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Essays on Digital Credit, Banking Business Models, and Bank Innovation

by

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Abstract

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This thesis provides insights into financial technology development, and its interaction with banking institutions. To this end, three distinct research investigations are conducted. First, we examine the determinants of the global online lending market expansion, known as "digital credit". Next, we link the financial technology development with the banking sector through the examination of the role of banking business models in explaining the decision of banks to acquire fintech firms. Following this, we analyze the impact of bank-fintech collaboration through the equity investment channel on bank innovation capabilities.

Through the use of several econometric methodologies, this thesis presents robust findings. First, we find that digital credit provided by fintech and bigtech firms complements the credit provided by incumbents. Second, we find that diversified and investment banking business models are more likely to conduct acquisitions of fintech firms than wholesale and traditional banking business models. We further show that the structure of a bank's business model may explain both the propensity of a bank to acquire a fintech firm with a particular specialization and the motivations behind such acquisitions. Finally, we present results indicating that banks' investments in fintech firms' funding rounds increase their financial innovation output. We document that this positive impact holds even when we restrict the participation of banks to only the initial investment.

The results give rise to several important policy implications. We provide evidence demonstrating the positive impact of the advancement of financial institutions on digital credit volumes. As such, policymakers aiming to promote financial innovation in their jurisdiction should implement strategies that focus on developing the banking sector. Furthermore, our findings on the role of banking business models in banks' fintech acquisitions should inform policymakers about the significance of considering the intricate business model structures when formulating efficient and targeted policies to address the dynamics of bank-fintech partnerships. In addition, the results regarding the impact of bank-fintech equity investment on bank innovation suggest that when banks increase their participation in the funding rounds of fintech firms, it leads to a higher bank innovation output. Therefore, regulators aiming to foster financial innovation should ensure that the regulatory environment facilitates beneficial collaboration between banks and fintech firms, while simultaneously preserving the stability of financial markets.

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Declaration of Authorship

I declare that this thesis and the work presented in it is my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. None of this work has been published before submission;

Signed:.. Date:..................

Acknowledgments

In the name of Allah, most gracious and most merciful. I must begin my piece by acknowledging the abundance of blessings in my life granted by Allah subhanahu wa ta'ala. I pray that through his guidance, this great achievement of mine becomes a stepping stone towards benefiting the Islamic nation and all of mankind.

I consider myself extremely fortunate to be under the supervision of a stellar team. Professor Simon Wolfe and Dr. Mohamed Bakoush possess remarkable harmony and complementary expertise, making them truly exceptional team. They believed in my abilities and encouraged me to reach for heights I hadn't thought possible. Thanks to their patience and guidance, I can confidently say that I have grown significantly as a researcher since beginning my PhD journey. I am forever grateful for their support and will always be in their debt.

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Chapter 1: Introduction

1 Introduction

1.1 Research Background

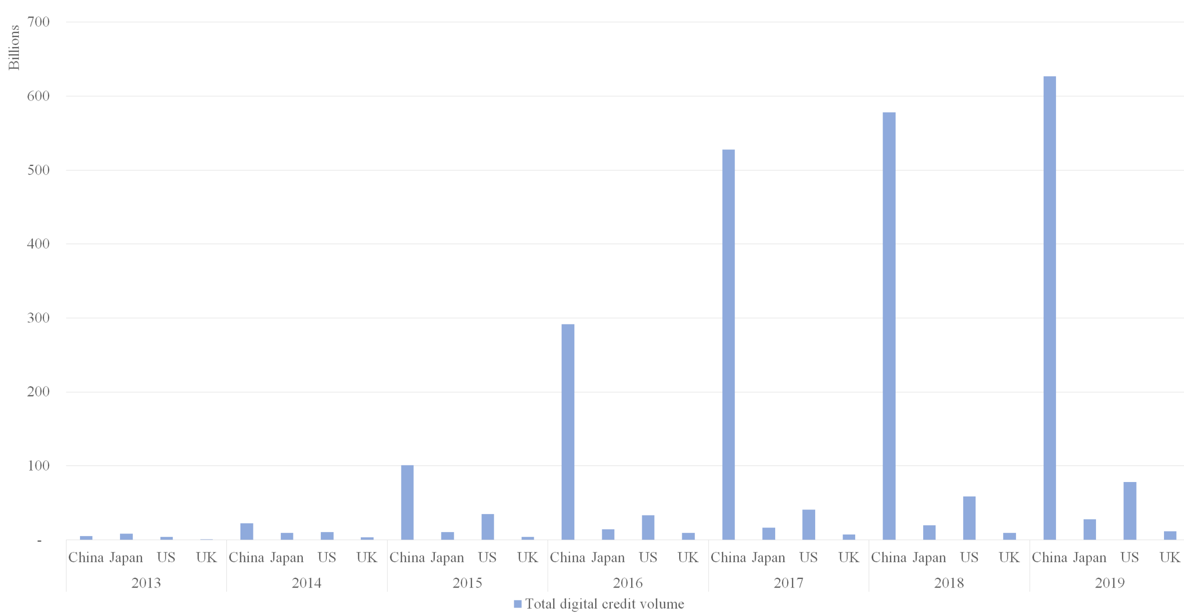
The emergence of new innovative startups that offer financial services has placed banks under competitive pressure through their use of technology-driven solutions (Navaretti et al., 2017). The essence of such fierce competition might stem from fintech firms' advancement in product customization that accommodates the rising expectations of clients. Examples of these products include peer-to-peer lending, cryptocurrencies, and smart contracts (Thakor, 2020). The perception among clients that there is an innovative approach to delivering financial services and the relative maturity of fintech firms may have sparked investors' interest in the fintech industry (Carbó-Valverde et al., 2021). This interest has enabled fintech firms to generate more than 1 trillion US dollars in equity investment since 2010 and complete over 35,000 deals globally by 2021 (Cornelli et al., 2021).

In response to such advancement, banks may consider collaborating with fintech firms as an effective strategic move to be involved in modern financial technology. Forms of such collaboration include banks acquisition of fintech firms and banks making equity investments in fintech firms. Recent literature has identified two potential catalysts for the increased involvement of US banks in the development of financial technology. First, the passing and implementation of Gramm-Leach-Bliley Act (GLBA) in 1999, as well as the relaxing of the Volcker rule in 2020, may have both incentivized banks to increase their participation in venture capital investment in fintech firms (Li et al., 2023). The GLBA has allowed commercial banks to undertake investment banking and insurance activities, including private equity investment (Akhigbe and Whyte, 2004). While the Volcker rule, enacted in the aftermath of the 2008 global financial crisis, prevents banks from engaging in trading with their own capital and investing in hedge funds and private equity funds (Li et al., 2023). Second, the ongoing advancement in financial technology, driven by breakthroughs in areas commonly used by banks and individuals, such as payment technology and digital credit, may have prompted banks to expand their product offerings. According to Hornuf et al. (2021), bank-fintech collaboration can expedite the process of modernizing the product suit of banks.

1.1.1 The Fintech Industry

Chapter 2 sheds light on digital lending, one of the most developed fintech innovations. Digital lending is a form of credit that is facilitated online. It combines both fintech credit and big tech credit. Fintech credit is defined as credit given via a platform that links investors and borrowers (Claessens et al., 2018). While a big tech credit is a loan facilitated by a large technology company (Cornelli et al., 2020).

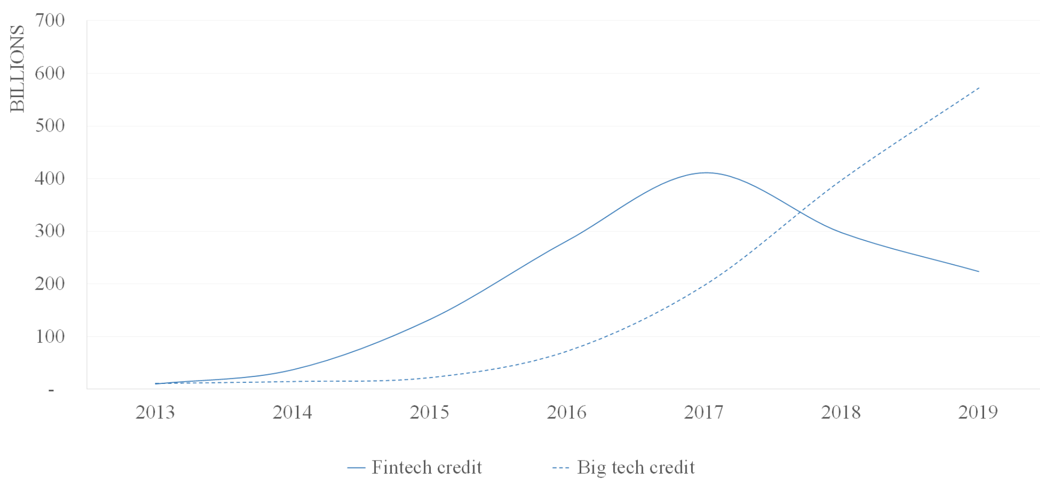
Figure 1: Total Digital Credit - Proportion of Countries (2013-2019)



Source: Author's calculation based on the data by Cornelli et al. (2020)

Overall, as shown in Figure 1, China has been the most dominant nation in terms of the proportion of countries contributing to total digital credit volumes for the majority of the years (2013-2019), with a total cumulative digital credit of $2.15 trillion issued, equivalent to 81 percent of all digital credit issued globally from 2013 to 2019. The United States (US) has the second largest volumes with a 10% share of total digital credit, and a total of $261 billion digital credit. Japan and the United Kingdom (UK) accounted for 4% and 2% of the market, with a total digital credit of $107 billion and $45 billion respectively. The remaining 3% was distributed across the world, raising a total of $86 billion. By the end of 2014, a total digital credit of $46 billion had been facilitated, representing a 158% increase compared to the previous year's total of $18 billion. Next, the largest year-on-year rise occurred at the end of 2015, with a growth rate of 229% and a total of $152 billion in digital credit issued worldwide. Following that, credit growth increased at a slower pace, reaching a total of $350 billion and $603 billion in 2016 and 2017, with a growth rate of 130% and 72%, respectively. In 2018, the digital credit market expanded by just 14% over the previous year, totaling $685 billion, before ending 2019 with $795 billion in digital credit and a growth rate of 16 percent.

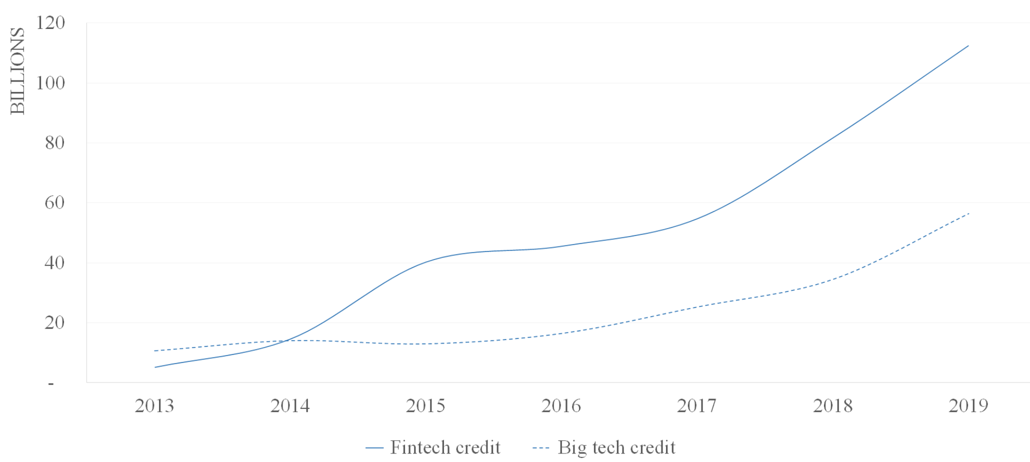
Figure 2: Total Digital Credit Volume (2013-2019)



Source: Author's calculation based on the data by Cornelli et al. (2020)

Figure 2 depicts the overall digital credit volumes from 2013 to 2019, divided into fintech credit and big tech credit. According to Cornelli et al. (2020)'s initial dataset, fintech credit volumes increased year after year until 2017, owing to the development of new P2P platforms. However, overall fintech loan volumes have been declining in 2018 and 2019, due to a rise in the number of Chinese defaults (borrowers unable to repay their debt) and platform failures, with just 343 active platforms as of the end of 2019, down from 3600 in 2015. Given that China accounts for the most digital credit volumes in the majority of years under study, the downward trend for fintech credit might have another contributing factor that is linked to the Chinese authorities' extensive crackdown on the peer-to-peer (P2P) platforms industry in order to curb the exponential growth of online lending platforms in China. He and Li (2021) documents, based on Wangdaizhijia data[1], that by the end of 2018, the number of online P2P platforms in China has reached 6621 platforms issuing a cumulative total of $1.209 trillion in unsecured loans. They also stated that, as a result of what local authorities have done, the total number of problematic P2P platforms in China has risen to 5357, divided into platforms that have gone bankrupt or vanished (platform owners fled with investors funds).

Figure 3: Total Digital Credit Volume (Without China) (2013-2019)



Source: Author's calculation based on the data by Cornelli et al. (2020)

The ongoing rise is being supported by the widespread acceptance of innovative lending

[1]The Chinese authoritative portal for peer-to-peer online operations. wdzj.com

channels in countries all over the world. This point of view is backed by the data in Figure 3, which excludes China's volumes and shows an upward trend in both forms of digital credit. With a total cumulative credit of $249 billion issued from 2013 to 2019, the United States (US) accounts for the second highest proportion of fintech credit. Japan generated $102 billion in big tech credit throughout the years, ranking second as the largest big tech credit market. According to market research estimates (Altfi, 2021), China's fintech credit market is anticipated to have grown at an annual growth rate of 18% and issued $224.4 billion in P2P credit to business by the end of 2021. While the US will expand to $7.9 billion by the end of 2021, demonstrating a growth rate of 10.4%.

