growth	*RGDPG*	Real GDP growth (%)	OECD
Crisis dummy	*Crisis*	Indicates Systemic Banking Crisis (0–1)	Laeven and Valencia (2020).
Monetary Policy rate	*MPR*	Monetary policy rate (%)	BIS Central Bank Policy Rate when available; otherwise, CEIC for ECB main refinancing operations (MRO) rate for Eurozone countries.
Exchange rate	*REER*	Real effective exchange rate. A positive value represents depreciation against the USD.	BIS
De Jure openness index	*FINOP*	An index measuring a country's degree of capital account openness, taking values 0 and 1.	Measured by the KAOPEN index developed by Chinn and Ito (2006;2008).
Regulatory Quality	*REGQ*	Captures perceptions of the ability of the government to develop and implement sound policies and regulations that permit and promote private sector development. Values range from approximately -2.5 to 2.5.	WGI produced by Kaufmann et al. (2011).

Source: Authors derived based on various sources.

Notes: †GFDD: Global Financial Development Database; BIS: Bank for International Settlements; OECD: Organisation for Economic Co-operation and Development; CBIRC: China Banking and Insurance Regulatory Commission; ECB: European Central Bank; WGI: Worldwide Governance Indicators available at WGI 2021 Interactive > Home (worldbank.org); iMaPP: Integrated Macroprudential Policy; CBIRC: China Banking and Insurance Regulatory Commission; US S&P GMI 2018: US Standard & Poor's (S&P) Global Market Intelligence; Brismo (formerly known as AltFi data); UK P2PFA: UK Peer-to-Peer Finance Association; AFSAL: Alternative Financial Services Association of Latvia, Korea P2PFA: Korea P2P Finance Association, SMLA: Swiss Marketplace Lending Association; WDZJ: Wang Dai Zhi Jia.

7.4. Descriptive statistics

7.4.1. Summary statistics

The summary statistics for macroprudential variables are presented in *Table 7.3*. *Table 7.4* shows the descriptive statistics for the main regression variables. Overall, a large variation is found for the dependent variables. For instance, the natural log of FinTech credit share (*FIN_S*) ranges from -14.757 to 1.405, with a standard deviation of 2.716 and a mean of -6.535. The same pattern is observed for the other dependent variables; the natural log of FinTech credit as a percentage of GDP (*FIN_GDP*) and FinTech credit per capita *(FIN_PC*). Concerning MaPP action variables, the overall policy stance variable (*MaPP*) averaged 0.254 with a standard deviation of 0.435, while the tightening policy action variable ($MaPP^T$) and loosening policy action variable ($MaPP^L$) averaged 0.215 and 0.056, respectively. In terms of other control country variables, the variation is also large. For example, the monetary policy rate (*MOP*) varies between -0.75% and 12.75%. Moreover, there is much variation in terms of country control macroeconomic variables; for example, the real effective exchange rate (*REER*) varies from 23.5% to 401.2%, with a standard deviation of 64.766 and a mean of 158.35%.

Table 7.5 presents the total MaPP instruments used by countries. *Table 7.6* shows the usage of individual MaPP variables by country. Liquidity requirements (*LQR*) are the most used MaPP tool by all countries. Other commonly used tools include Conservation Buffers (*CV)*, followed by the Systemically important financial institution (*SIFI*), Capital requirements (*CR*), Loan restrictions (*LR*) and Reserve requirements (*RR*).

Table 7.3: Summary statistics for macroprudential variables

	All sample					Advanced countries					EMDEs				
	Obs.	Mean	Std. dev.	Min.	Max.	Obs.	Mean	Std. dev.	Min.	Max.	Obs.	Mean	Std. dev.	Min.	Max.
Macroprudential instruments															
CCB	1,400	0.008	0.088	0	1	1,120	0.009	0.094	0	1	280	0.004	0.060	0	1
CV	1,400	0.044	0.204	0	1	1,120	0.040	0.196	0	1	280	0.057	0.233	0	1
CR	1,400	0.038	0.191	0	1	1,120	0.035	0.183	0	1	280	0.050	0.218	0	1
LVR	1,400	0.012	0.110	0	1	1,120	0.010	0.099	0	1	280	0.021	0.145	0	1
LLP	1,400	0.009	0.096	0	1	1,120	0.006	0.079	0	1	280	0.021	0.145	0	1
LCG	1,400	0.002	0.046	0	1	1,120	0.000	0.000	0	1	280	0.011	0.103	0	1
LR	1,400	0.030	0.171	0	1	1,120	0.022	0.148	0	1	280	0.061	0.239	0	1
LFC	1,400	0.005	0.071	0	1	1,120	0.003	0.052	0	1	280	0.014	0.119	0	1
LTV	1,400	0.051	0.219	0	1	1,120	0.041	0.199	0	1	280	0.089	0.286	0	1
DSTI	1,400	0.024	0.152	0	1	1,120	0.027	0.162	0	1	280	0.011	0.103	0	1
TAX	1,400	0.015	0.122	0	1	1,120	0.013	0.115	0	1	280	0.021	0.145	0	1
LQR	1,400	0.059	0.236	0	1	1,120	0.050	0.218	0	1	280	0.096	0.296	0	1
LTD	1,400	0.004	0.060	0	1	1,120	0.001	0.030	0	1	280	0.014	0.119	0	1
LFX	1,400	0.008	0.088	0	1	1,120	0.005	0.073	0	1	280	0.018	0.133	0	1
RR	1,400	0.044	0.206	0	1	1,120	0.023	0.151	0	1	280	0.129	0.335	0	1
SIFI	1,400	0.036	0.186	0	1	1,120	0.038	0.190	0	1	280	0.029	0.167	0	1
OT	1,400	0.027	0.163	0	1	1,120	0.022	0.148	0	1	280	0.046	0.211	0	1

Source: Author computed from iMaPP database.

Table 7.4: Summary statistics for regression variables

Variable	Observations	Mean	Std. Dev.	Min	Max
MaPP	1,400	0.254	0.435	0	1
$MaPP^T$	1,400	0.215	0.411	0	1
$MaPP^L$	1,400	0.056	0.231	0	1
FIN_S	673	-6.535	2.716	-14.757	1.405
FIN_GDP	673	-6.360	2.880	-14.343	1.313
FIN_PC	673	-0.488	2.870	-8.669	6.452
Real GDP growth rate	1,500	0.623	1.327	-12.702	23.246
Real effective exchange rate	1,500	99.809	8.387	75.59	131.7
Domestic credit to private sector	1,500	158.350	64.766	23.5	401.2
Financial crisis	1,500	0.095	0.294	0	1
Monetary policy rate	1,500	2.115	2.277	-0.75	12.75
Financial openness	1,400	1.804	0.949	-1.219	2.334
Regulation quality	1,500	1.206	0.606	-0.625	2.089

Source: Author's estimates

Table 7.5: Total macroprudential instruments by countries

	All	Per cent	Advanced	Per cent	EMDEs	Per cent
1	216	60.8	149	62.3	67	57.8
2	76	21.4	49	20.5	27	23.3
3	44	12.4	28	11.7	16	13.8
4	15	4.2	10	4.2	5	4.3
5	3	0.8	2	0.8	1	0.9
6	1	0.3	1	0.4	0	0
Total	355	100	239	100	116	100

Source: Author's estimates from iMaPP database.

Table 7.6: Use of macroprudential variables by countries.

	Total countries	Per cent	Advanced economies	Per cent	EMDEs	Per cent
CCB	6	24	5	25	1	20
CV	24	96	19	95	5	100
CR	21	84	17	85	4	80
LVR	9	36	6	30	3	60
LLP	8	32	5	25	3	60
LCG	2	8	0	0	2	40
LR	18	72	13	65	5	100
LFC	3	12	1	5	2	40
LTV	15	60	12	60	3	60
DSTI	11	44	10	50	1	20
TAX	8	32	7	35	1	20
LQR	25	100	20	100	5	100
LTD	2	8	1	5	1	20
LFX	3	12	1	5	2	40
RR	17	68	13	65	4	80
SIFI	23	92	18	90	5	100
OT	17	68	12	60	5	100
Total	25	100	20	100	5	100

Source: Author's estimates from iMaPP database.

7.4.2. Correlation analysis

Table 7.7 presents the Pearson correlation matrix for the investigated variables used in the empirical estimations. Overall, all the explanatory variables show a moderately weak correlation with all the dependent variables (FinTech credit variables). The low correlation indicates no serious multicollinearity issues in this study. The study finds a statistically significant and robust correlation between variables.

Table 7.7: Correlation coefficient matrix

	FIN_S	FIN_GDP	FIN_PC	MaPP^{T}	MaPP^{L}	MaPP	GDPGR	REER	DCPS	CR	MPR	KAP
FIN_GDP	0.961***											
FIN_PC	0.931***	0.985***										
MaPP^{T}	0.141***	0.110***	0.092***									
MaPP^{L}	0.055	0.076*	0.046	0.060**								
MaPP	0.127***	0.105**	0.076*	0.898***	0.420***							
GDPGR	0.255***	0.240***	0.205***	0.112***	-0.043	0.073***						
REER	0.271***	0.354***	0.323***	-0.053**	0.043	-0.031	-0.074***					
DCPS	-0.053	0.180***	0.258***	-0.045*	0.011	-0.033	-0.104***	0.175***				
CR	-0.287***	-0.227***	-0.220***	-0.148***	0.020	-0.115***	-0.226***	0.075***	0.212***			
MPR	-0.088**	-0.123***	-0.226***	-0.011	0.079***	0.026	0.102***	0.034	-0.467***	-0.088***		
KAP	-0.141***	-0.085**	0.044	-0.202***	-0.121***	-0.228***	-0.232***	-0.023	0.449***	0.189***	-0.562***	
REGQ	-0.151***	-0.055	0.080**	-0.141***	-0.143***	-0.182***	-0.158***	0.061**	0.585***	0.101***	-0.512***	0.704***

Source: Author's estimates

FIN_S: FinTech credit share; FIN_GDP: FinTech credit to GDP; FIN_PC: FinTech credit per capita; MaPP: MaPP activation; MaPP^{T}: MaPP Tightening; MaPP^{L}: MaPP Loosening ; GDPGR: GDP growth rate; CPI: Inflation; REER: Real effective exchange; Domestic credit:DCPS: Domestic credit; Crisis: CR; MOP: Monetary Policy rate; FINOP: De Jure openness index; REGQ: Regulatory Quality. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively.

7.5. Empirical approach

This chapter examines the effect of MaPP on FinTech credit growth. First, for the empirical strategy, the $MaPP_{j,t}$ dummy variable capturing the overall MaPP policy stance is used in the baseline regression model to examine the joint effect of the MaPP policy action on FinTech credit growth. Following the existing empirical literature on macroprudential policies that have focused on MaPP expressed as a dummy variable, the following model specification is employed:

$$LnFIN_t^j = \alpha_0 + \theta * MaPP_{j,t} + \varphi * \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \tag{7.1}$$

where FIN_t^j is the measure of FinTech credit in country *j* at time *t*, $MaPP_{j,t}$ is the overall MaPP policy action for country *j* at time *t*; $\boldsymbol{X}_t^j$ denote the vectors of observable country-level control variables for country *j* at time *t*; c_j is a country-specific fixed effect capturing the effect of country-level variation; h_t captures time fixed effect, which controls for possible cross-sectional dependence; ε_{jt} captures stochastic error term; α_0 is a constant; and θ and φ are vectors of parameters to be estimated.

Second, to distinguish between the two policy actions of tightening and loosening, the study includes two separate dummy variables: $MaPP_{j,t}^T$ and $MaPP_{j,t}^L$ in separate empirical models to examine their effect separately on FinTech credit growth. In addition, this study uses both policy action variables to assess their overall effect. The empirical models are specified as follows:

$$LnFIN_t^j = \alpha_0 + \theta * MaPP_{j,t}^T + \varphi * \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \tag{7.2}$$

$$LnFIN_t^j = \alpha_0 + \vartheta * MaPP_{j,t}^L + \varphi * \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \tag{7.3}$$

$$LnFIN_t^j = \alpha_0 + \theta * MaPP_{j,t}^T + \vartheta * MaPP_{j,t}^L + \varphi * \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \tag{7.4}$$

where FIN_t^j is the measure of FinTech credit in country *j* at time *t*; $MaPP_{j,t}^T$ and $MaPP_{j,t}^L$ are respectively, MaPP tightening and loosening policy actions for country *j* at time *t*; $\boldsymbol{X}_t^j$ denotes the vectors of observable country-level control variables for country *j* at time

t; c_j is a country-specific fixed effect capturing the effect of country-level variation; h_t captures time fixed effect, which controls for possible cross-sectional dependence; ε_{jt} captures stochastic error term; α_0 is a constant; and θ, ϑ and φ are vectors of parameters to be estimated.

Third, this study employs two dummy variables; Borrower-targeted instruments ($MaPP_{j,t}^{Bw}$) and Financial institution-targeted measures (lenders) ($MaPP_{j,t}^{FI}$) to capture the group policy stance of these two instruments. Individual models are estimated separately for each group, and an overall model including both groups. The empirical models are specified as follows:

$$LnFIN_t^j = \alpha_0 + \theta * MaPP_{j,t}^{Bw} + \varphi * \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \quad (7.5)$$

$$LnFIN_t^j = \alpha_0 + \vartheta * MaPP_{j,t}^{FI} + \varphi * \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \quad (7.6)$$

$$LnFIN_t^j = \alpha_0 + \theta * MaPP_{j,t}^{Bw} + \vartheta * MaPP_{j,t}^{FI} + \varphi * \boldsymbol{X}_t^j + c_j + h_t + \varepsilon_{jt} \quad (7.7)$$

where FIN_t^j is the measure of FinTech credit in country j at time t; $MaPP_{j,t}^{Bw}$ and $MaPP_{j,t}^{FI}$ are respectively, MaPP borrower-targeted instruments (borrowers) and financial institution-targeted instruments (lenders) for country j at time t; $\boldsymbol{X}_t^j$ denotes the vectors of observable country-level control variables for country j at time t; c_j is a country-specific fixed effect capturing the effect of country-level variation; h_t captures time fixed effect, which controls for possible cross-sectional dependence; ε_{jt} captures stochastic error term; α_0 is a constant; and θ, ϑ and φ are vectors of parameters to be estimated.

Last, for further robustness checks and to capture the strength of policy actions, the intensity-adjusted policy action variable ($\Delta MaPP_{j,t}$) is included (see Richter et al. 2019). Even though most studies on the impact of MaPPs relied mostly on indices or binary indicators to measure MaPP policies, they have been criticised for neglecting variations in the intensity (i.e., the strength) of MaPP policies (Richter et al. 2019). Building on the specifications in Claessens et al. (2021), Alam et al. (2019), Kang et al. (2021) and Richter et al. (2019), the measure is obtained using the difference between the tightening and loosening policy actions denoted by $\Delta MaPP_{i,t}$. Algebraically this is expressed as:

$$\Delta MaPP_{j,t} = MaPP_{j,t}^{T} - MaPP_{j,t}^{L} \qquad 7.8$$

where $MaPP_{j,t}^{T}$ and $MaPP_{j,t}^{L}$ are MaPP tightening and loosening in country *j* at time *t*. The intensity-adjusted measure $\Delta MaPP_{j,t}$ is used to derive an additional measure, $\Delta MaPP_{j,t}^{Index}$ based on the intensity-adjusted policy action variable:

$$\Delta MaPP_{j,t}^{Index} = \begin{cases} 1 & if\ \Delta MaPP_{j,t} > 0, \\ 0 & if\ \Delta MaPP_{j,t} = 0, \\ -1 & if\ \Delta MaPP_{j,t} < 0. \end{cases} \qquad (7.9)$$

The $\Delta MaPP_{j,t}^{Index}$ is used as an alternative MaPP variable in the baseline regression model to examine the effect of the intensity-adjusted policy action on FinTech credit. A positive (negative) coefficient of the intensity-adjusted MaPP variable indicates a net tightening (loosening) in the overall macroprudential environment.

Similarly, based on the intensity-adjusted measure $\Delta MaPP_{j,t}$, two dummy variables were derived, $\Delta MaPP_{j,t}^{T}$ and $\Delta MaPP_{j,t}^{L}$ for MaPP net tightening and loosening, respectively.

$$\Delta MaPP_{j,t}^{T} = \begin{cases} 1\ if\ \Delta MaPP_{j,t} > 0 \\ 0\ if\ \Delta MaPP_{j,t} \leq 0 \end{cases} \qquad (7.10)$$

$$\Delta MaPP_{j,t}^{L} = \begin{cases} -1\ if\ \Delta MaPP_{j,t} < 0 \\ 0\ if\ \Delta MaPP_{j,t} \geq 0 \end{cases} \qquad (7.11)$$

7.6. Results and discussions

This chapter examines the effect of MaPP on FinTech credit growth. First, as various MaPP tools were active at the same time, an overall measure of macroprudential policy stance (MaPP) is used on the baseline regression model to examine the joint effect of the policy action on FinTech credit. Second, the study examines the effects of tightening and loosening actions on FinTech credit growth. Third, several robustness checks are carried out to assess if the main results are stable and reliable using alternative regression models. Last, for further robustness checks, the intensity-adjusted measure is employed.

7.6.1. Baseline results

Table 7.8 presents the baseline regression results of the joint effect of MaPP policy action on FinTech credit. Using the FE model, column 1 presents the baseline results, while columns 2 and 3 are based on alternative measures of FinTech credit for robustness checks. The baseline regression results (column 1) show that $MaPP_{j,t}$ is positively related to FinTech credit and is statistically significant, implying that the activation of MaPP policy action has significant proliferating effects on FinTech credit growth. The main findings reveal that the joint activation of MaPP policy action increases FinTech credit growth. This result is consistent with those of Claessens et al. (2021) and Irani et al. (2021), who noted that MaPP increases the share of NBFIs. Furthermore, this can be explained in part by the standpoint that activation of MaPP may shift credit activities towards the nonbank sector through “cross-sector substitution” and “waterbed” effects (Claessens et al. 2021; Irani et al. 2021; Cizel et al. 2019).

The results may indicate that while MaPP curbs credit growth, especially from the banking system, it produces the opposite effect on the growth of FinTech credit. This may generate some diversification benefits to the financial stability as credit and risks migrate to the nonbank sector, thus boosting market liquidity (Cizel et al. 2019; Bats and Houben 2020). However, the outcome may also produce unintended MaPP outcomes, such as opening up non-negligible regulatory arbitrage conduits, which may further lead to an excessive and unmonitored build-up of household leverage and consequently disrupts financial stability (Braggion et al. 2021; Cizel et al. 2019). These findings are not coherent with the mainstream literature that contends that MaPP measures curb credit growth (e.g., De Schryder and Opitz 2021; Pochea and Niţoi 2021; Akinci and Olmstead-Rumsey 2018). This may be because MaPP interventions are mostly directed to banks, thus creating gaps and opportunities for regulatory arbitrage and “spillage” to the nonbank sector. The results remain robust when using alternative measures of FinTech credit (columns 2 and 3).

Table 7.8: MaPP and FinTech credit: Baseline regression models (FE model)

	FIN_S (1)	FIN_GDP (2)	FIN_PC (3)
MaPP	0.2675*	0.2551*	0.2457*
	(0.1409)	(0.1453)	(0.1405)
Real GDP growth rate	0.1012	0.1031	0.0905
	(0.0910)	(0.0938)	(0.0907)
Real effective exchange rate	-0.0652***	-0.0617***	-0.0589***
	(0.0137)	(0.0141)	(0.0136)
Domestic credit to private sector	-0.0152**	-0.0120*	-0.0113*
	(0.0064)	(0.0066)	(0.0064)
Crisis	-2.7360***	-2.7431***	-2.6351***
	(0.3025)	(0.3118)	(0.3015)
Monetary policy rate	-0.6305***	-0.6526***	-0.6247***
	(0.0677)	(0.0698)	(0.0675)
Financial openness	0.2797	0.3950	0.2718
	(0.3557)	(0.3667)	(0.3546)
Regulation quality	3.4580***	3.6507***	3.3604***
	(0.7617)	(0.7852)	(0.7593)
Constant	-1.9281	2.7983	-2.8687
	(1.8765)	(1.9345)	(1.8707)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes
Observations	573	573	573
R-squared	0.4035	0.3822	0.3902
Number of countries	25	25	25
Wooldridge test	150.86***	155.601***	156.144***
Modified Wald test	12040.65***	18521.21***	18222.57***
Pesaran CD test	25.406***	25.407***	27.926***

Source: Author's calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model. Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models. FIN_S: FinTech credit share of total private credit; FIN_GDP: FinTech credit as % of GDP; FIN_PC: FinTech credit per capita.

The findings of all independent and control variables are consistent across the two alternative measures of FinTech credit (columns 2 and 3). The coefficient for domestic credit to the private sector (*DCPS*) is negative and statistically significant. The negative relationship is consistent with the "substitution effect" that suggests that FinTech credit may compete with other domestic credit, particularly bank credit (Havrylchyk et al. 2020; Vives 2019a; de Roure et al. 2022). This is, however, contrary to the complementary relationship (see., Cornelli et al. 2021; 2020; Tang 2019; de Roure et al. 2022).