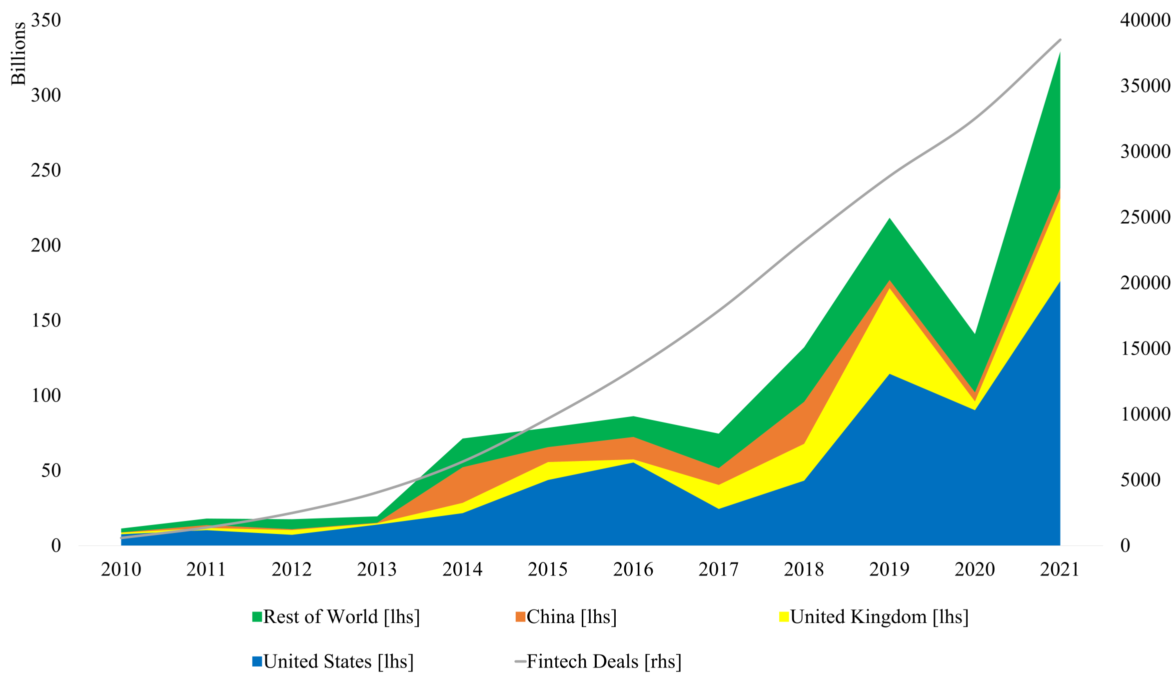
Chapters 3 and 4 examine the bank-fintech collaboration. It is possible that following the 2007-2008 global financial crisis (GFC), the financial landscape has changed. Most significantly, clients are served by more than just financial intermediaries like banks. Utilizing cutting-edge technology, new players in the financial markets are providing clients with services that were previously typically provided by incumbents (Chen et al., 2019). The development of fintech globally seems to be significantly altering how banks carry out their core activities. For instance, a fintech industry analysis by KPMG details how JP Morgan Chase, a prominent U.S. financial institution, has partnered with a fintech company in 2021 to improve their client base's online experience (KPMG, 2022).

The collaboration between banks and fintech firms is a fresh topic of debate between scholars. Dranev et al. (2019) are among the first to analyse this relationship from the standpoint of market reaction. They discover that following an acquisition of fintech firm, banks had a positive average abnormal return in the short-term. In a similar vein, Akhtar and Nosheen (2022) document the positive impact of fintech on banks' performance measures following an acquisition. Cappa et al. (2022) explore the impact of banks' M&A deals with fintech firms on the stock market. They do not show a positive effect for all forms of fintech mergers and acquisitions; rather, the impact depends on the particular service provided by the fintech firm.

As fintech is the application of technology to improve financial services (Thakor, 2020), the bank-fintech relationship dates back to the late 19$^{\text{th}}$ century and has developed through three major periods (Arner et al., 2015). The period of Fintech 1.0 (1866-1967) witnessed the rise of digital financial transactions in the form of the introduction of credit cards, and the establishment of double-entry bookkeeping accounting system, laying the groundwork for future innovations. The following distinct era, Fintech 2.0 (1967-2008), experienced the emergence of automated teller machines (ATMs), the shift from physical to electronic stock trading, and the widespread use of internet banking. The turning point in the development of the third major era of financial technology, known as Fintech 3.0 (2008-present), was the global financial crisis (GFC) of 2008. This event significantly impacted public trust in banks, creating opportunities for new innovative entrants to offer services directly to consumers. Vives (2017) argues that fintech firms focus on millennials to capitalize on their distrust of traditional institutions and their familiarity with technology, which sets them apart from older generations.

Figure 4 shows the amount of fintech funding and the number of deals worldwide between 2010 and 2021. A notable contribution to this market comes from the United States. With a total of around 610 billion US dollars worth of fintech equity investment, representing 51% of the total amount raised, and around 15,000 deals, accounting for 38% of all fintech equity investment deals. Thus, the United States represents a significant portion of the fintech industry that is worth investigating. It might be argued that due to its advancement in fintech and extensive data availability, the US market stands out as a notable market for academic inquiry. For example, in the mortgage market, Fuster et al. (2019) document how technological innovation has improved the efficiency of the US mortgage market by

Figure 4: Amount of Worldwide Fintech Funding and Number of Deals (2010-2021)



Source: Author's calculations based on data from Cornelli et al. (2021)

accelerating mortgage processing without increasing loan risk. Buchak et al. (2018) show that fintech firms contributed approximately 25% of all shadow bank residential mortgage lending loans in the US in 2015.

1.2 Research Problems

This subsection discusses the key problems that this thesis seeks to address. Although the existing bank-fintech literature provides insights into the factors that affect the growth of fintech firms, there is a pressing need to understand the relationship from different aspects (Choudhary and Thenmozhi, 2024). The empirical analyses conducted in this PhD thesis extend and contribute to the existing bank-fintech literature through introducing a new aspect to this field. This is achieved by modeling the bank-fintech interaction from three unique perspectives, therefore offering valuable insights to supervisors and policymakers.

First, chapter 2 focuses on examining the determinants of digital credit volumes, a topic that has posed significant challenges to scholars attempting to research it, possibly due to the limited data availability. A study by Rau (2020) shows that prior to 2015, only a few countries around the world had established explicit regulations governing fintech equity crowdfunding platforms, which may have contributed to limited data availability of these services around the world.[2] Despite this, a growing strand of literature has emerged, focusing on understanding the relationship between digital credit and factors such as its financing success, interest rates and default rates (Basha et al., 2021). However, there is no consensus between scholars on whether lending facilitated by new entrants substitutes or complements the credit provided by banks (Tang 2019; Hodula 2021; Cornaggia et al. 2018). Scholars show that digital lending can act as a substitute to traditional lending and serve borrowers looking for low interest rate through peer to peer platforms (Butler et al., 2017). Others find that digital lending complements bank credit, as it caters to borrowers with higher risk profiles who have been rejected by banks due to their low credit score (de Roure et al., 2022). Furthermore, there exists a significant knowledge gap in understanding the drivers of global digital credit from an institutional characteristics and macroeconomic factors. To fill this gap, we rely on a newly developed dataset on global digital credit that includes 79 countries, and we link this development with banking sector development indicators such as access, depth, efficiency, and overall development. Additionally, we explore the role of macroeconomic factors, including economic freedom, economic globalization, public debt, and human development index, in shaping the rise of digital credit. By examining the interplay between banking, macroeconomic development, and digital credit, this chapter addresses a critical knowledge gap in the field.

In chapter 3, we focus on explaining the growth of bank-fintech acquisitions by examining

[2]The number of countries with such regulations increased to reach 24 during their study period.

the role of banking business models. A significant lack of comprehensive documentation exists in the current literature on the effects of bank-fintech collaboration (Choudhary and Thenmozhi 2024; Chernoff and Jagtiani 2023). Despite that, in recent years, a limited number of scholars have examined various characteristics of the bank-fintech relationship. These include investigating the features of banks' boards (Kwon et al. 2024; Del Gaudio et al. 2024), analyzing the nature of fintech firms (Bellardini et al. 2022; Li et al. 2023), and identifying factors that determine the type of collaboration between banks and fintech firms (Hornuf et al., 2021). We are among the first in examining bank-fintech interaction through the viewpoint of banking business model structure. Existing literature on banking business models primarily examines their relationship with financial crises (Altunbas et al., 2011), bank performance (Ayadi et al., 2021), and financial stability (Köhler, 2015), among other risk-related characteristics. We extend the current knowledge in this area by examining banks' internal structure and its influence on fintech acquisitions.

Finally, in chapter 4 we address a critical gap in literature by examining the impact of bank-fintech equity investment on bank innovation. little is known about the effect of such collaboration on bank innovation capabilities. Zheng and Mao (2024) examines the impact of bank acquisition of fintech firms on bank innovation, focusing on the number and quality of patent applications of 14 banks. This thesis extends this strand of literature and investigates the impact of bank investment in fintech on banks' innovation capabilities by using a unique dataset of bank-fintech equity funding rounds.

1.3 Aims and Objectives

The purpose of this thesis is to bring new perspectives into the relationship between banks and financial technology, or fintech. To achieve this ambitious aim, this thesis consists of three core chapters. It begins by investigating the factors driving the development of the digital credit market. Following that, in the second core chapter, we analyze the relationship between fintech and the banking sector through bank-fintech acquisitions, highlighting the role of banking business model structures. The last empirical chapter examines the effects of banks' involvement in fintech firms' equity investment rounds on the innovation capabilities of banks.

1.4 Thesis Contributions

1.4.1 Chapter 2: Determinants of Digital Credit

This chapter empirically investigate the banking and macroeconomic forces that drive the growth of the online lending market. With the assistance of a newly constructed global fintech and big tech database, and the use of a fixed effects model, we were able to study the relationship between banking development dynamics and the new innovative online credit platforms. We add to a growing strand of literature that examines digital credit (Cornelli et al. 2023; Tang 2019; Cornaggia et al. 2018). We also investigate if macroeconomic factors could influence the development of the digital credit market. We document a complementary relationship between online lending and traditional lending. We further discover that the usage of digital lending platforms is positively correlated with human capital development. While a negative association is found between the level of a country's sovereign debt and its involvement in digital credit activity. Finally, given that the development of financial technology is of great importance for policy makers, we provide the policy recommendations in light of this chapter's conclusion.

1.4.2 Chapter 3: The Role of Banking Business Models in Banks' Fintech Acquisitions

The third chapter presents an interesting evaluation of the role of the banking business model on the likelihood of bank-fintech acquisitions. We make use of a large U.S. bank-level sample, and we complement it with a unique bank-fintech acquisitions data. We use K-Means cluster analysis to identify banking business models that we then use in a logistic regression to find the likelihood of bank-fintech acquisitions. The cluster algorithm has provided us with the characteristics of four banking business model structures, these are: Diversified Banking (BM1), Wholesale Banking (BM2), Traditional Banking (BM3), and Investment Banking (BM4). Our results indicate that banking business models significantly affect banks' propensity of acquiring fintech firms. This chapter contributes to the banking business model literature (Altunbas et al. 2011; Hryckiewicz and Kozłowski 2017; Ayadi et al. 2011) as well as the bank-fintech literature (Kwon et al. 2024; Kueschnig and Schertler 2024; Collevecchio et al. 2023). We believe that the findings of this chapter is of great relevance to the management of banks since it will help them make well-informed strategic choices, including M&A with a fintech company. The insights of this chapter, which investigates how the structure of banks business models influences choices to acquire financial technology firms, may be of interest to policymakers.

1.4.3 Chapter 4: Examining the Impact of Bank-Fintech Equity Investment on Bank Innovation

Chapter 4 examines the influence of bank equity investment in the funding rounds conducted by financial technology firms on the innovation of banks. To the best of our knowledge, this chapter is among the first to conduct bank-fintech collaboration analysis from the perspective of bank innovation. The results suggest that greater involvement of banks in fintech investment is associated with higher bank innovation, as measured by the number of trademark and patent applications. This result holds when we consider only the initial investment by banks. Our results add significant knowledge to existing literature on financial innovation (Beck et al. 2016; Wu et al. 2024; Zhang et al. 2023. We further contribute to the home bias literature (Solnik and Zuo 2017; Levis et al. 2016) and show that bank equity investment in domestic fintech firms is associated with higher bank innovation capabilities compared with foreign ones. These findings support the argument that through equity investment, banks are able to control fintech firms, aligning the services and products developed by the fintech firm with the bank's strategy, facilitating easier integration into the bank's existing functions.

1.4.4 Chapter 5: Summary, Conclusions, and Future Research

The last chapter of the report outlines the summary of core chapters, policy implications, limitations, and avenues for future work.

Chapter 2: Determinants of Digital Credit

Determinants of Digital Credit

Abstract

We empirically investigate the driving forces behind the expansion of the global online lending market known as digital credit using a fixed effects model and a panel dataset of 79 countries from 2013 to 2018. We examine the nexus between banking development dynamics and new innovative credit platforms, and we document a positive relationship between the two. In particular, we show that digital credit complements that of traditional credit. We also discover that human capital development has a significant impact on the adoption of digital lending platforms. On the other hand, we report a strong negative correlation between public debt and levels of digital credit activity. These findings remain robust to different specifications.

JEL Classification: G21, G23, O31

Keywords: Fintech, Financial Innovation, Banking Development

2 Determinants of Digital Credit

2.1 Introduction

> "... what if there are other places that could act as that intermediary? Why does it have to be a bank that sits in-between depositors and people who are borrowing money?"
>
> — Dave Nicholson (Atz and Bholat, 2016)

Following these comments, Dave Nicholson created and co-founded Zopa, the first peer-to-peer (P2P) lending platform, in 2005. From that point forward, the digital credit market age began. P2P lending platforms connect borrowers with lenders online bypassing financial intermediaries. However, it wasn't until the 2008 global financial crisis that alternative lending channels started to flourish, as commercial banks tightened their lending policies, creating a funding gap for other, non-traditional sources of finance to fill (Dömötör and Ölvedi Carbo, 2021).

In this chapter, we analyze the drivers behind the growth of digital credit. Most previous research has been limited to studying the impact of fintech in a single country, possibly due to data scarcity. Existing research in the realm of digital lending concentrates on factors impacting financing success, interest rate and default (Basha et al., 2021), with just a small portion of literature studying the influence of macroeconomic variables on P2P platforms. In contrast, this chapter is among the first to utilize a global database on alternative forms of credit to investigate the link between the digital credit market and key banking and economic factors in a cross-country setting. This research differs from the work of Cornelli et al. (2023) by exploring the relationship between digital credit volumes with institutional and macroeconomic factors, which to the best of our knowledge, have not been previously examined in the literature. In particular, we examine the nexus between new innovative credit platforms and financial institutions development dynamics constructed by Svirydzenka (2016) as measured by access, depth and efficiency. Furthermore, we are able to compare the relative importance of economic and financial factors such as economic freedom, economic globalization, public debt and human development, and their influence on the growth of the digital credit market.

This chapter adds a unique perspective to the development of global digital credit and makes several contributions to existing literature. Specifically, we add to a growing strand of literature that examines digital credit and its relationship with traditional credit (Cornelli et al. 2023; Tang 2019; Cornaggia et al. 2018). We also contribute to the debate on how financial deepening can foster innovation, as evidenced in Ho et al. (2018), by examining the impact of financial institutions credit depth on digital credit volumes. Moreover, we add to existing literature that examines the relationship financial markets development and innovation (Trinugroho et al., 2021). Furthermore, macroeconomic factors could influence the development of the digital credit market. We make our contribution to this strand of literature through exploring the impact of government debt on digital credit volume, adding to a limited number of studies that explored the debt-innovation relationship (Chi et al. 2021; Coccia 2012). We further contribute to existing literature examining human development effect on innovation (Dakhli and De Clercq, 2004), and link human development index with digital credit activities.

Our results provide insights into the relationship between digital credit and a variety of banking and economic variables. Consistent with related literature (de Roure et al. 2022; Tang 2019), we document that a complementary type of relationship exists between traditional and digital forms of credit issuers. We further show that financial deepening is a significant predictor of the creation and financing of innovative firms such as P2P platforms.

Ho et al. (2018) also found a positive relationship between a country's deep banking market and innovation, supporting our findings. The chapter also provides a unique perspective on the positive relationship between the overall development of a banking sector and levels of digital credit activity. Trinugroho et al. (2021) support our findings, showing that developed financial markets are critical in the creation of innovative firms within a country. In terms of macroeconomic variables, we find a negative a statistically significant relationship between public debt and digital credit volumes. This result aligns with related literature such as (Coccia, 2012), who found that a country's higher levels of debt impedes its ability to invest in innovative initiatives. In terms of human capital, we find strong evidence that greater levels of human development have a positive impact on the expansion of the digital credit market. Technology adoption was identified in Danquah and Amankwah-Amoah (2017) to be higher in countries with higher levels of human capital, supporting our main findings.

The development of financial technology is an important policy concern. In light of the findings of this chapter, the following are our policy recommendations: (1) The relationship between financial institutions development and financial innovation demonstrates the critical role of the banking sector in boosting a country's financial innovation level. As a result, policymakers seeking to promote financial innovation in their jurisdictions should consider adopting policies related to banking sector reform and development. (2) The Sovereign-debt-to-financial-innovation nexus indicates that, in general, countries with greater levels of debt have lower levels of digital credit. Therefore, policymakers must consider the significance of the government's ability to invest in financial sector's research and development initiatives in order to raise the degree of financial innovation. (3) With regards to human capital development interaction with financial innovation, government spending on education increases population knowledge and skills, both of which are viewed as catalysts for financial innovation. Policymakers should encourage investment in human capital development in order to achieve better levels of financial innovation.

The remainder of this chapter is as follows. Section 2.2 presents a review of the related literature. Section 2.3 discusses the data and model that were used in this chapter. Section 2.4 presents and discusses the chapter's main results. Finally, Section 2.5 concludes this chapter.

2.2 Literature Review

Financial institutions, such as banks, serve as intermediaries between lenders and borrowers, and so the theory of financial intermediation as noted in Allen and Santomero (1997) specifies the key roles in this function and emphasises incumbents' significance as a direct influence on the development of financial markets and economic prosperity. Scholtens and van Wensveen (2000), on the other hand, have criticised the theory for failing to account for the changes brought about by technology advancement and financial innovation in the financial sector. In this chapter, we focus on digital lending as a segment of the financial innovation ecosystem and show its relation to the theory of financial intermediation through traditional lending. Scholars still believe that financial technology field is still underexplored and poses a significant threat to the traditional financial industry players (Milian et al., 2019).

According to Allen et al. (2020), the development of new kinds of financial technology has been the primary driver for the rapid digital change of the financial environment in recent years. Chen et al. (2019) identify seven categories in which technology has facilitated the use of in the financial industry; these are: cybersecurity, mobile transactions, data analytics, peer-to-peer (P2P), robo-advising, the internet of things (IoT) and blockchain[3]. Goldstein et al. (2019) identify two unique features of today's technological upsurge in the

[3]It is the technology responsible for the development of the Bitcoin cryptocurrency by Nakamoto (2008).

financial sector that set it apart from past innovations. First, these technology solutions are being brought to the market at a quicker rate than ever before. Second, the disruptive shift is being driven by players outside of the financial sector, particularly start-up and big tech businesses. Thakor (2020) says that the industry's products have experienced significant development, with more product customization in order to meet the needs of clients; examples of these products include peer-to-peer lending, cryptocurrencies and smart contracts.

This chapter investigates whether marketplace lending is a replacement for traditional lending or a supplement to it. Some scholars have found mixed results. For instance, Tang (2019) examines the US market and discovers that when banks experience a credit supply shock, P2P loans grow and replace banks in markets exposed to the shock. On the other hand, results show that P2P platforms may supplement banks in offering small loans. Similarly, de Roure et al. (2022) analyse the German market and find that when banks are subject to higher capital requirements, P2P loan activity rises, implying a replacement relationship. At the same time, they discover that P2P platforms might serve as a supplement to banks in servicing riskier borrowers. Hodula (2021) also finds that in less concentrated banking sectors, fintech credit may operate as a supplemental lending channel, whereas in highly concentrated banking sectors, they can act as a direct alternative. Other papers have found a substitute-type of relationship. For example, in the US, Butler et al. (2017) came to the conclusion that borrowers with greater access to traditional financing seek lower interest rates on a P2P platform. This indicates that for some borrowers, digital loans are a feasible alternative. Along the same line, Cornaggia et al. (2018) find that the US P2P platforms could outbid most commercial banks on interest rates in their low-risk loan offerings and that the present regulatory framework is facilitating the growth of fintech companies in the financial sector by imposing greater capital requirements on conventional banks.

This chapter also explores the financial deepening effect on financial innovation. Innovation increases in countries with deeper financial systems as they effectively channel available resources to more profitable innovation products (Ho et al., 2018). Several papers have empirically examined the relationship of financial deepening on innovation and economic growth (Ho et al. 2018; Bhattarai 2015; Rousseau and Wachtel 2011; Hasan et al. 2009). We differ from previous papers in which we examine a country's financial institutions depth to explain the variation in digital credit activity. Furthermore, we investigate bank efficiency and its relationship to higher digital credit activity. The emergence of new digital credit issuers intensifies competition with traditional lenders, and empirical evidence suggests that competition improves efficiency (Schaeck and Cihák 2014; Zarutskie 2013). However, this literature is thin and hindered by a lack of available data. A positive relationship between fintech development and bank efficiency is found in the literature. For example, Lee et al. (2021) employed a stochastic metafrontier approach and the generalized method of moments to find that the rise of fintech innovation in China has two advantages for banks: one, it increases Chinese banks' efficiency levels, and two, it improves the technology used.

A separate stream in the literature examines macroeconomic characteristics and their influence on economic growth and innovation. In this chapter, we link economic freedom, economic globalization, public debt and human capital development to the growth of one of fintech innovation segments, digital credit. With regards to economic freedom and innovation, some scholars in the literature have documented a positive impact of economic freedom, as introduced by The Heritage Foundation (Miller et al., 2013), on innovation. For instance, Herrera-Echeverri et al. (2014) find evidence that economic freedom, as measured by the rule of law, limited government, regulatory efficiency and open markets, has a positive influence on the creation of new innovative enterprises since it provides entrepreneurs with the necessary institutional infrastructure to succeed. Similar to economic freedom's impact, empirical evidence found in the literature suggest that higher levels of economic globalization stimulates innovation levels within a country. The reasoning for this relationship is that economic globalization incorporates international trade and foreign direct investment levels into its calculations, and that these two factors are critical in the process of transferring knowledge and technology across countries (Chi et al., 2021). For example, Lee et al. (2020) find evidence of a positive impact of globalization on the relationship between financial innovation and bank growth. They find that globalization affects bank growth through its effect on financial innovation.

The empirical literature on the relationship between government debt and economic development is vast. In this chapter, we are interested in examining the effect of higher public debt on financial innovation. Some researchers suggest that public debt hinders innovation because it reduces a country's ability to invest in R&D initiatives, resulting in poor innovation performance and weaker innovation platforms. For example, Croce et al. (2019) used a cross-section data of US stock returns and show that high-R&D firms are more exposed to government debt which made them pay higher expected returns. Similarly, Chi et al. (2021) studied 7 decentralised countries and find that public debt has a negative impact on R&D investment. Furthermore, Coccia (2012) find that higher government debt is linked to lower levels of technological innovation, owing to lower investment in R&D initiatives. We also investigate the relationship between human capital and the increase of digital credit volume. Relevant literature emphasises the importance of human development in advancing innovation and technology. Nelson and Phelps (1966) highlight the significance of human capital in stimulating innovation and foreign technology adaptation. Dakhli and De Clercq (2004) analyse the effect of human and social capital on innovation in 59 countries. They provide evidence of a strong influence of human capital as measured by educational attainment, average income and longevity on innovation.

2.3 Data and Methodology

This part of the chapter presents our research variables and the data sample, before presenting and discussing the econometric model used in the analysis.

2.3.1 Sample Selection

We use data at the country level that includes fintech and big tech credit volumes. Three factors influence the selection of this dataset: first, it provides a global perspective on the status and developments in the digital credit markets; second, it includes data on two types of alternative credit, fintech and big tech credit; third, and most importantly, it is one of the first open source databases for alternative forms of credit. We obtain the data from the Bank for International Settlements (BIS) website, Cornelli et al. (2020). The dataset spans a six year period, from 2013 to 2018[4].

Fintech credit data was collected from the Cambridge Centre for Alternative Finance (CCAF) database[5]. Data on big tech credit is gathered from three sources: central banks, big tech companies and other public sources. The final dataset contains 492 observations at the country level for 79 countries[6]. The summary statistics are shown in Table 1.

[4]We exclude 2019 data from calculations since it is estimated based on 2018 volumes, as noted in the author's notes.

[5]As stated in the dataset's original notes, Fintech companies are sent an online questionnaire to report their loan volumes.

[6]Please see Table A.1 in Appendix A for the list of countries included in the analysis.

Table 1: Summary Statistics

Variable	Obs	Mean	SD	Min	Max	Skewness	Kurtosis
Digital credit per capita (ln)	492	0.89	1.40	-1.97	5.11	1.31	4.44
Financial institutions access (ln)	472	-1.26	1.04	-4.57	0	-0.78	2.53
Financial institutions depth (ln)	472	-1.39	0.98	-3.90	0	-0.28	2.16
Financial institutions efficiency (ln)	472	-0.54	0.25	-1.55	-0.23	-1.39	4.81
Financial institutions index (ln)	472	-0.86	0.57	-2.60	0	-0.48	2.26
Economic freedom (ln)	484	4.14	0.17	3.35	4.50	-0.45	3.83
Economic globalization (ln)	458	4.06	0.28	3.40	4.50	-0.22	1.86
Public debt (% GDP)	487	0.56	0.35	0.01	2.33	2.02	9.63
Human development index (ln)	484	-0.33	0.25	-0.91	-0.04	-0.65	2.13
GDP growth (%)	486	3.51	2.85	-20.60	25.18	0.14	22.36
Fintech regulation dummy (0-1)	492	0.12	0.32	0	1	2.49	7.23
Depth of credit information (0-8)	486	5.89	2.61	0	8	-1.45	3.70
Normalized depth of credit information (0-1)	486	0.705	0.351	0	1	-1.45	3.70
Mobile phone subscriptions (%)	486	113.57	35.48	26.59	269.93	0.30	4.63

Source: Author's preparation.
Note: This table presents the summary statistics of each variable used in this chapter. It covers the period 2013-2018. It contains information about the number of observations, mean, standard deviation (SD), minimum and maximum indicators. We perform the transformation of eight variables to the natural logarithm form in order to reduce the skewness of the data and make it more normally distributed. Table A.2 in Appendix A provides summary statistics for the original values of these eight variables. It should be noted that the variable (Mobile phone subscription) has an average value of 113.57, suggesting that individuals may have more than one phone subscription.

2.3.2 Variables

In this subsection, three categories of research variables are discussed in detail: dependent, explanatory and control variables.

Our dependent variable is digital credit, which is the combination of both fintech and big tech credit. In this chapter, we define fintech credit as containing all loan-based business models. Where marketplace lending activities (i.e. P2P) to consumers and businesses are included. Furthermore, fintech credit covers balance sheet lending, invoice trading as well as debt-based instruments. It does not, however, include equity-based, donation-based, or reward-based crowdfunding in its calculations. While a loan is classified as a big tech credit if it was supplied directly by a large company whose primary business is technology, or in cooperation with a financial institution (i.e. bank) (Cornelli et al., 2020).

With the help of the recently constructed financial development dataset by Svirydzenka (2016), researchers are more able to accurately quantify financial development of a country, taking into consideration the complexity and multidimensional nature of it instead of a single indicator measurement. Following related literature (Devereux and Yu 2020; Baloch et al. 2021; Sobiech 2019; De Vita et al. 2020; Wang et al. 2020; Owen and Pereira 2018; Demir et al. 2022), we rely on the work done by Svirydzenka (2016) and utilize a total of four variables that capture the level of financial institutions development within a country in terms of access, depth and efficiency.

First, the financial institutions access index measures the availability of financial institutions and is calculated as the sum of bank branches per 100,000 adults and ATMs per 100,000 adults. A positive sign indicates that banks and digital credit are complementary, while a negative correlation indicates that digital credit is a substitute for banks. As discussed in the preceding subsection, the relationship might be either positive or negative, therefore the sign cannot be expected. Second, financial institutions depth index compiles data on bank credit to the private sector (% GDP), pension fund assets (% GDP), mutual fund assets (% GDP) and insurance premiums, life and non-life (% GDP). As financial deepening is associated with higher innovation levels (Ho et al., 2018), the relationship between depth and digital credit is expected to be positive. Third, financial institutions efficiency index compiles data on banking sector net interest margin, lending-deposits spread, non-interest to total income, overhead costs to total assets, return on assets and return on equity. Given that digital credit issuers are increasing competition within the banking industry, and that competition enhances efficiency (Schaeck and Cihák 2014; Zarutskie 2013), we predict greater efficiency levels to be positively related with larger digital credit volume. Fourth and lastly, financial institutions index is an aggregate of financial institutions access, financial institutions depth and financial institutions efficiency indices. We expect it to be positively associated with higher digital credit volume.