The crisis dummy indicator (*Crisis*) is negative and statistically significant. These findings are consistent with the pre-crisis literature that observed credit growth as a reliable crisis predictor (Röhn et al. 2015; Aikman et al. 2014). As expected, excessive credit or credit risks may cause financial instability and intensify bank distress during the crisis (Vazquez and Federico 2015; Aikman et al. 2014). This is backed by the "too much finance" and vanishing positive effects theories (see., Zhu et al. 2020a; Arcand et al. 2015; Gründler 2019). The financial crisis literature indicates that traditional bank credit was constrained during the financial crisis. Furthermore, FinTech credit began during the pre-crisis period but only began to skyrocket during the recovery phase. However, their resilience is yet to be tested over a complete financial cycle (Claessens et al. 2018; FSB 2017).

The coefficient for the monetary policy rate (*MPR*) is negative and statistically significant. The policy rate negatively relates to FinTech credit and is highly significant, highlighting the countercyclical nature of monetary policy and the effectiveness of its tool (Gómez et al. 2020). This may also confirm the complementarity effects between macroprudential and monetary policies, as they both have a moderating effect on credit growth (Gómez et al. 2020). The results are consistent for alternative measures of FinTech credit (columns 2 and 3). These findings may suggest the dampening effects of higher interest rates (Cerutti et al. 2017a).

However, in economic terms, the effect of the *MPR* is relatively smaller (less than one percentage point). This effect is less compared to the effect of MaPP, suggesting that MaPP implementation, on average, may have been relatively more powerful compared to monetary policy (Cerutti et al. 2017a). Similar findings exist in the empirical literature; hence a negative coefficient was expected as an increase in policy rate lowers credit growth (Akinci and Olmstead-Rumsey 2018). This is also consistent with Nier et al. (2020) that the tightening of *MPR* reduces aggregate demand and increases the cost of borrowing. The negative relationships may be due to the fact that certain countries, particularly advanced economies, have maintained low policy rates since the financial crisis and have simultaneously tightened MaPP in recent years. The finding might also reflect the trade-offs faced by policymakers in dealing with credit booms using the monetary policy rate (Akinci and Olmstead-Rumsey 2018).

The results also exhibit a negative and statistically significant relationship for the real effective exchange rate (*REER*). By convention, a negative value indicates that the currency is appreciating against the US dollar. An appreciating *REER* can fuel the build-up of credit through multiple channels (Carstens 2019) and ease domestic financial conditions, thereby boosting the demand and supply of domestic credit (Nier et al. 2020).

The estimated coefficient of regulation quality (*REGQ*) alone is positive and statistically significant. As expected, the positive coefficient represents better institutional quality. While the values of *REGQ* range from -2.5 to 2.5, a higher value, therefore, signals better institutional quality. This is confirmed by Alam et al. (2019) and Nagaraj and Zhang (2019). However, the coefficients for the De Jure openness index or financial openness (*FINOP*) and real GDP growth rate (*RGDPG*) are both positive but statistically insignificant. As might be expected, economic growth boosts FinTech credit growth. A higher KAOPEN index value would indicate a higher level of capital account openness and lesser restrictions (Arif-Ur-Rahman and Inaba 2020).

7.6.2. The effects of tightening and loosening actions

The effectiveness of MaPP action measures depends on whether the policy is aimed at tightening or loosening actions (BIS 2018). *Table 7.2* presents the estimates of the FE model that differentiate between the impact of MaPP tightening and loosening. The three columns report the results for the loosening, tightening and overall effect, respectively. Column 1 presents the results based on the tightening action of MaPP policies (MaPP^{T}). The MaPP^{T} variable is positive and highly significant, implying that an overall tightening in MaPP policy stance is by and large effective in increasing FinTech credit growth. The results are consistent with those of Claessens et al. (2021) and Braggion et al. (2021), who concluded that a tightening in the conditions of traditional banks favours FinTech credit and other non-bank intermediaries to supplement bank lending. Similarly, Cizel et al. (2019) also found evidence that a tightening of MaPP may shift credit activities towards the NBFI. These results are not consistent with the mainstream views that suggest that a MaPP tightening shock reduces credit (De Schryder and Opitz 2021; Jurča et al. 2020; Basto et al. 2019).

Column 2 presents the results based on the loosening effect of MaPP policies (MaPP^{L}). The result shows that MaPP^{L} is negatively related to FinTech credit but is statistically non-significant. This result means that overall the loosening action of the MaPP policy stance may have no effect on FinTech credit growth. Column 3 presents the results considering both tightening and loosening actions. Consistent with Claessens et al. (2021), the overall results reveal that the positive effect of MaPP policy action is due to the tightening actions. The signs and significant levels of control variables across the three models remain unchanged, suggesting the results are robust.

Table 7.9: MaPP and FinTech credit: Effects of tightening and loosening actions (FE model)

	Tightening	Loosening	Overall
	(1)	(2)	(3)
$MaPP^T$	0.4292***		0.4509***
	(0.1449)		(0.1454)
$MaPP^L$		-0.3238	-0.4095
		(0.2764)	(0.2757)
Real GDP growth rate	0.1001	0.0940	0.0979
	(0.0905)	(0.0911)	(0.0904)
Real effective exchange rate	-0.0652***	-0.0668***	-0.0655***
	(0.0136)	(0.0137)	(0.0136)
Domestic credit	-0.0154**	-0.0133**	-0.0146**
	(0.0064)	(0.0064)	(0.0064)
Crisis	-2.6995***	-2.8147***	-2.7119***
	(0.3010)	(0.3014)	(0.3008)
Monetary policy rate	-0.6223***	-0.6391***	-0.6218***
	(0.0674)	(0.0677)	(0.0674)
Financial openness	0.2576	0.2578	0.2239
	(0.3541)	(0.3571)	(0.3545)
Regulation quality	3.4011***	3.5178***	3.4033***
	(0.7585)	(0.7628)	(0.7576)
Constant	-1.8391	-1.9776	-1.8594
	(1.8680)	(1.8804)	(1.8660)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes
Observations	573	573	573
R-squared	0.4092	0.4011	0.4116
Number of countries	25	25	25
Wooldridge test	151.143***	146.840***	150.744***
Modified Wald test	14188.63***	12090.94***	25995.03***
Pesaran CD test	25.539***	24.151***	24.429***

Source: Author's calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model. Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models. $MaPP^T$: MaPP Tightening; $MaPP^T$: MaPP Loosening.

7.6.3. *MaPP groupings*

Further, MaPP groupings are expressed as borrower-targeted (MaPP_Bw) and financial institution-targeted measures (MaPP_FI). *Table 7.10* presents the results. The results indicate a positive and statistically significant relationship between MaPP_FI and FinTech credit. This result indicates that the MaPP measures aimed at financial institution-targeted instruments (lenders) boost the growth of FinTech credit. This is to say, the developments in the FinTech credit market tend to boom in response to the implementation of MaPP aimed at lenders or financial institutions. However, the results are in contrast with those of Alam et al. (2019), who suggest that traditional lender-targeted instruments significantly impact household credit.

The borrower variable is positive but statistically non-significant, implying that borrower-targeted instruments (MaPP_Bw) do not influence FinTech credit growth. The results contrast with studies that contend that borrower-based measures are more effective in mitigating the build-up of systemic vulnerabilities than financial institution-targeted instruments (Ayyagari et al. 2018; Dimova et al. 2016; Claessens et al. 2013). The findings provide important policy implications regarding how different MaPP groups respond to MaPP activation. Specifically, the results are consistent with the arguments in most studies that MaPP leakages are likely to occur when policies target lenders instead of borrowers (Ayyagari et al. 2018). Concerning the other control variables, the signs of the coefficients of all control variables remain unaltered. The significant variables remain the same as with the baseline results, suggesting the results are robust.

Table 7.10: MaPP groupings and FinTech credit: Regression models by groups

	Borrower	Lender	Overall
	(1)	(2)	(3)
Borrower	0.1605		0.0749
	(0.2719)		(0.2760)
Lender		0.2577*	0.2505*
		(0.1442)	(0.1468)
Real GDP growth rate	0.0966	0.1022	0.1024
	(0.0912)	(0.0910)	(0.0911)
Real effective exchange rate	-0.0666***	-0.0652***	-0.0652***
	(0.0137)	(0.0137)	(0.0137)
Domestic credit	-0.0145**	-0.0150**	-0.0151**
	(0.0065)	(0.0064)	(0.0065)
Crisis	-2.7907***	-2.7435***	-2.7404***
	(0.3019)	(0.3023)	(0.3028)
Monetary policy rate	-0.6359***	-0.6334***	-0.6323***
	(0.0679)	(0.0676)	(0.0678)
Financial openness	0.2909	0.2754	0.2791
	(0.3570)	(0.3559)	(0.3564)
Regulation quality	3.5117***	3.5020***	3.5023***
	(0.7635)	(0.7615)	(0.7621)
Constant	-1.9071	-2.0090	-1.9844
	(1.8840)	(1.8774)	(1.8812)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes
Observations	573	573	573
R-squared	0.3999	0.4031	0.4032
Number of countries	25	25	25
Wooldridge test	147.119***	147.299***	146.633***
Modified Wald test	12907.30***	12169.89***	12069.47***
Pesaran CD test	24.958***	25.277***	25.309***

Source: Author's calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model. Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models.

7.6.4. Robustness checks

Table 7.11 to *Table 7.14* present robustness checks. First, the study uses alternative regression models for robustness checks. Specifically, the FGLS regression model is employed to address the three key issues associated with FE models (heteroskedasticity, serial correlation and cross-dependence) (de Mendonca and Nascimento 2020; Reed and Ye 2011). The selection of the FGLS is justified since the number of time periods (*T*) is higher than the cross-section entities (*N*). *Table 7.11* presents the results. Overall, the results remain robust when using the FGLS model across all the alternative measures of FinTech credit. The results remained unchanged for other control variables across the three models.

Table 7.11: Robustness checks: MaPP and FinTech credit (FGLS model)

	FIN_S (1)	FIN_GDP (2)	FIN_PC (3)
MaPP	0.3385**	0.2804*	0.2694*
	(0.1538)	(0.1585)	(0.1641)
Real GDP growth rate	0.4410***	0.4270***	0.4374***
	(0.1108)	(0.1119)	(0.1135)
Real effective exchange rate	0.1178***	0.1328***	0.1248***
	(0.0104)	(0.0106)	(0.0109)
Domestic credit to private sector	0.0004	0.0116***	0.0126***
	(0.0019)	(0.0019)	(0.0019)
Crisis	-2.5265***	-2.5865***	-2.6636***
	(0.2869)	(0.3034)	(0.3162)
Monetary policy rate	-0.6527***	-0.6408***	-0.6519***
	(0.0715)	(0.0746)	(0.0761)
Financial openness	-0.5237***	-0.4466**	-0.2395
	(0.1633)	(0.1764)	(0.1761)
Regulation quality	0.0982	0.1279	0.4054*
	(0.2092)	(0.2169)	(0.2190)
Constant	-17.2796***	-20.5438***	-14.7602***
	(1.0552)	(1.0939)	(1.1099)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes
Observations	573	573	573
Number of countries	25	25	25

Source: Author’s calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model. Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models. FIN_S: FinTech credit share of total private credit; FIN_GDP: FinTech credit as % of GDP; FIN_PC: FinTech credit per capita.