The Index of Economic Freedom, created by The Heritage Foundation (Miller et al., 2013), is used to measure economic freedom. It focuses on ten institutional qualities that can be grouped into four categories: rule of law, limited government, regulatory efficiency and open markets. Each of these factors is scored on a scale of 0 to 100, with a higher score indicating greater economic freedom, then averaged equally to provide a country's overall score. This index has been excessively used in the literature to measure the economic freedom of countries (Malanski and Póvoa 2021; Sayari et al. 2018; Economou 2019; Assi et al. 2020; Zhu and Zhu 2017). As it measures institutional qualities and infrastructure, we predict that greater economic freedom in a country would lead to increased digital credit activities. To measure economic globalization, we employ the overall KOF Globalization Index that was updated by Gygli et al. (2019) and firstly introduced by Dreher (2006). The index is measured through 43 variables across economic, financial, social, informational, cultural and political aspects. A score is assigned to each country ranging from 1 to 100, with 100 being the highest value for a variable for the full sample and time period. Because the KOF Globalization Index measures a country's globalization from several aspects rather than relying on a single indicator, it is commonly used in empirical work (Chi et al. 2021; Zheng et al. 2019; You and Lv 2018; Wang et al. 2020; Dreher and Langlotz 2020; Shahbaz et al. 2018). We expect a positive association between globalization and digital credit activity in a country, as it stimulates the economy by allowing open cross-border trade of goods and services, as well as technology and labour (Lee et al., 2020).

We measure public debt as the total amount of debt owed by a country's government to lenders, and it is exported from the Euromonitor Passport database. We predict a negative relationship between public debt and digital credit in a country since public debt is believed to be adversely linked with innovation development (Coccia 2012; Chi et al. 2021). Next, human capital is measured by the Human Development Index (HDI) which is constructed by the United Nations. It is a composite indicator that takes into account three dimensions: a long and healthy life (life expectancy index), education (education index) and a decent standard of living (gross national income index). HDI has been employed as an indicator for human capital in many empirical investigations (Mas and Gómez 2021; Kebede et al. 2021; Salari et al. 2022). Given that higher levels of education and knowledge are linked with higher levels of innovation and technological adaptation (Dakhli and De Clercq 2004; Ang et al. 2011; Vandenbussche et al. 2006), we expect that higher levels of human development in a country will be positively related with higher levels of digital credit activity. All explanatory variables are lagged by one period to mitigate endogeneity and reverse causality potential concerns.

Since this chapter is focusing on explaining the differences in country-level analysis, we have to control for possible cross-country effects and hence construct a number of control variables that are regularly used in the financial innovation literature (Beck et al. 2013; Asongu et al. 2021; Hodula 2021; Desbordes and Wei 2017; Banna et al. 2021). Due to differences in economic strength across countries, we control for Gross Domestic Product (GDP) growth as a universal indicator for the strength of an economy. The necessary data for it is retrieved from the World Bank database. We predict that higher GDP growth would be associated with increased digital credit market activity. We also control for mobile phone subscriptions as we consider the digital lending market to have many mobile-based platforms. Data on mobile phone subscriptions is also gathered from the World Bank database, and we expect a positive relationship between mobile subscriptions and digital credit.

We further control for fintech regulation to reflect variations in regulatory effect between jurisdictions. Fintech regulation is a dummy variable that takes the value of 1 if an explicit fintech regulation was in a country, and 0 otherwise. It is exported from the work done by Rau (2020). Evidence shows that regulation may stimulate the volume of financial innovation in some countries as it encourages local investors to trust the platforms they intend to invest in. Regulation also paves the way to new entrants to the market as it increases the trust of entrepreneurs. For example, Ran et al. (2022) finds a positive effect of regulatory clarity on crowdfunding volume across a sample of 191 countries. As such, we expect that a clear legal framework promotes the growth of the digital credit market.

We also control for the depth of credit information which is an index that ranges from 0 to 8.[7] It is calculated through three measures; coverage, scope and accessibility of credit information and is available through credit bureaus or credit registries. A higher value implies greater credit data availability, and as a result, we predict a positive relationship between credit information depth and digital credit volume. We retrieve the data from the World Bank database. All definitions, calculations and sources of research variables are included in Table 2. We further show in Table 3 the correlation matrix of the variables included in the regression analysis.

[7]We include in Table A.3 in Appendix A a normalized depth of credit information variable and rerun the regression analysis.

Table 2: Variable Definitions

Variable	Definition
Digital credit per capita	Digital credit is the combination of two variables; fintech credit and bigtech credit. Fintech credit is an online based credit issued by digital platforms. Big tech credit is a loan that is issued by a large technology company, and it includes companies with core businesses in telecommunications, social media platforms, internet search, software and online retail industries.
Financial institutions access index	A measure which compiles data on bank branches per 100,000 adults and ATMs per 100,000 adults.
Financial institutions depth index	A measure which compiles data on bank credit to the private sector in percent of GDP, pension fund assets to GDP, mutual fund assets to GDP and insurance premiums, life and non-life to GDP.
Financial institutions efficiency index	A measure which compiles data on banking sector net interest margin, lending-deposits spread, non-interest to total income, overhead costs to total assets, return on assets and return on equity.
Financial institutions index	An aggregated index for a country's financial institutions level of financial development based on three measures: financial depth, financial access and financial efficiency.
Economic freedom index	A composite index measuring the economic freedom based on 10 quantitative and qualitative factors, grouped into four broad categories, or pillars, of economic freedom: rule of law, limited government, regulatory efficiency and open markets.
Economic globalization index	A composite index measuring a country's level of globalization, and it is based on 43 variables along the economic, financial, social, information, cultural and political dimensions.
Public debt	The total amount of debt owed by a country's all levels of government (central government, local government and social security funds) to lenders as a percentage of gross domestic product (GDP).
Human development index	A composite indicator that takes into account three dimensions: a long and healthy life (life expectancy index), education (education index) and a decent standard of living (gross national income index).
GDP growth	Gross domestic product (GDP) is the sum of all goods and services produced within a country in a specific year.
Fintech regulation	A dummy variable that takes the value of 1 if an explicit fintech regulation is in a country, and 0 otherwise.
Depth of credit information	An index of depth of credit information that ranges from 0 to 8. It is calculated through three measures; coverage, scope and accessibility of credit information available through credit bureaus or credit registries. Higher value means better availability of credit data.
Mobile phone subscriptions	Mobile phone subscriptions per 100 people.

2.3.3 Econometric Model

Following the financial innovation literature (Abbasi et al. 2021; Yang and Wang 2022; Lee et al. 2020; Dutta and Meierrieks 2021), we adopt the fixed effects estimation technique. FE fits our data well since it accounts for all time-invariant heterogeneity across countries.

Table 3: Correlation Matrix

	Access	Depth	Efficiency	Financial institutions	Economic freedom	Economic globalization	Public debt	Human development	GDP growth	Fintech regulation	Depth of Credit	Mobile phone subscriptions
Access (ln)	1											
Depth (ln)	0.77	1										
Efficiency (ln)	0.38	0.43	1									
Financial institutions (ln)	0.92	0.91	0.55	1								
Economic freedom (ln)	0.63	0.73	0.38	0.71	1							
Economic globalization (ln)	0.71	0.73	0.33	0.75	0.78	1						
Public debt (%)	0.11	0.24	0.1	0.2	0.07	0.14	1					
Human development (ln)	0.89	0.81	0.38	0.89	0.71	0.77	0.11	1				
GDP growth (%)	-0.03	-0.04	0.1	-0.05	0.05	0.08	-0.23	-0.01	1			
Fintech regulation (0-1)	0.14	0.23	0.09	0.20	0.23	0.23	0.05	0.21	-0.01	1		
Depth of credit (0-8)	0.30	0.17	0.05	0.22	0.13	0.09	0.09	0.30	-0.11	0.19	1	
Mobile phone subscriptions (%)	0.29	0.29	0.14	0.29	0.19	0.24	-0.03	0.32	-0.12	0.19	0.48	1

Source: Author's preparation.
Note: This table shows the pairwise correlation matrix for the independent variables used in the regression analysis. Table 2 shows the definition of all variables.

This is critical for our investigation since many countries have significant social and cultural variations that affect financial development. For example, Stulz and Williamson (2003) and Ang (2019) claim that cross-country cultural differences (such as religion and individualism) are important in explaining the growth of financial development. FE method accounts for these unobservable variances across countries that may bias the findings. In addition, we use the hausman test (Hausman, 1978), which rejects the null hypothesis that the variations among countries are random and unrelated to the regressors. Hausman test results are shown in Table 4. As such, to investigate the determinants of digital credit growth, the following fixed effects (FE) regression model is employed:

$$credit_{i,t} = \alpha_i + \beta Y_{i,t-1} + \gamma X_{i,t-1} + C_i + \theta_t + \epsilon_{i,t} \tag{1}$$

Where $credit_{i,t}$ represents digital credit, for country i at time t. α_i is a constant term, $Y_{i,t-1}$ denotes explanatory variables, $X_{i,t-1}$ represents a set of control variables. To account for unobserved variations at the country level and over time, C_i and θ_t signify country and year fixed effects, respectively. $\epsilon_{i,t}$ is the error term. Furthermore, our set of control variables includes: GDP growth, depth of credit information, mobile phone subscriptions and a fintech regulation dummy that takes the value of 1 if an explicit fintech regulation was in a country, and 0 otherwise. Moreover, all variables have been winsorized at the 1% and 99% levels to avoid outliers from distorting the findings. All variables were discussed in Subsection 2.3.2 and are summarised in Table 2.

2.4 Results and Discussion

This part of the chapter presents the findings of the aforementioned econometric model, as well as a series of robustness check analyses.

2.4.1 Determinants of Digital Credit

The main findings are presented in Table 4. As shown in column (1), a country's digital credit volume is higher when traditional financial institutions are more easily accessible, as measured by the number of ATMs and bank branches. The results reveal that a 1% increase in the access index is associated with a 0.32 percent increase in digital credit activity, with the result appearing significant at the 1% level. This suggests that conventional lending channels and digital credit volumes have a complimentary relationship. This is in line with the findings of Tang (2019) and de Roure et al. (2022), who show that alternative credit may supplement traditional credit in certain circumstances.

Column (2) displays the regression findings for the depth of financial institutions. Financial deepening has been shown to be a strong predictor of a country's development in the alternative credit market, as increased liquidity from the banking sector to the private sector facilitates the establishment of the digital credit market inside a country. Our findings are consistent with those of Ho et al. (2018). We reach a similar finding in terms of innovation and show that a country with a deeper banking market is connected with greater innovation. However, as shown in column (3), we do not find a significant result that associates the level of financial institutions efficiency with greater digital market activity.

In the same context, in column (4), we investigate the aggregated banking sector development index and its relationship with the digital credit market. Our empirical finding shows a positive and statistically significant (1%) association between the two. Suggesting that economies with more advanced banking sectors stimulate activity in the alternative credit market. One possible explanation for this empirical finding is the essential role that banks play in the formation of new innovative enterprises. According to Trinugroho et al. (2021), the growth of financial markets (both credit and equity) promote the activity of new innovation firms since banks cover their required financial needs. The regression findings for economic freedom and economic globalization are shown in columns (5) and (6), respectively, with no statistical significance found.

Column (7) shows a strong negative and significant relationship (at 1% level) between sovereign debt and digital credit volumes, implying that a 1% rise in public debt leads to a -2.55% decline in digital credit volumes. The result support the findings of Coccia (2012) who discovers that greater levels of public debt are connected with lower rates of innovation and employment as governments are unable to invest in innovation initiatives and R&D projects. Along the same lines, Croce et al. (2019) and Chi et al. (2021) find that higher levels of government debt hinder a country's innovation. We further add to this debate by demonstrating a negative link between total government debt levels and one of the financial innovation segments, the digital credit market. This might indicate how

Table 4: Main Results: Determinants of Digital Credit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial institution access	0.324***								2.132***
	(0.099)								(0.745)
Financial institution depth		0.276***							-1.142
		(0.093)							(0.953)
Financial institution efficiency			0.251						1.001
			(0.387)						(0.678)
Financial institution development				0.486***					-3.420**
				(0.156)					(1.361)
Economic freedom					0.930				-1.532
					(0.604)				(1.344)
Economic globalization						0.846			1.172
						(0.865)			(0.813)
Public debt							-2.555***		-2.730***
							(0.777)		(0.794)
Human development								1.349***	-9.429
								(0.334)	(8.386)
GDP growth	0.040*	0.040*	0.041**	0.039*	0.042**	0.045**	0.030*	0.041**	0.044***
	(0.021)	(0.020)	(0.019)	(0.021)	(0.200)	(0.021)	(0.017)	(0.020)	(0.015)
Fintech regulation	0.919***	0.918***	0.928***	0.908***	0.920***	0.785***	0.798***	0.793***	0.881***
	(0.183)	(0.181)	(0.180)	(0.181)	(0.188)	(0.197)	(0.196)	(0.199)	(0.155)
Depth of credit information	-0.042	-0.039	-0.044	-0.042	-0.037	-0.023	-0.027	-0.043	-0.001
	(0.045)	(0.044)	(0.045)	(0.045)	(0.047)	(0.046)	(0.047)	(0.044)	(0.038)
Mobile phone subscriptions	0.004	0.003	0.003	0.003	0.004	0.002	0.002	0.003	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	392	392	392	392	398	377	401	402	363
R^2	0.390	0.385	0.373	0.386	0.377	0.372	0.377	0.367	0.486
Hausman Test	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004

Notes: Analysis period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significance at the 1/5/10%. The dependent variable is digital credit and it has been winsorized at the 1% and 99% levels. Independent variables were lagged by one period. Control variables include the following: GDP growth; depth of credit information; mobile phone subscriptions; fintech regulation dummy that takes the value of 1 if a country is explicitly implementing fintech regulation within its jurisdictions, and 0 otherwise.

important it is for the government of a country to invest in R&D activities in order to establish new innovative platforms.