Second, robustness checks are conducted using the FGLS model based on the two policy actions (MaPP tightening and loosening actions). *Table 7.12* presents the results. The overall results for MaPP tightening remain highly significant and positive as in the baseline results (column 1). Similar to baseline results, MaPP loosening is statistically non-significant (column 2), while the overall model shows that the impact of MaPP on FinTech growth is largely due to the tightening policy action (column 3). The rest of the control variables remain unchanged, suggesting that the results are stable and robust.

Table 7.12: Robustness checks: Effects of tightening and loosening actions (FGLS model)

	Tightening	Loosening	Overall
	(1)	(2)	(3)
$MaPP^T$	0.4505^{***}		0.4674^{***}
	(0.1591)		(0.1657)
$MaPP^L$		0.1325	-0.0961
		(0.2438)	(0.2663)
Real GDP growth rate	0.4293^{***}	0.4612^{***}	0.4293^{***}
	(0.1093)	(0.1123)	(0.1094)
Real effective exchange rate	0.1194^{***}	0.1158^{***}	0.1195^{***}
	(0.0104)	(0.0102)	(0.0104)
Domestic credit	0.0002	0.0009	0.0003
	(0.0019)	(0.0019)	(0.0019)
Crisis	-2.5059^{***}	-2.5836^{***}	-2.5003^{***}
	(0.2845)	(0.2891)	(0.2849)
Monetary policy rate	-0.6588^{***}	-0.6452^{***}	-0.6577^{***}
	(0.0715)	(0.0720)	(0.0715)
Financial openness	-0.5321^{***}	-0.5295^{***}	-0.5307^{***}
	(0.1632)	(0.1619)	(0.1633)
Regulation quality	0.1242	0.0555	0.1157
	(0.2092)	(0.2086)	(0.2106)
Constant	-17.4269^{***}	-17.0170^{***}	-17.4382^{***}
	(1.0590)	(1.0356)	(1.0595)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes
Observations	573	573	573
Number of countries	25	25	25

Source: Author's calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model. Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models. $MaPP^T$: MaPP tightening; $MaPP^T$: MaPP loosening.

Third, robustness checks for the MaPP groupings using the FGLS model are undertaken. *Table 7.13* presents the results. The results confirm that MaPP_FI (lender) is positively related to FinTech credit growth, while the results based on MaPP_Bw are statistically non-significant. These results confirm that the main results are stable and robust.

Table 7.13: Robustness checks: MaPP groupings and FinTech credit (FGLS model)

	Borrower	Lender	Overall
	(1)	(2)	(3)
Borrower	0.1165		0.0042
	(0.3378)		(0.3442)
Lender		0.3132*	0.3132**
		(0.1556)	(0.1576)
Real GDP growth rate	0.4640***	0.4443***	0.4462***
	(0.1125)	(0.1109)	(0.1111)
Real effective exchange rate	0.1156***	0.1180***	0.1176***
	(0.0103)	(0.0104)	(0.0104)
Domestic credit	0.0008	0.0005	0.0004
	(0.0019)	(0.0019)	(0.0019)
Crisis	-2.5837***	-2.5373***	-2.5335***
	(0.2906)	(0.2848)	(0.2861)
Monetary policy rate	-0.6432***	-0.6573***	-0.6562***
	(0.0723)	(0.0717)	(0.0720)
Financial openness	-0.5116***	-0.5383***	-0.5347***
	(0.1664)	(0.1625)	(0.1665)
Regulation quality	0.0530	0.1007	0.1070
	(0.2088)	(0.2091)	(0.2100)
Constant	-17.0153***	-17.2632***	-17.2282***
	(1.0416)	(1.0543)	(1.0565)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes
Observations	573	573	573
Number of countries	25	25	25

Source: Author's calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model. Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models.

Last, for further robustness checks and to capture the intensity (strength) of policy actions, the intensity-adjusted policy action variable is included ($\Delta MaPP_{j,t}$) (see Richter et al. 2019). *Table 7.14* presents the results of the effect of the intensity-adjusted policy action variable ($\Delta MaPP_{j,t}$) on FinTech credit. In addition, the table presents the results based on the two dummy variables capturing the net tightening ($\Delta MaPP^{T}_{j,t}$) and net loosening ($\Delta MaPP^{L}_{j,t}$) intensity-adjusted policy actions, respectively. The results (column 1) show that $\Delta MaPP_{j,t}$ is positively related to FinTech credit and is statistically significant, implying that the net tightening of MaPP policy action increases FinTech credit growth. This result is consistent with the baseline results, confirming that the main results are stable and robust and can be used for policy analysis. Column 2 presents the results based on the net tightening of the intensity-adjusted policy action ($\Delta MaPP^{T}_{j,t}$). The $\Delta MaPP^{T}_{j,t}$ variable is positive and highly significant, implying that an overall net tightening in the MaPP policy stance is effective in increasing FinTech credit growth. Column 3 presents the results based on the net loosening of the intensity-adjusted policy action ($\Delta MaPP_{j,t}^{L}$). The result shows that $\Delta MaPP_{j,t}^{L}$ is negative but non statistically non-significant. Column 4 presents the results considering both $\Delta MaPP_{j,t}^{T}$ and $\Delta MaPP_{j,t}^{L}$ and the overall results reveal that the positive effect of MaPP policy action is due to the net tightening policy actions. The signs and significant levels of control variables across the three models remain unchanged, suggesting the results are robust.

Table 7.14: Robustness checks based on the intensity-adjusted policy action variable (FE model)

	(1)	(2)	(3)	(4)
ΔMaPP	0.4249***			
	(0.1309)			
$\Delta MaPP^{T}$		0.4292***		0.4509***
		(0.1449)		(0.1454)
$\Delta MaPP^{L}$			0.3238	0.4095
			(0.2764)	(0.2757)
Real GDP growth rate	0.0985	0.1001	0.0940	0.0979
	(0.0904)	(0.0905)	(0.0911)	(0.0904)
Real effective exchange rate	-0.0654***	-0.0652***	-0.0668***	-0.0655***
	(0.0136)	(0.0136)	(0.0137)	(0.0136)
Domestic credit to private sector	-0.0143**	-0.0154**	-0.0133**	-0.0146**
	(0.0064)	(0.0064)	(0.0064)	(0.0064)
Crisis	-2.7164***	-2.6995***	-2.8147***	-2.7119***
	(0.2998)	(0.3010)	(0.3014)	(0.3008)
Monetary policy rate	-0.6230***	-0.6223***	-0.6391***	-0.6218***
	(0.0673)	(0.0674)	(0.0677)	(0.0674)
Financial openness	0.2304	0.2576	0.2578	0.2239
	(0.3538)	(0.3541)	(0.3571)	(0.3545)
Regulation quality	3.3782***	3.4011***	3.5178***	3.4033***
	(0.7575)	(0.7585)	(0.7628)	(0.7576)
Constant	-1.8929	-1.8391	-1.9776	-1.8594
	(1.8647)	(1.8680)	(1.8804)	(1.8660)
Time fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Clusters by country	Yes	Yes	Yes	Yes
Observations	573	573	573	573
R-squared	0.4111	0.4092	0.4011	4116
Number of countries	25	25	25	25
Wooldridge test	150.86***	151.143***	146.840***	150.744***
Modified Wald test	20489.07***	14188.63***	12090.94***	25995.03***
Pesaran CD test	24.915***	25.539***	24.151***	24.429***

Source: Author's calculations. ***, ** and * indicate statistically significance at 1%, 5% and 10% levels respectively. Robust standard errors are reported in brackets. Intercept is included in the model. Wooldridge test for autocorrelation; Modified Wald test for heteroscedasticity after FE models. ΔMaPP: intensity-adjusted policy action; $\Delta MaPP^{T}$: Net tightening dummy variable; $\Delta MaPP^{L}$: Net loosening dummy variable.

7.7. Conclusions

Following the 2007/2009 global financial crisis, dedicated MaPP has been implemented to safeguard against the build-up of macroeconomic risks that can hamper the overall financial stability. Therefore, MaPP has since been actively used in both advanced economies and EMDES. However, MaPP instruments have predominantly been used in the traditional banking system. Moreover, having fewer safeguards in the non-bank space and the limited use of nonbank instruments in developing MaPP makes it difficult to estimate the participation of the nonbank sector properly. Against this background, the nonbank sector has been significantly expanding, including such activities as FinTech credit which in some instances is left unchecked. Despite this, no study has attempted to explore whether MaPP influences FinTech credit growth empirically. Few related studies have attempted to explore the link between NBFI and MaPP focused on country-specific case studies. This study, therefore, seeks to fill this gap and investigate whether MaPP influences the growth of FinTech credit based on 25 economies (both advanced economies and EMDES). The study employs unbalanced panel data covering the period 2005Q1 to 2018Q4.

The main results of the study reveal that tightening MaPP leads to increased growth in Fintech lending. Overall, the study provides evidence that suggests that MaPP tightening can cause the reallocation of credit intermediation from the regulated traditional banking sector to the less regulated sector. The results suggest that MaPP positively impact FinTech credit growth, particularly the net tightening of MaPP and the financial institution (lender) targeted interventions. The main findings of this study are consonant with a growing literature that suggests that macroprudential regulation drives nonbank growth (Claessens et al. 2021; Braggion et al. 2021; de Roure et al. 2022). In particular, Claessens et al. (2021) suggest that MaPP (more especially MaPP tightening) increases the growth of NBFIs. Relatedly, Braggion et al. 2021 show evidence that FinTech credit tends to rise in response to tighter LTV, consistent with the existence of regulatory arbitrage. The study extends and contributes (in part) to the emerging studies that suggest that MaPP may trigger cross-substitution effects toward nonbank credit (Claessens et al. 2021; Irani et al. 2021; Cizel et al. 2019). It, therefore, contributes to the growing debates and quest for the use of MaPP beyond the banking sector (Cizel et al. 2019; ESRB 2017).

CHAPTER 8: SUMMARY, CONCLUSIONS AND POLICY IMPLICATIONS

8.1. Introduction

The 2007-2009 global financial crisis revealed the delicate regulation of the financial system. It also emphasises the potential build-up of risks due to increased credit intermediation involving entities outside the regulated traditional banking system, especially when it involves liquidity, maturity and credit transformation and the build-up of leverage (OECD 2020b). The post-crisis highlights the shift of global intermediation from the bank to the nonbank sector, particularly the rise of alternative finance and risks from entities such as FinTech credit across various advanced and EMDEs. Understanding the interplay between these elements, i.e., their potential risks and opportunities thereof, provides a more comprehensive understanding of how FinTech credit could contribute to financial stability.

The main objective of this study was to investigate the impact of FinTech credit on financial stability. This was addressed in three distinct themes, which, even though crafted individually, aligned with the central objective of the research. Therefore, the objectives of this study aimed to: *(i)* investigate whether FinTech credit enhances or disrupts the overall financial stability; *(ii)* examine the effect of FinTech credit on bank risk-taking; and *(iii)* assess the impact of MaPP on FinTech credit growth.

To address these objectives of this study, a quarterly unbalanced panel dataset for economies for the period 2005Q1 to 2019Q4 was employed. More specifically, the study focused on FinTech credit, that is, credit facilitated by electronic or online platforms. The study also used several econometric estimations models, and robustness tests confirm the stability of these results. The chapter is structured as follows. Section 8.2 presents the summary of the results. Section 8.3 provides a detailed discussion on the contributions of the study, whilst Section 8.4. provides the policy discussions that highlight the main policy implications and policy recommendations of the study. Section 8.5 presents the research limitation and future research.

8.2. Summary of results

The results of this study are summarised as follows. The first empirical study focused on the implication of FinTech credit from a broader or overall financial stability perspective. The chapter answered the following research question: *Does FinTech credit enhance or disrupt the overall financial stability*? Based on the literature, an assumption for a linear relationship was initially made to explore whether FinTech credit could enhance or disrupt overall financial stability. The linear specification revealed a positive but statistically insignificant relationship between FinTech credit and financial stability, thus rejecting the null hypothesis of a linear relationship. Given the lack of consensus regarding the relationship between FinTech credit and overall financial stability, the study also looked into the possible existence of a non-linear association. The study addressed the bone of contention between two contrasting viewpoints that argue that FinTech credit may enhance or disrupt financial stability. The study provides a shred of empirical evidence revealing a significant relationship between FinTech credit and overall financial stability.

The overall results revealed a non-linear (inverted U-shape) association between FinTech credit and overall financial stability, which suggest that financial stability is strongly influenced by the degree to which alternative credit extends to financial services. The overwhelming evidence of nonlinearity implies that FinTech credit may initially enhance overall financial stability up to a certain threshold, after which the marginal benefits of financial stability begin to diminish. In other words, FinTech credit may enhance financial stability in the short run but may become detrimental to financial stability in the long run. However, in the long run, the opposite ensues. These findings are consistent with previous views that portray FinTech credit as a potential driver and disruptor of financial stability (Delabarre 2021). The non-linear findings are also consistent with various literature, such as the "vanishing effect" (Gründler 2019), "too much finance" hypothesis (Zhu et al. 2020a; Sahay et al. 2015a, 2015b; Arcand et al. 2015) and "innovation-growth" and "innovation-fragility" views (Beck et al. 2016). The results also suggest the possible existence of a policy trade-off where credit expansion promotes economic growth and triggers financial instability (Koong et al. 2017).

The second empirical study focused on bank stability by examining the impact of FinTech credit on bank risk-taking. First, the chapter addresses the following research question:

Does FinTech credit increase or decrease bank risk-taking? Overall, the results observe significant evidence of a non-linear (inverted U-shaped) relationship between FinTech credit and risk-taking, particularly through credit and liquidity risks. The findings of this study indicate that increased FinTech credit may initially induce banks to engage in risk-taking at lower levels, beyond which it may lead to a decline in bank risk-taking. The overall findings are relevant and collaborate with several works of literature. It is consistent with an emerging strand of literature that documents a non-linear (inverted U-shaped) relationship between internet finance or FinTech developments on traditional bank risk-taking (Wang et al. 2021). The overall results harmonise and complement the contrasting views of the consumer theory, i.e., substitution and complementary theories, and demonstrate that they may occur successively with varying impacts on bank risk-taking as FinTech credit expands.

While the overall results suggest a non-linear relationship between FinTech and bank risk-taking, amongst the five (5) risk measures, this relationship is explicitly demonstrated by credit and liquidity risks, amongst others. This may indicate that the expansion of FinTech credit affects bank risk-taking through credit and liquidity channels. Furthermore, the results complement existing studies that point to credit and liquidity risks as two leading sources of bank default risk (Kasman and Kasman 2015; Imbierowicz and Rauch 2014) and that their simultaneous exposure may intensify bank distress during the crisis (Vazquez and Federico 2015).

The third empirical study explored the association between FinTech credit and macroprudential policy. The chapter addresses the following research question: *Do macroprudential policies influence FinTech credit growth*? Building on a robust wealth of literature that reveals that MaPP tightening invention reduces traditional bank credit, this study demonstrates that the implementation of MaPP increases and promotes credit growth by nonbank financial intermediaries, in this case, FinTech credit. The result further rejects the null hypothesis that MaPP does not decrease FinTech credit. The overall results reveal that MaPP increases FinTech credit growth. These results complement the work by Braggion et al. (2021), who suggest that FinTech credit may undermine credit regulations by acting as a conduit to avoid LTV caps imposed on traditional banks. It also complements other emerging studies that demonstrate an increase in the share of NBFIs following the implementation of MaPP (e.g., Claessens et al. 2021; Irani et al. 2021; Hodula and Ngo 2021) and the "cross-sector substitution" and "waterbed" effects following the implementation of MaPP (Claessens et al. 2021; Irani et al. 2021; Cizel et al. 2019). However, the results contrast with the mainstream literature where MaPP have effectively restrained credit growth (e.g., De Schryder and Opitz 2021; Pochea and Niţoi 2021; Akinci and Olmstead-Rumsey 2018).

Moreover, the study reveals that the tightening of prudential interventions favours the growth of FinTech credit. This study is particularly consistent with Claessens et al. (2021) and Braggion et al. (2021), who show a positive relationship between MaPP tightening and other non-bank intermediaries. The results support the work of Cizel et al. (2019), who reveals evidence that the tightening of MaPP may shift credit activities toward the NBFI. On the contrary, the effects of MaPP loosening interventions have no significant effect on FinTech credit growth, in line with the work by Claessens et al. (2021). These results are not consistent with the conventional view that indicate that a MaPP tightening shock reduces credit (De Schryder and Opitz 2021; Jurča et al. 2020; Basto et al. 2019).

The results also reveal that MaPP measures aimed at financial institution-targeted instruments (MaPP lenders) promote the growth of FinTech credit whilst borrower-targeted instruments (MaPP borrow) are insignificant. The results contrast with Alam et al. (2019), who suggest that loan-targeted instruments significantly impact household credit. The study conflicts with several studies which argue that borrower-based measures effectively mitigate the build-up of systemic vulnerabilities compared to financial institution-targeted instruments (Ayyagari et al. 2018; Dimova et al. 2016; Claessens et al. 2013). Therefore, the findings of this study provide important policy implications regarding how different MaPP groups respond to MaPP activation. The conclusion of this study continues to pose a question on the effectiveness of MaPP. Moreover, the unintended outcomes from "cross-sector substitution" and "waterbed" effects may become a blind spot for policymakers and regulators, thus causing a possible trade-off with financial stability, especially when the benefits of MaPP are outweighed (Cizel et al. 2019). The study thus relates to the discussions and the call to use the MaPP framework in order to address financial stability concerns beyond the banking sector (Buch 2020; Boh et al. 2019; Constâncio et al. 2019).

8.3. Contributions of the study

Building on previous literature, policy and academic deliberations, this study relates and makes an original contribution to the paucity and growing literature. The study complements and contributes to the growing and existing knowledge such as FinTech, financial innovation, bank and financial stability, nonbank credit intermediation, bank risk-taking, MaPP etc. The findings of this study form a basis for future academic research and bear important policy implications. It also demonstrates how the respective empirical chapters distinctively complement and contribute to the existing literature, policy and other industry players in several ways.

First, this study contributes to the existing literature on measures of financial stability. Despite limitations on available measures of non-bank variables, the study attempted to construct an aggregate financial stability index (FSI) that takes into consideration risks across the financial market ecosystem, including some aspects that capture the effect of the nonbank sector. The study undertakes a multidimensional approach to measure overall financial stability in preference to widely-used single indicators such as Z-scores, largely limited to bank accounting entries. Moreover, most studies involving the construction of FSI tend to conduct single-country analyses (Dumičić 2016; Matkovskyy et al. 2016; Karanovic and Karanovic 2015), while a few that extended beyond single countries focused on either regions or sub-groups, such as Europe (EU), the United States (US), China and OECD (Kočišová and Stavárek 2015). This study broadens the research scope to provide global empirical evidence using cross-country data of 25 economies, comprising advanced and EMDEs, to capture the country-effect influence on financial stability. This comprehensive, evidence-based approach may provide a clearer and broader picture than what we currently have regarding how FinTech credit affects financial stability in the global banking sector.

Second, the study offers some data advantages. The use of higher frequency data allows for a more precise measure of FinTech credit intermediation and using FinTech credit as a nonbank credit aggregate. Credit aggregates are believed to carry significant information about risks to growth at longer horizons (IMF 2017) and equally serve as good predictors of systemic banking and financial crises and potential sources of financial instability (Alessi and Detken 2018; Kim and Mehrotra 2018; Röhn et al. 2015). Third, despite the challenges with the availability of FinTech credit data (as with many other previous studies), the study employs a higher frequency (quarterly) panel data than the regular use of lower frequency (annual) data (see. Cornelli et al. 2021; 2020; Rau 2021; 2020; Ziegler et al. 2021; 2020).[30] By considering a longer period, this study includes the periods before, during, and after the 2008 financial crisis; thus, the study captures the effect of the 2008 financial crisis on FinTech credit growth.

Fourth, to the best of the researcher's knowledge, this study provides the first attempt to empirically investigate the link between FinTech credit and overall financial stability on global data. The study reveals that the association between FinTech credit and overall financial stability is non-linear (inverted U-shaped), thus making a novel contribution to the literature. In particular, the study proposed a careful consideration for the possible existence of a non-linear relationship that preceding studies normally overlook. In so doing, this study also complements and contributes to the emerging literature on financial stability and nonbank financial intermediation. It thus provides interesting insights into explaining the theoretical contestation of the effects of the expansion of credit levels (more specifically, nonbank credit) on overall financial stability.