The development of human capital is shown in column (8) to be positive and statistically significant at the 1% level with higher digital credit market activity. A 1% increase relates to a 1.349% increase in digital credit volume, all else remaining constant. Our results indicate that countries with higher levels of human capital are more innovative and involved in one of the financial innovation categories, the digital credit market. We endorse the findings of Danquah and Amankwah-Amoah (2017), which indicate that countries with greater levels of human capital had higher rates of technology adoption. Similarly, Dakhli and De Clercq (2004) argue that human capital stimulates innovation within countries.

2.4.2 Robustness Checks

In order to provide empirical support for our findings, we undertake two robustness checks. First, we separate our sample countries. Second, we rerun the main analysis excluding China.[8]

2.4.2.1 Developed and Developing Countries

To begin, we segregate the sample countries into two categories: developed and developing/emerging.[9] The purpose of this test is to see whether there are any differences between these two groups of countries when our explanatory variables are examined. To do so, we include a dummy variable in the baseline analysis that takes the value 1 if a country's

[8] We further test for potential reverse causality in Table A.4 in Appendix A.

[9] We follow the International Monetary Fund's (IMF) categorization.

economy is considered developed, and 0 otherwise.

Tables 5 and 6 show the results of this test. When comparing developed and developing countries, the main results remain mostly consistent across the banking variables panel and macroeconomic variables panel. Throughout the two categories, there is a positive and significant association between digital credit volume and financial institution access, financial institution depth, financial institution index and human development. However, economic freedom shows a positive and significant effect (1% level) in only developed economies. Similarly, in only developed countries, there is a weakly significant negative relationship between public debt and our dependent variable.

Table 5: Robustness Check: Banking Variables

	Developed Economies				Developing/Emerging Economies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial institution access	0.442**				0.178**			
	(0.200)				(0.079)			
Financial institution depth		0.241**				0.227***		
		(0.107)				(0.085)		
Financial institution efficiency			0.241				-0.022	
			(0.839)				(0.251)	
Financial institution development				0.481**				0.312**
				(0.194)				(0.140)
GDP growth	0.008	0.007	0.004	0.007	0.022	0.019	0.023	0.020
	(0.037)	(0.037)	(0.039)	(0.037)	(0.019)	(0.019)	(0.018)	(0.020)
Fintech regulation	0.459*	0.486*	0.500**	0.468*	1.130***	1.115***	1.131***	1.122***
	(0.263)	(0.258)	(0.244)	(0.255)	(0.214)	(0.215)	(0.215)	(0.214)
Depth of credit information	0.564**	0.577***	0.586***	0.575***	-0.004	-0.001	-0.004	-0.004
	(0.206)	(0.190)	(0.199)	(0.196)	(0.046)	(0.045)	(0.045)	(0.046)
Mobile phone subscriptions	0.002	0.002	0.004	0.003	0.001	0.001	0.001	0.001
	(0.012)	(0.012)	(0.011)	(0.012)	(0.004)	(0.004)	(0.004)	(0.004)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	150	150	150	150	242	242	242	242
R^2	0.674	0.667	0.660	0.667	0.231	0.233	0.220	0.230

Note: This table shows the banking variables for two groups: developed economies and developing/emerging economies. Analysis period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significance at the 1/5/10%. The dependent variable is digital credit and it has been winsorized at the 1% and 99% levels. Independent variables were lagged by one period. Control variables include the following: GDP growth; depth of credit information; mobile phone subscriptions; fintech regulation dummy that takes the value of 1 if a country is explicitly implementing fintech regulation within its jurisdictions, and 0 otherwise.

Table 6: Robustness Check: Macroeconomic Variables

	Developed Economies				Developing/Emerging Economies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Economic freedom	1.595***				0.071			
	(0.539)				(0.786)			
Economic globalization		2.665				0.269		
		(1.853)				(1.056)		
Public debt			-1.713*				-0.186	
			(0.910)				(0.788)	
Human development				1.427***				0.668**
				(0.263)				(0.290)
GDP growth	0.004	0.019	-0.012	0.006	0.024	0.024	0.022	0.022
	(0.037)	(0.024)	(0.040)	(0.037)	(0.019)	(0.021)	(0.019)	(0.019)
Fintech regulation	0.463*	0.403	0.514*	0.443	1.110***	0.854*	0.859***	0.855***
	(0.269)	(0.258)	(0.271)	(0.268)	(0.218)	(0.317)	(0.316)	(0.317)
Depth of credit information	0.622***	0.617***	0.558**	0.555***	0.001	0.019	0.007	-0.001
	(0.185)	(0.175)	(0.213)	(0.195)	(0.048)	(0.045)	(0.048)	(0.045)
Mobile phone subscriptions	0.004	0.006	0.005	0.001	0.001	-0.001	0.001	0.001
	(0.012)	(0.013)	(0.013)	(0.012)	(0.004)	(0.005)	(0.004)	(0.004)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	150	141	146	150	248	236	255	252
R^2	0.672	0.705	0.681	0.673	0.223	0.204	0.185	0.191

Note: This table shows the macroeconomic variables for two groups: developed economies and developing/emerging economies. Analysis period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significance at the 1/5/10%. The dependent variable is digital credit and it has been winsorized at the 1% and 99% levels. Independent variables were lagged by one period. Control variables include the following: GDP growth; depth of credit information; mobile phone subscriptions; fintech regulation dummy that takes the value of 1 if a country is explicitly implementing fintech regulation within its jurisdictions, and 0 otherwise.

2.4.2.2 Results Excluding China

Additionally, since our sample contains a substantial portion of a single contributor, we examined whether the findings are being driven by that country. To this end, we excluded China, the sample's largest digital credit issuer. Fortunately, the findings in Table 7 are similar to our baseline model, and our results are broadly the same.

Table 7: Robustness Check: Results Excluding China

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial institution access	0.325***							
	(0.099)							
Financial institution depth		0.274***						
		(0.094)						
Financial institution efficiency			0.261					
			(0.396)					
Financial institution development				0.486***				
				(0.157)				
Economic freedom					0.924			
					(0.608)			
Economic globalization						0.773		
						(0.870)		
Public debt							-2.585***	
							(0.788)	
Human development								1.345***
								(0.336)
GDP growth	0.041*	0.040*	0.041**	0.039*	0.042**	0.045**	0.030*	0.042**
	(0.021)	(0.021)	(0.020)	(0.021)	(0.020)	(0.021)	(0.017)	(0.020)
Fintech regulation	0.905***	0.909***	0.916***	0.896***	0.909***	0.763***	0.762***	0.770***
	(0.197)	(0.195)	(0.195)	(0.195)	(0.203)	(0.213)	(0.210)	(0.215)
Depth of credit information	-0.042	-0.039	-0.043	-0.042	-0.036	-0.023	-0.028	-0.043
	(0.046)	(0.044)	(0.045)	(0.045)	(0.048)	(0.046)	(0.047)	(0.045)
Mobile phone subscriptions	0.004	0.003	0.003	0.003	0.004	0.002	0.002	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	387	387	387	387	393	372	396	397
R^2	0.383	0.378	0.366	0.379	0.370	0.363	0.370	0.360

Note: The table shows the results of the sample without China. Analysis period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significance at the 1/5/10%. The dependent variable is digital credit and it has been winsorized at the 1% and 99% levels. Independent variables were lagged by one period. Control variables include the following: GDP growth; depth of credit information; mobile phone subscriptions; fintech regulation dummy that takes the value of 1 if a country is explicitly implementing fintech regulation within its jurisdictions, and 0 otherwise.

2.5 Conclusion

Globally, policymakers and regulators are interested in understanding the relationship between financial innovation and the dynamics of banking development. This is possibly because fintech innovation promotes economic growth (Laeven et al. 2015; Qamruzzaman et al. 2021), and financial stability (Daud et al. 2022; Fung et al. 2020) in a variety of ways, including increased bank profitability, the use of artificial intelligence, cloud computing and data analytics. This chapter contributes to existing literature through analyzing the drivers behind the growth of digital credit in a cross-country setting. We investigate the relationship among digital credit, the growth of financial institutions and a set of macroeconomic variables for the period of 2013 to 2018 by using a fixed effects model.

We document that a complementary type of relationship exists between traditional and digital forms of credit issuers. Suggesting that banks and digital credit can co-exist. Our findings reveal that the banking sector's development, as measured by access, depth and efficiency, is positively correlated with the growth of the digital credit market. Additionally, we identified a strong negative correlation between governmental debt and digital credit activities. Moreover, we show that countries with a greater level of human capital development have a higher level of digital credit activities.

We believe that the results of this chapter aid policymakers in crafting targeted and effective policies across various areas. For example, we provide evidence that both traditional banks and fintech firms can co-exist within the same lending market. This can potentially increase financial inclusion by fostering digital lending services. It is well documented in the academic literature that fintech firms are subjected to a lower regulatory supervision compared with traditional banks (Buchak et al., 2018). Thus, it presents an area where policymakers and regulators could exploit the strengths of fintech firms for the purpose of increasing access to financial services to underbanked or unbanked individuals.

Chapter 3: The Role of Banking Business Models in Banks' Fintech Acquisitions

The Role of Banking Business Models in Banks' Fintech Acquisitions[10]

Abstract

This chapter examines the impact of banking business models on banks' decisions to acquire fintech firms. Our empirical findings demonstrate that banks with diverse asset, funding, and income structures are more inclined to engage in fintech acquisitions, as they possess the capacity to assume higher risks. Investment banks also display selectivity in their fintech acquisitions. In contrast, traditional banks adopt a risk-averse approach, while wholesale banks exhibit a reduced likelihood of conducting fintech acquisitions. Additionally, our research highlights that the propensity of a bank to acquire a particular type of fintech firm is influenced by its specific business model. Moreover, we provide evidence that bank business models determine the banks' motivations behind fintech acquisitions.

JEL Classification: G21, G34, O31

Keywords: Banks, Fintech, Business Model, Mergers and Acquisitions

[10]A research paper based on this chapter has received a minor revision decision and is currently in the fourth round of review at the Journal of Financial Services Research. In addition, this chapter was presented at the Essex Finance Centre (EFiC) 2024 Conference in Banking and Corporate Finance in July 2024.

3 The Role of Banking Business Models in Banks' Fintech Acquisitions

3.1 Introduction

Banks might achieve technological innovation through organic growth by developing their capabilities internally (Adams and Driscoll, 2018). However, as Mishra et al. (2022) highlight, organizational resistance to change and past practices, particularly in older banks, can hinder the adoption of new technologies. Consequently, banks may perceive acquiring fintech companies that already provide innovative services as a more viable strategic option relative to developing fintech capabilities internally.

Fintech firms combine financial expertise with technological advancements to create innovative financial products (Thakor, 2020). Mergers and Acquisitions (M&As) of fintech firms open up opportunities for banks to explore new markets and expand their service offerings beyond traditional boundaries. For instance, collaborations with fintech startups can enable banks to offer products such as mobile banking apps, digital wallets, robo-advisors, and personalized financial solutions.

This chapter empirically examines the role of the banking business models (BMs) in driving bank decisions to make fintech acquisitions. We add to prior research that examines banking business models and financial crises (Hryckiewicz and Kozłowski 2017; Altunbas et al. 2011; Ayadi et al. 2011), bank performance (Lagasio and Quaranta 2022; Ayadi et al. 2021; Mergaerts and Vander Vennet 2016; Roengpitya et al. 2014), stability (Köhler, 2015), interest margin (van Ewijk and Arnold, 2014), and financial shocks (Vinas, 2021). Our focus is on how a business model drives growth and specifically growth via fintech acquisitions.

We further examine the different types of fintech firms that banks find attractive and the motives behind their interest.

We start by identifying the banking business models of US banks. To achieve this, we use a robust clustering algorithm based on a sample of quarterly data ranging from 2005Q1 to 2021Q4. Our results indicate that the banks fall into four business model types: diversified, wholesale, traditional, and investment. These four business models exhibit varying characteristics in terms of asset composition, funding sources, and income streams. Next, we employ a textual analysis technique to classify the fintech acquisition deals included in our sample based on two dimensions: the type of the target fintech firm and the motivation of the bank to acquire a fintech firm. Our results show that, within our sample of fintech acquisition deals, the acquired firms can be categorized into five types: payment and settlements, data analytics, lending, financial services software, and investment services. Furthermore, the deals under consideration can be classified into four categories in terms of the bank motivation to acquire the fintech firm: introducing new products, enhancing capabilities, pursuing business scalability, and entering new markets.

We demonstrate that diversified banks are more likely to engage in fintech acquisitions. This appetite is closely tied to the diverse asset, funding, and income mix structures inherent in diversified banks, which afford them the flexibility to undertake additional risks. This aligns with the early findings in the literature (Berger et al., 1999), as well as more recent ones (Cappa et al. 2022; Zheng and Mao 2024) that technology innovation is one of the most important external motivating factors for banks to engage in M&As. The results concerning more financial institutions are consistent with other intuitions including the irrelevance of fintech (for wholesale banks), risk-aversion and depositor capture (for traditional banks), or organic capabilities (for investment banks). We will discuss these points in detail later.

We also provide novel insights concerning the specific types of fintech firms that banks target for acquisition. The empirical evidence indicates that diversified banks show a propensity for acquiring fintech firms specializing in data analytics, lending, and financial software services, reflecting their strategic focus on income and investment diversification. In contrast, wholesale and traditional banks display little interest in fintech acquisitions, likely due to their risk-averse approach and focus on maintaining stability in core business activities. Investment banks show an inclination toward acquiring fintech firms, particularly those specializing in payment technology and investment services, aligning with their core expertise and capabilities.

The remainder of this chapter is as follows: Section 3.2 reviews the related literature. Section 3.3 discusses the sample selection, outlines our approach to identifying bank business models, classifies fintech firms, provides an initial examination of bank-fintech acquisitions, and discusses the methodology. Section 3.4 presents the empirical findings. Finally, Section 3.5 provides a conclusion.