Fifth, this study contributes to the limited academic literature on measures of bank risk-taking. Most existing empirical studies that examine bank risk-taking usually employ a single-dimensional risk indicator, such as NPL or Z-scores, to capture bank risk (e.g., Davis and Karim 2019; de-Ramon et al. 2018; Noman et al. 2018). In addition, few related studies either used single-dimensional risk indicators such as NPL or Z-scores (Wang et al. 2021; Fung et al. 2020). However, this study employs five various measures of bank risks: insolvency, credit, liquidity, portfolio, and leverage risks, to explore the varying impact of FinTech credit on bank risk-taking measures on FinTech credit, thus adding to this limited literature. While most studies are based on a limited sample, mostly single country-specific cases (Cheng and Qu 2020; Guo and Shen 2019), the study employs cross-country data analysis of twenty-five (25) countries comprising advanced and EMDEs.

[30] While available databases (e.g., Cornelli et al. 2021; 2020; Rau 2021; 2020; Ziegler et al. 2021; 2020) have a significantly wider coverage, they are limited to annual data spanning from 2013 to 2019.

Sixth, the study contributes to the knowledge in various ways. This study provides an empirical assessment of how FinTech credit affects bank risk-taking, thus contributing significantly to the limited empirical literature on FinTech credit and bank risk-taking. It also contributes to the existing literature that explores the determinants of bank risk-taking. Fewer emerging studies investigating this link have focused on a linear relationship between bank risk-taking and FinTech developments (e.g., Dong et al. 2020; Fung et al. 2020; Deng et al. 2021; Phan et al. 2021). However, this study complements other emerging studies that found evidence of a non-linear (inverted U-shaped) relationship between FinTech development and bank risk-taking (e.g., Wang et al. 2021). To the best of the researcher's knowledge, no previous research evaluates empirical predictions concerning this inverse 'U'-shaped curve using a comprehensive FinTech credit dataset.

Wang et al. (2021) present the closest study to the findings of this study; significant differences still exist. The majority of these related studies (e.g., Deng et al. 2021; Haddad and Hornuf 2021; Wang et al. 2021; Phan et al. 2021) tend to pay more attention to the overall impact of general FinTech developments or "internet finance" on traditional bank risk-taking hence do not specifically capture the FinTech credit market. This study, therefore, provides a rather specific assessment of the FinTech lending sector to explain its impact on the risk-taking of traditional banks. To the best of the researcher's knowledge, this is the first study to investigate a non-linear relationship between bank risk-taking and FinTech credit, thus contributing to the limited literature.

Last, this study adds to the growing empirical literature that seeks to explore the relationship between emerging FinTech innovation and credit regulation (e.g., Braggion et al. 2021; de Roure et al. 2022; Buchak et al. 2018). Previous related studies were based on a single-country analysis and regulatory indicator (e.g., Braggion et al. 2021; Irani et al. 2021; de Roure et al. 2022). However, this study is broader in scope than extant ones, employing a more extended period (quarterly country-level panel data) and numerous countries (both advanced and EMDEs). More broadly, the study contributes to the emerging literature that examines the interaction between FinTech credit and financial regulation (e.g., Thakor 2020; Rau 2020; Navaretti et al. 2018; Buchak et al. 2018). Furthermore, it provides the first empirical investigation using a FinTech credit as a nonbank credit aggregate and a comprehensive and novel set of MaPP shock based on the latest iMaPP database developed by Alam et al. (2019). The inclusion of the regulatory reform indicator in the study provides an interesting experiment to study the ex-post effects of MaPP on FinTech credit within an empirical setting.

8.4. Policy discussions: implications and recommendations

8.4.1. Policy implications

The overall findings of this study present economically important policy implications, particularly to the financial stability policies and other related central bank policies. The policy implications are derived from the outcomes or the results from the distinctive empirical chapters that sought to address the main objectives of this study. As such, policymakers, regulators and academia may be interested in understanding the implications of FinTech credit on financial stability in their respective specific economies.

First, the non-linear findings offer a vital perspective for policymakers by showing the varying impact of FinTech credit on overall financial stability and bank risk-taking over time. Specifically, the results of a non-linear (inverted U-shaped) relationship between FinTech credit and financial stability suggest that FinTech credit may benefit the overall financial stability in the short run, but in the long run or beyond a certain threshold may disrupt the financial stability. This highlights the need for constant monitoring of financial imbalances and rapid growth of non-bank credit in the financial system, especially their growing share of total domestic credit. This may help policymakers and regulators develop optimal policies and establish a focal point where FinTech credit could no longer benefit financial stability. The study thus presumes the possible existence of trade-offs that presents the risk–benefit between financial innovations and financial stability.

Second, the findings of this study also bear important policy and industry implications, particularly at a time when Basel III seems to impose tougher regulatory capital requirements to reduce bank risk-taking, limit bank failure, and ensure soundness in the financial system (Dias 2021). The results have relevance and a probable generalisation about the impact of FinTech credit on bank risk-taking. The non-linear findings between FinTech and bank risk-taking inform policymakers of the varying impact of FinTech credit on bank risk-taking in the short and long run. The findings thus reveal the banks' risk exposures to FinTech credit, particularly through the credit, liquidity and portfolio channels. Moreover, the granularity of the risk-taking measures allows policymakers to identify and directly target specific areas of bank exposures concerning the emergence of FinTech credit. Practically, this study is also useful to traditional financial intermediaries, particularly banks, because it shows that FinTech credit can emerge as a bank competitor but may benefit traditional banks through partnership and “cooperation to compete”.

Third, the exploration of the link between FinTech credit and MaPP bears important policy implications. The results suggest that MaPP drives FinTech credit growth, particularly the net tightening of MaPP, and the lender-targeted interventions may promote FinTech credit growth. The findings of this study point to the broader conclusion that, although the current MaPP interventions are currently geared towards traditional financial institutions, the emergence of new intermediaries, particularly in the nonbank sector, could become a source of financial vulnerability and regulatory arbitrage opportunities to households and businesses. The outcome of this study also suggests that the nonbank sector may undermine the effectiveness of MaPP efforts. This may create a dilemma for policymakers regarding the effectiveness of MaPP on nonbank credit. This may further cause a regulatory and policy gap, especially concerning the migration of credit and risks to the nonbank sector, as well as new risks emerging from NBFIs that are otherwise not subjected to a prudential regulatory framework targeting their leverage.

Fourth, the findings of the study point to FinTech credit as a potential source of risks to financial and bank stability, thus calling for close monitoring of non-bank credit growth relative to total credit, as well as the extension of credit regulation beyond the banking sector. What is even clearer is that FinTech developments are continually becoming an integral part of the financial system and becoming even more interconnected with the banking system. Therefore, this study re-emphasises the remarks by Carney (2017) that policymakers need to maximise the benefits and minimise the risks of FinTech credit to financial stability.

Fifth, the study highlights the potential benefits of FinTech credit to financial stability in reducing over-reliance on the banking system and diversifying some of the risks associated with the traditional banking system (see. Bertsch and Rosenvinge 2019; FSB 2019a; Carney 2017). This also validates the view that a greater share of a more “market-based” finance may boost the financial system's resilience (Bats and Houben 2020; De

Fiore and Uhlig 2015). However, this outcome comes with some shortcomings, especially when the "leakage" results in unintended side-effects of the principal policy targets that harm financial stability (Davis et al. 2022). Some of these unintended consequences undermine MaPP and generate new vulnerabilities and risks (Forbes 2021; Cizel et al. 2019). Cizel et al. (2019) hold that household and corporate debt continues to accumulate in the nonbank sector. As Cizel et al. (2019) would suggest, household and corporate debt may continue to accumulate in the nonbank sector following a MaPP activation.

Last, although regulation is often portrayed as a damper on innovation, a lack of regulatory oversight and adequate monitoring of credit growth may make the financial system and new market players particularly susceptible to shocks (LaPlante and Watson 2018). Despite the ongoing efforts to address FinTech credit data gaps and recent advances, the national and global data coverage of the FinTech credit sector still needs to be improved. Improved data availability and coverage would enable policymakers to develop a more effective monitoring framework for NBFIs. This may further help mitigate problems of regulatory arbitrage, both domestic and across the border (Claessens et al. 2021; Hodula 2021).

8.4.2. Policy recommendations

The key potential issues were identified from the findings of this study to be further interpreted to infer the policy recommendations. In a nutshell, the study categorises the issues identified into six broad aspects:

a) Assess new risks emerging from new players entering the financial space.

The findings reinforce the need to holistically assess vulnerabilities arising from new players entering the financial space. In particular, the growth of non-bank intermediation and how it impacts financial and banking stability. The FSB (2020a) highlighted that macroprudential instruments for nonbanks are not yet fully developed and used. Therefore, this study underscores the need for policymakers to develop policy instruments that target financial stability risks emanating from NBFI entities. Given the diverse set of emerging entities and activities in the non-bank sector, such a framework should be developed with the flexibility to enable them to tackle and respond to various financial stability risks as they evolve. As such, to monitor and address vulnerabilities arising from non-banks, there is a need for globally consistent leverage metrics.

Tackling non-bank credit may sharpen incentives to curb risk-taking and help address emerging risks before they deepen. However, in the absence of reciprocity arrangements, this may further inhibit the effectiveness and responsiveness of credit-related interventions used to remedy threats to financial stability (Braggion et al. 2021; FSB 2019a; BIS and FSB 2017). Furthermore, the imbalances in each category should not be viewed in isolation as they tend to interact and potentially strengthen and reinforce each other in the boom phase of the business cycle. This is particularly relevant in this study, where FinTech credit is assessed relative to domestic private credit.

b) Enhance the regulatory framework and broaden its regulatory perimeter

The primary aim of MaPP is to enhance overall financial stability. However, the findings of this study and other existing evidence point to the boundaries and limitations of MaPP. The study suggests that macroprudential interventions may, in fact, not be effective in curbing nonbank credit growth. The shortcomings of MaPP may thus open up nonnegligible regulatory arbitrage opportunities and generate new vulnerabilities and risks to the less regulated sector (Forbes 2021; Cizel et al. 2019). As Cizel et al. (2019) would suggest, household and corporate debt may continue to accumulate in the nonbank sector, further undermining the intended efforts of prudential regulation.

The results of the study raise questions for policymakers regarding the optimal scope of MaPP. It further prompts policymakers to address issues that may arise from the spillage or the undesired effects of MaPP interventions. In order to safeguard financial stability, there is a need for the current regulatory framework to better reflect the fact that credit intermediation is increasingly taking place outside the regulated banking sector (Schnabel 2021). There is, therefore, a need to enhance the regulatory framework by broadening its regulatory perimeter beyond banking. This includes taking a comprehensive approach to strengthening the MaPP framework for non-banks. For instance, new MaPP instruments should include nonbank variables, especially credit aggregates. Looking forward, a more comprehensive macroprudential framework will reduce the need for extraordinary central bank interventions in the future, thus helping to alleviate concerns related to excessive bank risk-taking and moral hazards (de Guindos 2021).

There is a growing call to expand MaPP beyond traditional banks, as tackling non-bank credit may sharpen incentives to curb risk-taking and help address emerging risks before they deepen. However, in the absence of reciprocity arrangements, this may further inhibit the effectiveness and responsiveness of credit-related interventions used to remedy threats to financial stability (Braggion et al. 2021; FSB 2019a; BIS and FSB 2017). Furthermore, the imbalances in each category should not be viewed in isolation as they tend to interact and potentially strengthen and reinforce each other in the boom phase of the business cycle. This is particularly relevant in this study, where FinTech credit is assessed relative to domestic private credit.

Furthermore, the regulatory frameworks must be continually reviewed to ensure that they remain effective in endorsing competition as new technological innovations emerge. The focus of the regulatory perimeter should be technologically neutral to enable the substitutability of technology as opposed to restricting firms to vertically integrated technology monopolies (OECD 2020a). Particular attention should be placed on financial intermediation entities that provide the core banking-related activities such as the provision of loans and deposits. Furthermore, regulation must also account for interconnectedness arising from activities outside of the traditional banking system yet connected to banks. Moreover, policymakers and authorities should take into consideration the potential leakages and accommodate them in their measures.

c) Increase knowledge of emerging activities in the financial systems

Policymakers must have a profound understanding of the behaviour of emerging market players. In particular, they must have knowledge of how and to what extent these market players affect various aspects of financial stability, such as financial stability—as such, having an accurate picture of the FinTech sector is crucial. Given the nature of such participants or market entrants, policymakers must have a knowledge of the degree of interconnectedness between FinTech activities and the financial system, particularly the banking system. Increasing interconnectedness can as easily and quickly spread shocks. Understanding how risks could be transmitted or amplified across the entire financial system is also paramount (Marqués et al. 2021; Martinez-Jaramillo et al. 2019).

The lack of visibility of FinTech developments, such as its growth, interdependencies and the emerging risks they could generate, would, in turn, hamper the mandate of ensuring financial stability. Relevant information would enable policymakers, regulators and researchers to measure and identify potential structural changes to the financial system.

Some of these structural changes include i) the growth of FinTech credit; ii) the degree of how it interacts with traditional financial institutions; iii) the types of risks it could introduce or exacerbate, and iii) how these vulnerabilities could be increased and amplified throughout the entire financial system and to the real economy. Furthermore, academic research in this field is still in its infancy; hence, continuous research is needed to guide policy.

d) Maintain the balance between the risks and benefits of FinTech credit

The objective of minimising financial stability risks can sometimes conflict with the desire to allow for a regulatory landscape that enables innovation and experimentation with new business models (Bertsch and Rosenvinge 2019). Policymakers and regulators are often faced with a delicate balancing act between creating a balance between competition and financial stability without inhibiting the growth of financial innovation such as FinTech credit (OECD 2020a). The existence of such policy trade-offs also challenges policymakers to prudently strike the right balance in minimising the risks resulting from FinTech credit and allowing the benefits of innovation to diffuse through the system without endangering financial stability. Podkolzina (2021) also alludes to the presumption of the existence of a trade-off between competition, market integrity, and financial stability by FinTech-specific policies.

The regulators' dilemma rests on their ability to harmonise prudential regulation and competition policy so that compliance does not become an entry barrier and that such entry does not become destabilising (OECD 2020a). Achieving this mandate requires a deep understanding of the association between traditional intermediaries and evolving market players and the potential impact of this interaction on financial stability (Marqués et al. 2021; Brave and Butters 2011). Policymakers, therefore, need to harmonise the short, medium, and long-term effects of FinTech credit on financial stability.

e) Improve on monitoring and collation of FinTech credit data

Understanding the size, scope, and growth of the FinTech credit markets remains a key priority for policymakers responsible for monitoring credit markets and setting monetary and MaPP based on credit aggregates (Cornelli et al. 2020). Information relating to FinTech credit data is essential in understanding potential risks to financial stability and in conducting, among others, risk contagion research, systemic risk and stress test analysis (Marqués et al. 2021). As such early and timely detection of undue risk accumulation, such as credit booms and emerging vulnerabilities to financial stability, can provide policymakers with adequate information on all sources and forms of credit (Lee et al. 2016). Early detection can prevent some risks; hence continuous monitoring tools and processes should be developed to serve as early risk indicators.

There is, therefore, an urgent need for improved FinTech data availability and its adoption in national credit official statistics. The inclusion of FinTech credit data on official databases can contribute to clearer visibility of the overall non-bank credit sector. Evolving technological innovations such as FinTech credit can also provide regulators with the necessary tools and data to undertake systemic monitoring and supervision. This also ensures that the flow of credit information effectively mitigates financial stability risks and over-indebtedness. Therefore, this study suggests that the potential benefits of FinTech credit expansion must be counterweighted against its potential risks. FinTech credit data must be incorporated into official national statistics.

f) Enhance and leverage cooperation with other authorities

Fostering and leveraging internal and external cooperation and collaboration with other authorities may help address emerging developments in the financial sector and allow for a clear and unified approach to risk, innovation, and competition (OECD 2020a). This includes reviewing and modifying existing data collection standards, formulating common classifications, reporting practices from FinTech activities and defining various FinTech activities and data types. There is also a need to harmonise cross-border regulations to reduce the compliance burden, which may further impede the development of new innovations. Further policy initiatives should enhance data access and sharing within and between institutions as well as internationally.

8.5. Limitations and future research

This study has made efforts to provide solid empirical evidence to address the research questions. While the study offers an outstanding contribution to academic literature, it is not without some limitations. First, the main challenge is the limited availability and reliability of both official and privately disclosed FinTech data. This led to a limited sample size which consisted of only twenty-five (25) economies. Similar studies have also acknowledged this limitation of FinTech data, partly due to its uniqueness and diversity (Cornelli et al. 2020, 2021; Frost et al. 2019; Claessens et al. 2018). This is partly because these forms of credit intermediation are relatively new and often not subjected to regulatory data reporting in most jurisdictions or included in official national data (Cornelli et al. 2021; Claessens et al. 2018). The lack of official data on the FinTech sector makes it generally difficult to obtain and aggregate stock of total FinTech credit consistently and comparable across countries. FinTech data gaps, therefore, remain a policy challenge as it hinders not only financial stability but affects some of the central banks' main functions, such as monetary policy, payment systems, and economic activity financial statistics (Marqués et al. 2021).

Second, the study uses aggregate country-level data, which tends to pose an identification challenge despite the advantageous cross-country dimension (Hodula and Ngo 2021). However, due to the unavailability of data in most economies, this study could not employ other econometric models, such as the GMM, to deal with the endogeneity issue since the number of cross-section entities (N) is smaller than the number of periods (T). Third, the study could not undertake a comparative analysis between advanced and EMDEs, due to the limited availability of FinTech credit in EMDEs. Out of the total of twenty-five (25) economies, EMDEs comprise only five countries, translating to a sample size of 300. Moreover, FinTech adoption in EMDEs commenced late, while in advanced economies, the first countries started reporting FinTech data as early as 2005 compared to 2015 for EMDEs.

Fourth, the heterogeneity in the definitions of FinTech renders it virtually impossible to accurately identify the exact size of the FinTech industry (Thakor 2020). In the absence of a global definition of FinTech credit, data limitations in some jurisdictions extend to the exclusion of some types of lending activities that could otherwise be regarded as FinTech credit (Thakor 2020; Claessens et al. 2018; Fuster et al. 2019). For instance, a large group of lenders excluded from the FinTech credit data are FinTech securitisation and online mortgage lenders such as Quicken loans (Claessens et al. 2018; Buchak et al. 2018; Fuster et al. 2019) and BigTech credit (Frost et al. 2019; Cornelli et al. 2020). However, the nature of disclosure by BigTech firms is still very patchy and not easily accessible hence not suitable for comparison at this stage. Therefore, in this study, BigTech firms are excluded.

This study provides a basis for future research. FinTech credit presents a new breed of alternative credit whose impact is yet to experience a complete financial cycle (FSB 2017; 2019a), thus providing more room for future research. First, more available data on FinTech credit can be undertaken as a comparative study between advanced and EMDEs. Second, with more countries included, more analysis can be undertaken using other methodologies, such as GMM, to address endogeneity issues. Third, future research could also include FinTech credit (BigTech included) alongside other types of nonbank credit. Fourth, future research in this study could be further extended to find the focal or turning points between FinTech credit and both financial stability and bank risk-taking. Finally, future research could expand this study by exploring the impact of the overall nonbank credit sector on financial stability, thus including FinTech credit and other forms of nonbank credit.

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APPENDIX

Appendix A: Overview of the CCAF FinTech classification system

VERTICAL (SEGMENT)	LEVEL 1 (SUBSEGMENT)	LEVEL 2 (CATEGORY)	DEFINITION
FINTECH LENDING	Balance Sheet Lending	Business Lending	Platform entity that provides unsecured or secured loan directly to a business
		Property Lending	The platform entity provides a loan, secured against a property, directly to a consumer or business borrower
		Consumer Lending	Platform entity provides unsecured or secured loan directly to a consumer
	P2P / Marketplace Lending	Business Lending	Individuals and/or institutional funders provide a loan to a business
		Property Lending	Individuals and/or institutional funders provide a loan, secured against a property, to a consumer or business borrower
		Consumer Lending	Individuals and/or institutional funders provide a loan to a consumer borrower
	Debt-Based Securities	Debt-Based Securities	Individuals and/or institutional funders purchase debt-based securities, typically a bond or debenture, at a fixed interest rate
		Mini-Bonds	Individuals or institutions purchase securities from companies in the form of an unsecured bond which is ‘mini’ because the issue size is much smaller than the minimum issue amount needed for a bond issued in institutional capital markets.
		Invoice Trading	Individuals and/or institutional funders purchase invoices or receivables from a business at a discount
		Crowd-Led Microfinance	Interests and/or other profits are re-invested (forgoing the interest by donating) or provides microcredit at lower rates.
		Customer Cash-Advance	A buy now/pay later payment facilitator or Store Credit solution, typically interest bearing
		Merchant Cash-Advance	A merchant cash advance provided via an electronic platform, typically with a retail and/or institutional investor counterpart receiving fixed payments or future payments based on sales.
FINTECH CAPITAL	Investment-Based Crowdfu	Equity-Based Crowdfunding	Individuals and/or institutional funders purchase equity issued by a company