3.2 Literature Review

Bank business models have come under increased academic research scrutiny following the global financial crisis (GFC) of 2008. There exists a consensus in this line of literature that the banking business model determines how banks fared during the GFC. For instance, Ayadi et al. (2011) examine 26 major banks in Europe during the period 2006 to 2009, and find that banks with retail business model were superior to wholesale and investment banking business models, supported by their reliance on stable funding sources. Similarly, Roengpitya et al. (2014) employ a global sample of banks and document the varying responses to the GFC of banks based on their business model structures. Hryckiewicz and Kozłowski (2017) use a sample of banks from 65 countries during the period 2000 to 2012 and document the significant differences among banking business models during the crisis period. Vinas (2021) investigates the transmission of financial shocks from a sample of French banks to the real economy during the period 2003-2009. They find that during the GFC, banks' credit supply varied depending on the banking business model.

The decision of a bank to take part in a merger and acquisition (M&A) deal depends significantly on how it perceives the risk-reward trade-off. For instance, Altunbas et al. (2011) examine the role of the banking business model in explaining bank risk exposure. They show that, in contrast to retail and diversified banks, which are believed to be more stable due to their strong deposit base, wholesale banks are more likely to experience financial distress during a crisis. Moreover, Demsetz and Strahan (1997) demonstrate that a greater bank asset, funding, and income diversification, supported by its higher leverage, incentivizes banks to take on additional risks. Köhler (2015) find that while a larger share of non-interest revenue increases the risk of investment banks (as determined by their Z-score), it reduces the risk for retail-oriented banks. Additionally, they find that although a larger dependence on non-deposit funds supports bank stability, it exposes retail banks to a higher risk. Overall, these studies suggest that the business model's structure may determine the degree of bank risk exposure and impact its capacity to manage and mitigate this risk.

Bank acquisitions of fintech firms, in particular, might expose banks to a higher degree of risk than acquisitions of other types of firms for several reasons. For example, Navaretti et al. (2017) argue that many lending fintech firms are likely to have riskier asset and liability compositions than those of banks. Primarily owing to their adoption of an agency model in which they do not assume the risk of loans they facilitate, potentially attracting riskier borrowers. In addition, these firms charge commission-based fees, collecting from both parties involved in the transaction, which incentivizes volume over stability. Therefore, many fintech firms lack diversity in their assets and liabilities compositions compared with incumbents. Furthermore, banks may be reluctant to undertake M&A deals with fintech firms due to a lack of regulatory guidelines. For example, Boot et al. (2021) note that banks may perceive new technologies as more risky because of the regulatory ambiguity surrounding the usage of innovative products in the financial industry. Moreover, Del Gaudio et al. (2024) suggest that banks acquiring fintech firms is fast but can be the riskiest approach to obtaining necessary technology. This strategy exposes banks to higher risks due to the potentially high valuation of fintech startups and their increased risk of bankruptcy.

Although the mainstream literature on banking mergers and acquisitions provides a good understanding of what motivates banks to engage in M&A deals (DeYoung et al., 2009), less attention is paid to the fintech M&As. For example, Austin and Dunham (2022) show that acquirers' risk profile improves after the fintech acquisition, but no conclusive evidence was found in relation to the acquirers' operating performance. A related strand of literature has analyzed the operating performance of banks after the M&A of fintech firms. For instance, Akhtar and Nosheen (2022) find evidence of a positive effect on bank profitability, liquidity, and leverage. Most recently, Kwon et al. (2024) investigate the motivations behind the acquisition of fintech companies by banks. Using both institutional and financial characteristics, they provide evidence that banks with more capital and liquidity are more inclined to acquire fintech firms. Along the same line, de Boyrie and Pavlova (2024) report a positive impact of bank-fintech M&A on bank profitability in the US.

However, mixed results are found when the impact of bank-fintech acquisition was measured by market reaction. Using banks' stock market reaction, Kueschnig and Schertler (2024) show that banks have a higher abnormal returns following their first bank-fintech deal, as it may signal the commitment of banks to financial technology. While Cappa et al. (2022) argue that the impact of bank-fintech M&A depends on the type of service provided by the fintech firm. Collevecchio et al. (2023) document that the market reaction to bank stocks varies depending on the bank's sustainability and the type of fintech acquisition (e.g. minority and majority stakes). Conversely, Zheng and Mao (2024) find a negative stock market reaction to bank stocks, which could be due to investors believing that banks are overestimating the advantages of acquiring a fintech company.

3.3 Data and Methodology

This section discusses the sample selection, details our approach to identifying bank business models and fintech firms. It also explores the drivers of bank-fintech acquisitions. Next, it discusses the variables used in the analysis and outlines the econometric model of the baseline analysis.

3.3.1 Sample Selection

Our dataset contains information on US banks and their fintech acquisitions. We collect banks' financial statements from the Federal Financial Institutions Examination Council's (FFIEC) Reports of Condition and Income (Call Reports). The FFIEC database provides a full quarterly balance sheet, income statement, and other financial information for each bank. In this chapter, we first identify banking business models within our data and use clustering variables to perform the cluster analysis as outlined in subsection 3.3.2 on 9558 banks and 452,375 bank-quarter observations. Our sample period spans from 2005Q1 to 2021Q4. We investigate the deals from the beginning of 2005 to the end of 2021 since this time period has witnessed the introduction of new innovative financial companies. For example, 2005 marks the introduction of Prosper, America's first peer-to-peer (P2P) application. The fintech industry flourished quickly after that as shown by the launch of

GreenSky, a giant fintech consumer loan platform, among other enterprises.

We collect data on US bank-fintech mergers and acquisitions from Zephyr and Refinitiv databases, which are powered by Bureau van Dijk and Thomson Reuters, respectively. We follow specific criteria for each database in order to include target companies that operate in industries most closely associated with a fintech business. In particular, as in Dranev et al. 2019 and Austin and Dunham 2022, we use the following Standard Industrial Classification (SIC) codes in the Zephyr database: 60, 61, 62, 63, 64, 65, 67, 87, 88, 89, 7371, 7372, 7373, and 7374.[11] This results in identifying a total of 1545 deals from the Zephyr database. While in the Refinitiv database, we search for deals in the following industries: high technology, financials, consumer goods and services, healthcare, and real estate. A total of 4,190 M&A deals were identified from the Refinitiv database. We supplement these two databases with announced M&A deals that were not captured by either database.

To identify our final sample of fintech acquisitions, we apply the following criteria. First, we limit our sample to only include deals involving banks with headquarters in the United States as acquirers. Second, we only include completed or announced deals in which the acquirer controls at least 51% of the target firm shares. Third, we review the business description section of target firms available in both databases, focusing on details about the firm's services as it provides a more accurate way to identify fintech firms (Collevecchio et al., 2023). We include in our sample firms that explicitly identify themselves as providers of technology-enabled financial services. For example, in 2012, SunTrust Bank (now Truist

[11]The following are the names of each SIC code included in the Zephyr database: 60 - Depository institutions, 61 - Non-depository credit institutions, 62 - Security and commodity brokers, dealers, exchanges and services, 63 - Insurance carriers, 64 - Insurance agents, brokers, and service, 65 - Real estate, 67 - Holding and other investment offices, 87 - Engineering, accounting, research, management, and related services, 88 - Private households, 89 - Services not elsewhere classified, 7371 - Computer programming services, 7372 - Prepackaged software, 7373 - Computer integrated systems design, 7374 - Computer processing and data preparation and processing services.

Bank) acquired FirstAgain LLC, a firm that describes itself as "an online consumer finance company that offers innovative financial products to individuals". Additionally, in 2021, US bank acquired Bento Technologies, a firm that also describes itself as "a fintech company based in Chicago and San Francisco that provides payment and expense management services to small and mid-size businesses". Fourth, we thoroughly review each deal press release to confirm that the target firm is a fintech company, investigate the type of target firm, and explore the bank's motivation of acquisition.[12] Finally, we remove duplicates. Due to the fact that we use multiple databases, it is important to double-check each deal included to avoid counting the same deal twice.

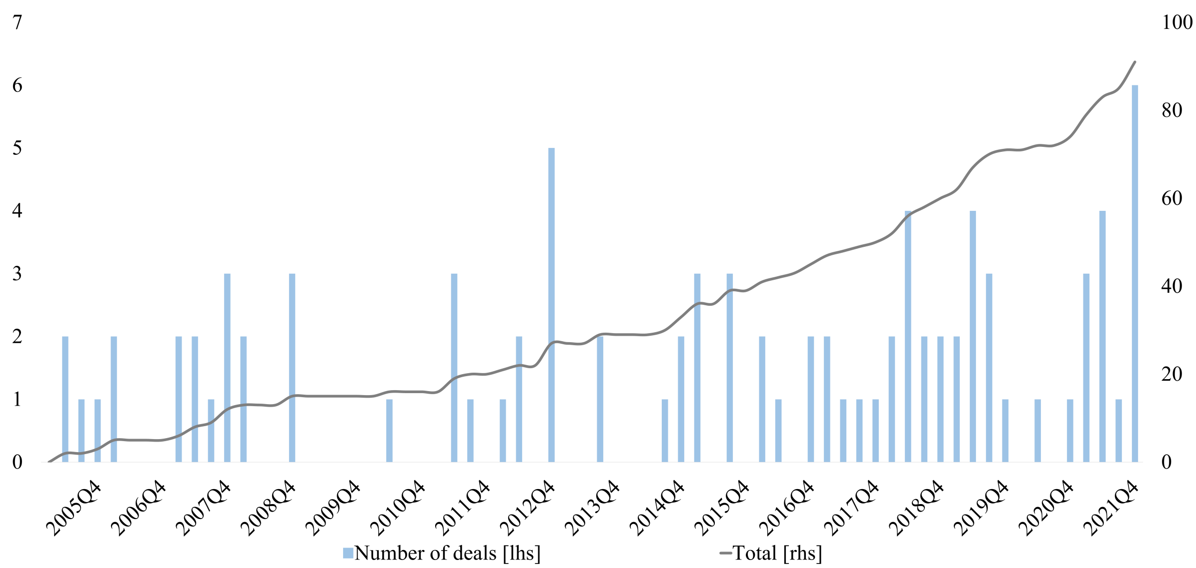
As a result of applying the above criteria, we obtain 39 bank-fintech deals from the Zephyr database, 36 deals from the Refinitiv database, and 16 announced deals manually added from banks' official websites. All identified deals were acquisitions of fintech firms made by banks. This results in a total of 91 fintech firm acquisition deals done by 30 banks.[13] Although the small sample size limits our ability to generalize our findings, it is a common trait in the literature of bank-fintech M&As. For example, de Boyrie and Pavlova (2024) find 155 fintech deals done by 55 US banks in the period 2010-2022. Kwon et al. (2024) use 105 international fintech acquisitions done by 80 banks in 15 OECD countries during the period 2010-2018. Collevecchio et al. (2023) investigate 107 international bank-fintech M&A deals and utilize a total of 60 observations spanning from 2010-2020. Akhtar and Nosheen (2022) identify a sample of 81 bank-fintech M&A deals in the US, UK, Canada, and France in the period 2010-2020. Zheng and Mao (2024) employ 196 M&A deals between fintech and US public banks, nonbank financial institutions, and tech companies (US banks had full-control in 22 fintech firms) in a period between 2010 to 2021. In addition, our strict inclusion

[12] Detailed discussion of methodology used to identify the types of firms and motivations of banks is outlined in subsection 3.3.4. Empirical analyses of the types and motivations are provided in subsections 3.4.3 and 3.4.4.

[13] Please see Table B.1 in Appendix B for the list of fintech-acquiring banks.

criteria based on our definition of a fintech firm is another contributing factor that limits the number of bank-fintech acquisitions in the sample (Kwon et al., 2024). We specifically focus on target companies that embody both financial and technological expertise, excluding deals involving target firms that solely offer either technology or financial services. Figure 5 shows the number of deals in each quarter under investigation, as well as the cumulative number of deals over time.

Figure 5: Number of Bank-Fintech Acquisitions (2005Q1-2021Q4)

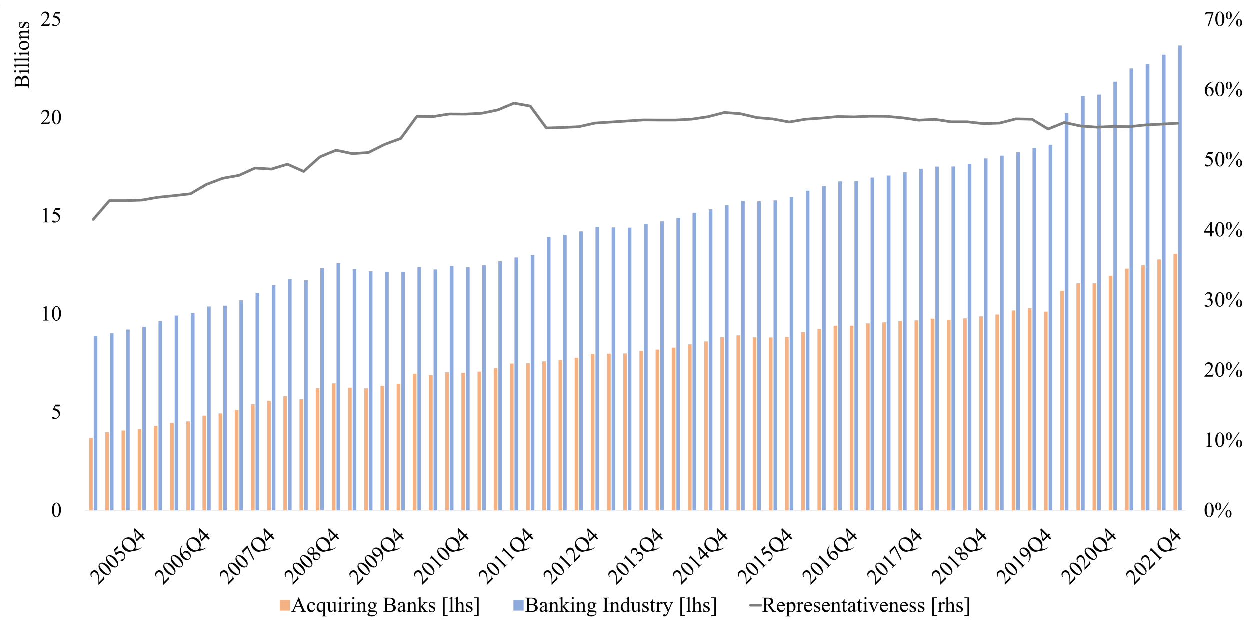


Source: Author's calculations

As our sample of fintech-acquiring banks includes 30 banks, it is essential to assess its representativeness, particularly considering that the total number of FDIC-insured banks varied during the period under study from 8140 in 2005Q1 to 4886 in 2021Q4. Given this limitation, we compare in Figure 6 the total assets of acquiring banks to the industry's in each quarter throughout the study's duration. Although the number of acquiring banks in our sample is small, yet they account for a significant portion of about 44% of the banking industry's assets in 2005. The proportion peaked at 58% in 2011 and then remained constant at 55% until 2021. Furthermore, banks in our sample size constitute a higher portion of industry's total assets than that observed in related literature of the US banking sector

(Adams and Mehran, 2012). This suggests that despite our sample's limited number of acquiring banks compared to the overall population, it nevertheless represents a substantial portion of the US banking system that is worth investigating.[14]

Figure 6: Comparison Between Acquiring Banks and the US Banking Industry in Terms of Total Assets (2005Q1-2021Q4)



Source: Author's calculations

3.3.2 Identification of Banking Business Models

The banking business model represents the choices that the bank makes about collecting and spending money. Roengpitya et al. (2014) and Mergaerts and Vander Vennet (2016) note that the strategic decisions of bank management are expressed in its financial variables. Therefore, to identify the business models of banks included in our sample, we follow the extant literature by adopting a cluster analysis called the non-hierarchical K-means clustering technique based on variables from the banks' financial reports (see, for example, Farne and Vouldis 2021; Vinas 2021; Martín-Oliver et al. 2017; Hryckiewicz and Kozłowski

[14]We further tackle the issue of sample selection bias in subsection 3.4.2.2 and use propensity score matching (PSM) analysis.