		Revenue / Profit Share Crowdfunding	Individuals and/or institutions purchase securities from a company, such as shares, and share in the profits or royalties of the business
		Real Estate Crowdfunding	Individuals and/or institutional funders provide equity or subordinated debt financing for real estate
		Community Shares	Raising money by offering a local community a chance to own shares in a community-local organisation
		Capital Raising Retail Brokerage	Raising money on behalf of a client form a retail audience in exchange for a commission
		Capital Raising Institutional Brokerage	Raising money on behalf of a client form a institutional audience in exchange for a commission
	Non-Investment-Based Crowdfunding	Donation-Based Crowdfunding	Donors provide funding to individuals, projects or companies based on philanthropic or civic motivations with no expectation of monetary or material
		Reward-Based Crowdfunding	Backers provide funding to individuals, projects, or companies in exchange for non-monetary rewards or products
		Token Hosting Platform	Platform (most often exchanges) offering to host a token sale selected against a set of criteria
FINTECH BANKS	Retail-Facing	Fully Digitally Native Bank (Retail)	Provide banking services to individual consumers exclusively through digital platforms
		Marketplace Bank (Retail)	Banking provider offers products and services from a range of providers including its own to individual consumers
	MSME-Facing	Fully Digitally Native Bank (MSME)	Provide banking services to businesses exclusively through digital platforms
		Marketplace Bank (MSME)	Banking provider offers products and services from a range of providers including its own to businesses
		Banking-as-a-Service (BaaS)	An end-to-end process that allows other organisations to set up and offer digital banking services
		Agent Banking (Cash-In / Cash-Out)	Performs services in some capacity on behalf of another banking entity
FINTECH SAVINGS		Digital Money Market / Fund	Allows fundraising through the selling of short-term debt which can be bought by investors
		Digital Micro Saving Solutions	Small savings opportunities identified within individuals existing budget and automatically put money into a savings account to encourage positive behavioural change

		Digital Savings Collective / Pool	Members pay into a common platform, and contributions are pooled for issuing loans. Interest from the loans shared among the members
		Savings-as-a-Service (SaaS)	An end-to-end process that allows other organisations to set up and offer saving services
FINTECH PAYMENTS	Payment Services	Digital Remittances (Cross Border-P2P)	Provide cross-border remittances services
		Digital Remittances (Domestic-P2P)	Provide domestic remittances services
		Money Transfer (P2P / P2B / B2P / B2B)	Provide digital means of payment to access and utilize funds stored in an account (e.g. Virtual debit/credit card, Wallet)
		eMoney Issuers	Issue electronic funds and provide digital means of payment to access and use those funds (e.g. Virtual prepaid card, E-Money)
		Mobile Money	Use of a mobile phone in order to transfer funds between banks or accounts, deposit or withdraw funds or pay bills
		Acquiring Services Providers for Merchants	Provide means for the acceptance of digital payments by merchants
		Points of Access (PoS / mPoS / Online PoS)	Provide hardware or software to capture payment transactions to transmit to a network
		Bulk Payment Solutions	Provides payments to multiple beneficiaries from a single transaction
		Top-ups & Refills	Provider facilitating the top-ups or refill of various products and services such as mobile phone contracts
	Backend Services	Payment Gateways	Provides digital payment acceptance services on behalf of multiple acquirers to integrate different types of digital payments mechanisms/instruments
		Payment Aggregators	Collect payments on behalf of multiple merchants and accept different digital payments instruments
		API Hubs for Payments	Integrate different online payment services through a unified API service
		Settlement & Clearing Services Providers	Manage and operate digital platforms where different entities exchange funds on their behalf or on behalf of their customers
	Crypto-asset Payments	Money Transfer (Crypto-asset)	Provides means of payment to access, utilise, and transfer funds for various use cases (e.g. remittances, bill payments)
		Consumer Spending	Provides debit card or other ways for consumers to spend their crypto-assets
		Top-ups & Refill (Crypto-asset)	Provider facilitating the top-ups or refill of various products and services (e.g. mobile contract, prepaid card)
		Payment Processor	Provides services for the processing of electronic transactions

		Points of Access (Crypto-asset)	Provides hardware or software to capture payment transactions to transmit to a network (PoS, mPoS, on-line PoS)
	Stablecoin Issuance	Asset-Backed Stablecoin	Issues tokens whose value is pegged to the value of an asset or a basket of assets
		Algorithmic Stablecoin	Issue token whose market value is maintained using algorithmic means
CRYPTO-ASSET EXCHANGE	Trading	Order-Book	Central limit order book using a trading engine to match buy and sell spot orders from users
		Decentralised Exchange (DEX) Relayer	Peer-to-peer relay exchange built on top of a public blockchain
		Single Dealer Platform / OTC Trading	Provider enabling clients to engage in bilateral trades outside of formal trading venues
		Trading Bots	Platform using an algorithm to optimise trading strategies
		High-Frequency Trading (HFT) Services	Provider enabling automated market-making and arbitrage strategies
		Advanced Trading Services	Services allowing users to buy portfolio bundles and get access to more sophisticated trading tools (e.g. margin, derivatives)
	Intermediation & Brokerage	Retail Brokerage Services	Platform allowing users to acquire and/or sell crypto-assets at fixed prices and submit orders
		Institutional Brokerage Services	Service providers executing trade orders on behalf of their institutional clients
		Aggregation	Platform aggregating prices to facilitate trade selection for consumers
	Other Financial Transaction Processing	Bitcoin Teller Machines (BTM)	Machine allowing users to buy and sell crypto-assets in exchange for physical cash
		P2P Crypto-asset Marketplaces	Buyer and seller matching platform often coupled with cryptocurrency escrow services
		Clearing	Transmitting, reconciling and, in some cases, confirming transfer orders from the time a commitment for a transaction is made until it is settled
DIGITAL CUSTODY	Institutional Custody	Third-Party Custody	Fully-managed custody solutions often using an omnibus model

		Co-Managed Custody	Sophisticated custody solutions using multi-party computation (MPC), often associated with a 'walled garden' setup/closed environment
	Retail Custody	Hardware Crypto-assets Wallet	Small devices that securely store private keys without exposing them to connected machines
		Unhosted Crypto-assets Wallet	Non-custodial applications that store Crypto-assets s on a device (e.g. mobile, desktop, tablet)
		Hosted Crypto-assets Wallet	Custodial applications that store Crypto-assets s on a device (e.g. mobile, desktop, tablet) or that can be accessed from any connected device via a browser
		eMoney Wallet	Online applications that can be accessed from any connected device via a browser
		Key Management Services	Providers offering technology infrastructure to self-custody their Crypto-assets
INSURTECH		Usage-Based Insurance	Premiums or level of cover are determined by usage behaviour
		Parametric-Based Insurance	Compensates policy holders automatically based on pre-defined triggers associated with losses
		On-Demand Insurance	Insurance is extended in real-time for a specific risk event and duration
		P2P Insurance	Risk-sharing network where a group of individuals pool premiums
		Technical Service Provider (TSP)	Enables distribution partnerships with MNOs, virtual marketplaces and other consumer aggregation points
		Digital Brokers or Agents	Allows users to buy insurance cover, underwritten by one or multiple insurers
		Comparison Portal	Compares insurers and insurance options to facilitate policy selection
		Customer Management	Supports insurers in managing customer acquisition
		Claims & Risk Management Solutions	Supports insurers in risk management and the processing digital claims
		IoT (including Telematics)	Remote devices connected to insurance services
WEALTHTE CH	Asset Management	Digital Wealth Management	Online platforms to supply and provide asset management services
		Social Trading	Platforms that provide investment advice through a social network
		Robo-Advisors	Asset management automated solutions based on algorithms or artificial intelligence
		Pension-Led Funding	Enabling companies to borrow funds from a company director's personal pension, which are then paid back with interest

		Robo Retirement / Pension Planning	Robo-advisors use algorithms and machine learning to offer pension advice
	Personal Financial Services	Personal Financial Management / Planning	Allows the ability to understand and effectively apply various financial skills, including personal financial management, budgeting, and investing
		Financial Comparison Sites	Online and mobile platforms comparing financial products
REGTECH		Profiling & Due Diligence	Collects and integrates data from multiple sources to build a profile of a person or entity to allow identity confirmation and categorisation according to regulation
		Blockchain Forensics	Captures and records key biographical attributes such as location of birth for identification, BF: Monitors customer deposits and withdrawals for signs of "tainted" coins that may have been involved in criminal activity
		Risk Analytics	Uses big data to assess the risk of fraud, market abuse or other misconduct at the transaction level
		Dynamic Compliance	Facilitates and monitors regulatory changes to ensure that policies and controls adapt seamlessly to changing requirements
		Regulatory Reporting	Reporting and Dashboards
		Market Monitoring	Matches market-level outcomes to regulatory or internal rules to, for example, identify poor product performance
ALTERNATIVE CREDIT ANALYTICS		Psychometric Analytics	Connects an individual's personality type and behaviour with a credit or insurance product
		Sociometric Analytics	Analyzes social communication patterns with social sensing technology to drive innovative transformation services
		Biometric Analytics	Discovers patterns within biometric signals to ascertain potentially valuable information about a person such as emotional state or longevity.
		Alternative Credit Rating Agency	Issues corporate ratings on corporate issuers not considered a financial institution or insurance undertaking
		Credit Scoring	Helps lenders see the true creditworthiness of their customers by removing unconscious biases and adding much-needed nuance to credit applications.
DI GI TA L ID EN TI TY		Security & Biometrics	Captures and records key biometric attributes such as fingerprints for identification

		KYC Solutions	Supports companies by verifying the identity of their clients (to comply with laws & regulations)
		Fraud Prevention & Risk Management	Aims to prevent theft and misuse of personal data
TECH. FOR ENTERPRISE		API Management	The process of creating and publishing web application programming interfaces (APIs) by, for example, enforcing their usage policies and analyzing usage statistics
		Cloud Computing	The on-demand availability of computer system resources, especially data storage (cloud storage) and computing power, without direct active management by the user
		AI / ML / NLP	Artificial Intelligence/ Machine Learning/ Natural Language Processing
		Enterprise Blockchain	The features of blockchain technology that will solve major enterprise problems
		Financial Management & Business Intelligence	Business intelligence tools that help finance professionals gain insight in internal and the external factors that affect the bottom line
		Digital Accounting	The formation, representation and transmission of financial data in an electronic format
		Electronic Invoicing	A form of electronic billing to allow collection of payment
CONSENSUS SERVICES	Mining	Hardware Manufacturing	Entities designing and building component of mining equipment (e.g. chip, GPU, ASIC)
		Remote Hosting Services	Services hosting and maintaining customer-owned mining equipment
		Cloud Mining	Services renting out hashpower generated by their own machines to consumers for a fixed period of time
		Hashrate Brokerage	Marketplace connecting sellers of hashpower (hashers) with buyers
			Miners operating mining equipment on their own behalf
		Pool Operation	Services combining computational resources from multiple hashers and distributing rewards
		Equipment Procurement & Financing	Services facilitating the sale and/or financing of mining equipment
		Firmware & Software Development	Entities developing software or firmware for mining
		Staking-as-a-Service	Third-party offering services to pool stakeholders' staking capacity and participate in the validation process on their behalf

Source CCAF, WBG and WEF (2022, 2020)