2017; and Ferstl and Seres 2012).

To implement the clustering analysis, we use a total of five variables that reflect the fundamental operations of banks and are represented in their balance sheets and income statements.[15] First, we use the share of loans to banks scaled by total assets (Lagasio and Quaranta 2022; Ayadi et al. 2021; Roengpitya et al. 2017; Hryckiewicz and Kozłowski 2017; Roengpitya et al. 2014) which reveals the share of bank's participation in the interbank market. Second, we employ the share of loans to consumers over total assets (Ayadi et al. 2021; Ferstl and Seres 2012; Lagasio and Quaranta 2022) which indicates the loan portfolio activities by banks. The third variable in our clustering analysis is the share of total investments over total assets (Roengpitya et al. 2014; Hryckiewicz and Kozłowski 2017) as it reveals the involvement of the bank in investment activities such as trading accounts and federal funds sold. Fourth, we use the ratio of core deposits to total assets (Roengpitya et al. 2014; Roengpitya et al. 2017) to capture the strength of the bank's deposit base which enables the bank to avoid using other sources of funding (Milcheva et al., 2019). The fifth and last variable is the non-interest income over adjusted operating income (Tran et al. 2021; Köhler 2015) which shows the share of other sources of income.

We use the non-hierarchical K-means clustering technique to identify the bank business models. It is a widely used technique that produces robust clustering results for a wide range of practical applications (Alsabti et al., 1997). The first step of the K-Means method is to generate at random the centroids (or centers) of a pre-defined number of clusters. Each bank in the sample is allocated to the centroid closest to it as calculated by the Euclidean distance. The centroids are then calculated again after the initial clusters are formed by calculating the mean value of all banks in the cluster in order to fit the centroids' position

[15] We performed the clustering analysis based on a variety of other combinations of variables, and the result is very similar to the grouping we got with five variables.

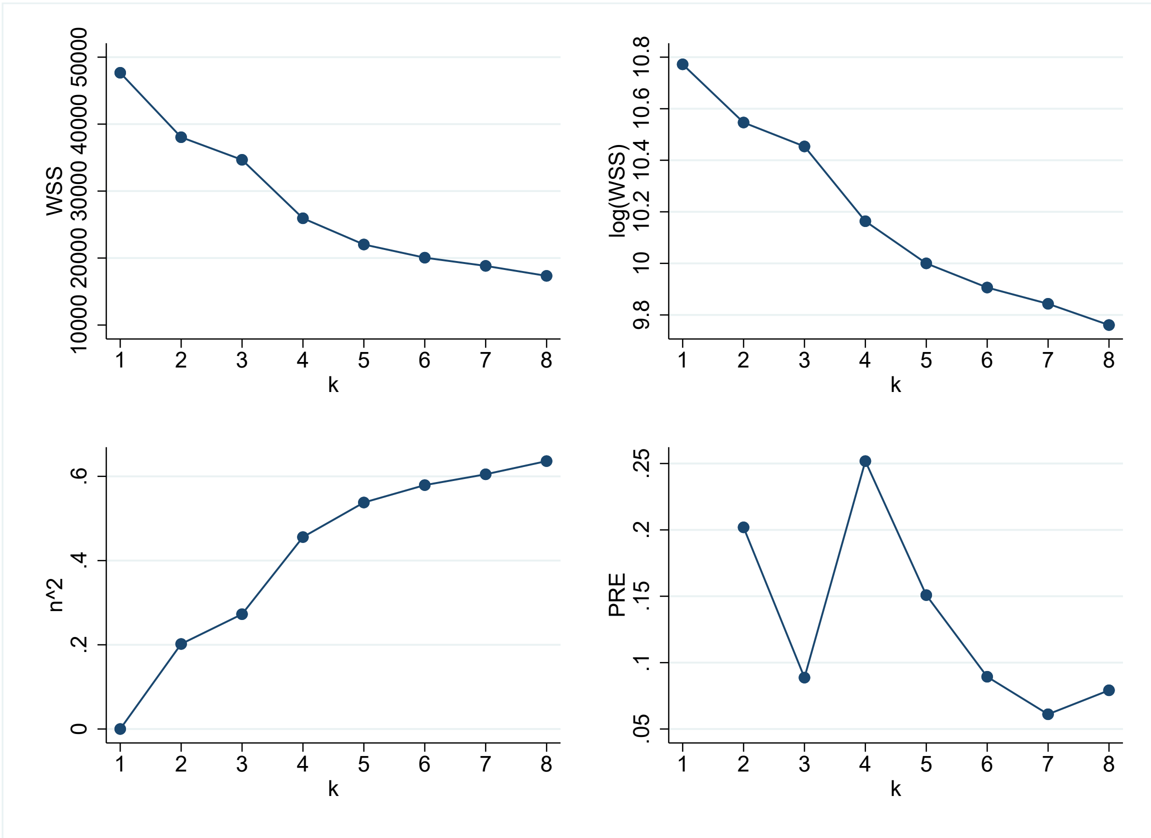
to be in the middle of the cluster. The centroids are calculated by minimizing the sum of squared errors as per the following objective function (Ding and He, 2004):

$$E = \sum_{k=1}^{k} \sum_{i \in C_k} (x_i - m_k)^2 \tag{2}$$

where x_i is the input observations and m_k is the centroid of cluster C_k. For the purpose of implementing this technique, we collapse the dataset by the mean value of the five variables used for clustering (Consumer Loans Ratio, Bank Loans Ratio, Total Investments Ratio, Core Deposits to Assets Ratio, and Non-Interest Income Ratio). This ensures that each bank in the sample has a unique business model throughout the period under study. The algorithm then repeats the computation of the Euclidean distance between the centroids and data points (banks) of the clusters, allocating the closest data point to the cluster to which it belongs. The method will loop until the centroids of clusters stop moving, indicating that the most homogeneous clusters (business models) that contain the most similar banks and the least similarity between clusters have formed (see Reynolds et al. 2006 for details).

The most challenging part of the k-means clustering analysis is identifying the optimal number of k clusters. To aid in this process, we follow the work done by Makles (2012) to calculate the within-cluster sum of squares, or WSS (also known as the elbow method). It is an optimization criterion designed to reduce within-cluster heterogeneity as evaluated by the WSS. Figure 7 shows that $k = 4$ is the optimal number of clusters for our investigation. As the number of clusters rises, the distance between clusters' centroids and data points reduces, creating an elbow-shaped curve between WSS and k. The optimal k is determined when a kink is visible in the curve between WSS and k clusters, indicating that the WSS does not significantly change as the number of clusters increases. At $k = 4$, a kink in the curve of WSS and its logarithm form log(WSS) can be seen.

Figure 7: Determining The Appropriate Number of Clusters



Another criterion for choosing the optimal number of k clusters is the n^2 coefficient which measures the proportional reduction in the intra-cluster sum of squares in relation to the total sum of squares as per $n_k^2 = 1 - \frac{WSS(k)}{TSS}$. While PRE_k indicates this reduction of WSS in relation to $k-1$ cluster and can be expressed in $PRE_k = \frac{WSS(k-1)-WSS(k)}{WSS(k-1)}$. Referring to Figure 7, at n_4^2 a reduction of WSS by 42% and PRE_4 suggests a reduction of WSS by 25% compared with PRE_3. Both results give further support to $k = 4$.

3.3.3 Characteristics of Identified Banking Business Models

The results of the K-Means clustering analysis are presented in Table 8 which identifies four distinct business models. After analyzing the characteristics of each bank business model, we label them as follows: Diversified Banking (BM1), Wholesale Banking (BM2), Traditional Banking (BM3), and Investment Banking (BM4).

Table 8: A Comparison of Average Values By Banking Business Models

	Diversified		Wholesale		Traditional		Investment	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Consumer Loans Ratio (%)	3.64	4.21	2.87	5.55	3.83	3.74	2.16	6.23
Bank Loans Ratio (%)	9.63	6.65	11.0	8.73	6.03	4.93	2.07	5.93
Total Investments Ratio (%)	22.74	10.22	19.93	13.0	47.39	13.75	54.04	28.43
CDA Ratio (%)	74.23	10.49	52.51	17.85	76.37	10.66	13.31	24.40
Non-Interest Income Ratio (%)	16.17	11.07	13.38	13.19	14.10	9.69	88.41	16.40
Bank-quarter Observations	269,797		50,566		122,884		9128	
Number of Banks	5359		1587		2370		242	

Note: This table shows a comparison of mean and standard deviation values of variables used in the clustering algorithm across the four banking business models identified—diversified banking (BM1), wholesale banking (BM2), traditional banking (BM3), and investment banking (BM4) in the period under study (2005Q1-2021Q4). The number of banks is the total number of banks that have adopted the banking business model. Consumer loans ratio is a bank's lending to consumers divided by its total assets. Bank loans ratio is the bank's lending to depository institutions divided by total assets. Total investment ratio is the sum of all investment activities divided by total assets. CDA ratio is the bank's core deposits to assets ratio. Non-Interest Income ratio is the sum of net income from non-interest-bearing assets and bank services divided by the adjusted operating income.

The first identified business model is Diversified Banking (BM1). Relative to other business models, banks in this group have the most balanced average values of the clustering variables. On the asset side, banks with this business model have the second-highest percentage of consumer loans (3.64%) and bank loans (9.63%). While having an average value of 22.74% investment activities ratio, demonstrating a mix of asset structure. On the funding side, diversified banks have the second-highest average ratio of core deposits to assets (74.23%) which gauges the percentage of assets that are financed through a stable funding source. Having an average non-interest income of 16.17% is another sign of the diversified income structure of this group of banks. Diversified banking business model is the biggest cluster with 5359 banks accounting for more than half of all banks in the sample (56.07%).

The second identified business model is Wholesale Banking (BM2). Banks under this business model category have the highest percentage of loans to banks (Bank loans ratio) with 11%, indicating a wholesale orientation of loans through active participation in the interbank market. Wholesale banks have an average value of 2.87% loans to consumers while having the lowest average total investment ratio (19.93%) and non-interest income ratio of (13.38%). Wholesale banking is the business model of about 1587 banks in our sample which accounts for 16.60% of all banks.

The third identified business model is Traditional Banking (BM3). Banks with this type of banking business model generate their income mainly from traditional banking activities such as accepting consumer deposits and lending funds. It shows high dependence on loans provided to consumers compared with other banking business models, with an average consumer loans to total assets ratio of 3.83%. It also has the second-highest mean value of investment activities (47.39%). On the funding side, it shows the highest core deposits to assets ratio (76.37%), indicating its reliance on deposits as the main funding source. The traditional banking business model is the second largest cluster as it includes a total of 2370 banks, accounting for (24.80%) of all banks.

The Investment Banking (BM4) is the fourth identified business model. On the asset side, this group of banks is highly active in investment operations, as reflected in their total investment to total assets ratio of 54.04% on average. While loan portfolio averages are the lowest when compared with other business models, as seen in their consumer loans ratio (2.16%) and bank loans ratio (2.07%). On the liabilities side, investment banks also have the lowest average of CDA ratio (13.31%) indicating the reliance on volatile and risky financing resources. Investment banking contains the fewest number of banks (242), accounting for just 2.53% of the whole sample.

3.3.4 Classifying Bank-Fintech Acquisitions

Part of our analysis is based on the types of fintech firms and the motivations of banks to acquire them. Identifying these two aspects of a fintech acquisition deal is not straightforward. Therefore, we rely on a robust textual analysis technique to classify the bank-fintech acquisitions. Textual analysis is a practical method to extract meaningful qualitative text from unstructured data, such as announcements of bank acquisitions. In particular, we conduct a qualitative content analysis (QCA) methodology to answer the following questions:

- What are the types of fintech firms that banks acquired?
- What are the motivations behind banks' acquisitions of fintech firms?

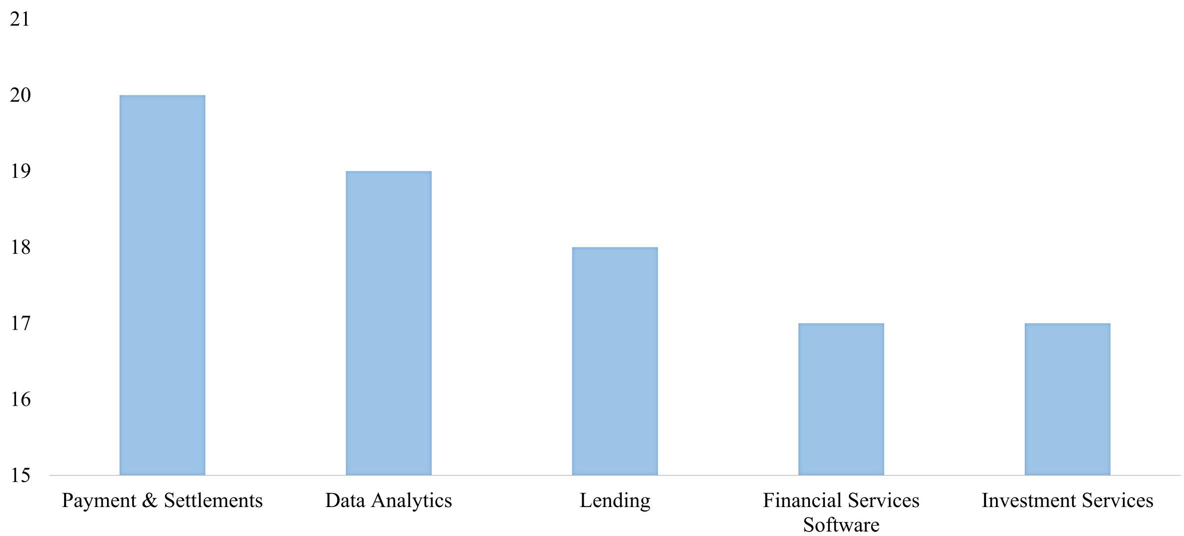
To answer the first question, we review the business description provided by Zephyr and Refinitiv databases for target firms in all 91 bank-fintech acquisitions included in the study in order to determine the type of services provided by the fintech firm. The business description section in both databases offers a comprehensive overview of the target firm, including its name, location, service, and industry. In the case of manually added bank-fintech acquisitions, we use the same methodology to examine each announcement to determine the type of fintech service and the motivations for the acquisition. A limited number of papers focus on analyzing the different categories of fintech firms. Haddad and Hornuf (2019) identify a global sample of fintech firms into 9 types including lending, payment, asset management, insurance, loyalty programs, risk management, exchanges, regulatory, and other business models. Similarly, Cappa et al. (2022) identify three main categories of fintech firms acquired by US and European banks in the period between 2015 - 2020: personal finance, payment, and fundraising. Building on the previous studies and using our QCA methodology, we distinguish between five types of fintech firms and identify their main characteristics as shown in Table 9.

Table 9: Identifying the Types of Fintech Firms

Type	**Characteristics**
Payment	Firms in this category provide electronic payment services such as mobile payment, payment platforms, payment management, payroll and payment processing services.
Data Analytics	This category include fintech firms that provide data analytics services such as loyalty programs, marketing tools, online promotions, rewards and benefits programs, deals & coupons and cashback applications.
Lending	Fintech firms providing financing solutions are included within this category. Services include digital lending, financing & leasing services and point-of-sale financing.
Financial Services Software	This category include fintech firms that provide innovative financial software. It includes services such as financial security and safety applications, money transfer, credit card and online banking services.
Investment Services	Investment fintech firms included in this category provide services in the domain of investment such as wealth management, online hedge fund platforms, financial models and investment advisory.

The results of implementing the QCA methodology to identify the types of fintech firms are summarized in Figure 8. In our sample of bank-fintech acquisitions, the firms acquired can be classified into five types: payment and settlements (20 deals), data analytics (19 deals), lending (18 deals), financial services software (17 deals), and investment services firms (17 deals). It should be noted that although there are further categories of fintech companies as documented in the literature, there is no evidence that any banks in our sample have acquired any fintech firms that belong to one or more of these categories.

Figure 8: Types of Fintech Firms (2005Q1-2021Q4)

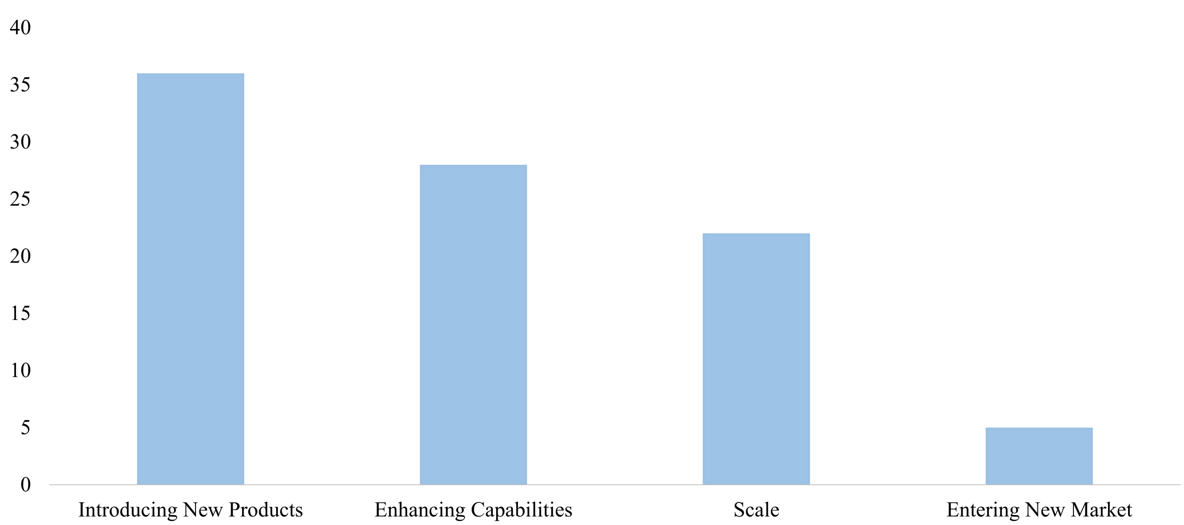


Next, in order to identify the motivations driving banks' acquisitions of fintech firms, we employ a similar QCA methodology. We thoroughly analyze each announcement of a bank-fintech acquisition, gathering information from regulatory authorities, official websites, and media sources. By utilizing our QCA methodology, we identify four distinct motives that drive banks to acquire fintech firms. These motives are outlined in Table 10, along with their key characteristics. A comprehensive overview of the findings obtained through the implementation of the QCA methodology, specifically pertaining to the identification of motivations behind fintech acquisitions, is presented in Figure 9. The deals under consideration were classified into the following four categories: introducing new products (36 deals), enhancing capabilities (28 deals), pursuing business scalability (22 deals), and entering new markets (5 deals).

Table 10: Identifying the Motivations Driving Banks' Acquisitions of Fintech Firms

Motivation	**Characteristics**
Introducing New Products	Acquiring fintech firms allows banks to create and offer new innovative financial solutions.
Enhancing Capabilities	Some banks see fintech acquisition as a means of improving their current financial technology skills as it supports in-house fintech development.
Business Scalability	Fintech acquisitions can support the growth strategy of banks, and it includes expansion in a financial product line.
Entering New Markets	A handful of banks acquire fintech firms with expertise in offering services that are novel to the bank for the purpose of reaching new markets.

Figure 9: Motivations Driving Banks' Acquisition of Fintech Firms (2005Q1-2021Q4)



3.3.5 Initial Examination of Bank-Fintech Acquisitions

This chapter examines whether the bank business model plays any significant role in fintech acquisitions. To this end, Table 11 provides an initial examination of how the types of target fintech firms in our sample, and the announced motives for acquiring these firms differ across the four business models identified above. We classify the services provided by fintech firms in our sample into five groups: Payment and settlements (20 deals), data analytics (19 deals), lending (18 deals), 17 deals for financial services software firms and 17 deals for investment services firms. In addition, we identify the main motives for banks to acquire fintech firms as Introducing new products (36 deals), enhancing capabilities (28 deals), business scalability (22 deals), and entering new markets (5 deals). Please see subsection 3.3.4 for the detailed methodology we use to identify the types of fintech firms and the motives of banks for acquiring them.

Table 11: An Initial Examination of Bank-Fintech Acquisitions

Panel A: Types of Fintech Services

	Diversified Banking	Wholesale Banking	Traditional Banking	Investment Banking	Total
Payment & Settlements	12	2	1	5	20
Data Analytics	15	0	0	4	19
Lending	12	3	0	3	18
Financial Services Software	12	1	2	2	17
Investment Services	4	2	1	10	17
Total	55	8	4	24	91

Panel B: Motives of Bank-Fintech Acquisitions

	Diversified Banking	Wholesale Banking	Traditional Banking	Investment Banking	Total
Introducing New Products	20	4	0	12	36
Enhancing Capabilities	19	1	2	6	28
Business Scalability	14	3	2	3	22
Entering New Markets	2	0	0	3	5
Total	55	8	4	24	91

Panel A in Table 11 shows the services provided by target fintech firms across the different banking business models. Diversified banking is the most active in four out of five services: payment and settlements, data analytics, lending, and financial services software. Investment banking is the most active in acquiring investment services firms. Also, diversified banks completed 12 acquisitions of payment and settlements firms, followed by investment banking with five acquisitions, wholesale banks with two, and traditional banks with one. This is likely due to the dynamic and growing nature of the payment industry that drives banks to acquire such firms. For data analytics firms, diversified banks completed 15 acquisitions, investment banking completed four, while wholesale and traditional banking did not acquire any fintech firms. It should be noted that the acquisition of data analytics enterprises allows banks to offer targeted deals to clients such as debit card marketing efforts. Regarding lending firms, diversified banks come first with 12 acquisitions, investment and wholesale banking each have three acquisitions, while traditional banking did not acquire any. Acquiring technology-driven financing firms allows banks to streamline loan processing and attract new customers. In the case of financial services software firms, diversified banking completed 12 deals, while traditional and investment banking each completed two, and wholesale banking completed one. These companies provide banks with API software for integrating third-party features, such as fraud detection tools, into their mobile apps. Finally, in terms of acquiring investment services firms (e.g., portfolio management, trading systems, and advisory solutions), investment banking is the most active with ten deals. Diversified banking comes next with four, wholesale banking with two, and traditional banking with one acquisition.

Panel B in Table 11 summarizes the strategic motives behind banks acquiring fintech firms across different banking business models. We can make the following observations. First, diversified banking and investment banking intensively utilize fintech acquisitions to offer a wide range of financial services, with 20 and 12 deals respectively. Wholesale banks only made 4 deals for this purpose, while traditional banks do not utilize fintech acquisitions to introduce new products. Second, in terms of enhancing internal technological capabilities, diversified and investment banking models made the most acquisitions, with 19 and 6 acquisitions respectively. Traditional banks completed two deals for the same motive, while wholesale banking only completed one deal. These acquisitions allow banks to improve their tech-enabled services, such as accepting online deposits and automating portfolio design and delivery. Third, diversified banking models pursued growth strategies the most, with 14 acquisitions, followed by wholesale and investment banking with three deals each. Traditional banks completed two acquisitions for this purpose. These fintech acquisitions enabled banks to expand and increase their market share by meeting growing market demands and enhancing business scalability. Lastly, investment and diversified banking models completed a total of five fintech deals to access new markets. Fintech firms were acquired for their specialized technological expertise in specific market segments. For instance, an investment bank acquired a fintech firm with expertise in the travel business industry, aiming to capitalize on the potential of that new market opportunity.

3.3.6 Variables

This chapter investigates whether banks with a certain business model are more likely to participate in acquisitions of fintech firms. To this end, our main variable of interest is a binary variable called $FintechAcquisition$ that takes the value 1 if a bank was involved in a fintech acquisition agreement in a given quarter, and 0 otherwise. However, it should be noted that some banks in the sample have conducted multiple acquisitions in the same quarter. To account for these duplicates, we have counted the deals made during that quarter as 1, disregarding other deals that occurred for the same bank during the same quarter. This has led to a reduction in the total number of bank-fintech acquisitions from 91 to 84 deals.

Furthermore, we follow the literature to include other variables that could explain the bank's decision to acquire a fintech firm. Specifically, we use *Size* which is estimated using the natural logarithm of bank total assets. We follow Collevecchio et al. (2023) and include bank size in our baseline model as it differentiates larger banks, which benefit from greater financial resources and economies of scale, from smaller banks. We argue that larger banks are more capable to conduct innovation acquisitions, facilitated by their higher ability to build an innovative environment through the availability of necessary human, material, and financial resources, as empirically documented by Pi and Yang (2023). Moreover, several studies agree on the significant effect of bank size on its decision to acquire other firms (Beccalli and Frantz 2013; Pasiouras et al. 2011; Focarelli et al. 2002). Consequently, we expect a positive relationship between bank size and the likelihood of acquiring fintech firms.

We further include bank's equity (*Capitalization*) in our model, measured by total equity over total assets. The theoretical background of the relationship between bank capital and bank risk-taking suggests multiple views. For instance, according to the capital buffer theory, well-capitalized banks with levels above the regulatory minimum requirement have a greater cushion against potential losses (Milne and Whalley, 2001). Therefore, banks with higher capitalization may be better positioned to engage in risky activities such as the acquisition of fintech firms, which often operate in a rapidly evolving environment. A contrary view maintains that banks with a higher capitalization ratio might prioritize prudent risk management strategies to preserve their capital position.

Next, we use the ratio of return on equity (*ROE*) as a measure of bank profitability. The relationship between bank profit and fintech acquisitions can take different forms. For example, it can be argued that a positive relationship exists when more profitable banks are able to conduct fintech acquisitions due to their financial freedom (Pasiouras et al. 2011;

Focarelli et al. 2002). On the other hand, a negative association may exist if less profitable banks seek out fintech acquisitions as a means to get the necessary technology for profit and expansion. We further use the non-performing loans ratio (NPL) to indicate the quality of the loan portfolio. Kwon et al. (2024) provide evidence that bank NPL can be considered as a hinder to a bank's capital which could limit its involvement in fintech acquisitions. As such, it is expected to be negatively associated with the bank's fintech acquisition activity.

Moreover, we use the ratio of bank non-interest expenses over total assets to measure bank cost efficiency ($Efficiency$). The expected sign can be either positive or negative. Efficient banks with a lower non-interest expense to total asset ratio may be in a stronger financial position to assume additional risks in the form of acquiring fintech firms, enabling them to integrate cutting-edge technologies into their operations. In a related literature, Pasiouras et al. (2011) find that cost efficiency has a positive and statistically significant impact on a bank's decision to acquire targets. However, less efficient banks might consider financial technology companies as an appealing option for streamlining and automating internal operations. For example, payment fintech firms can support banks in managing their non-interest expenses by implementing new payroll and payment processing solutions. Kwon et al. (2024) provide additional evidence to this argument as they empirically show that less efficient banks may improve their cost efficiency through the acquisition of new technologies facilitated by the acquisition of fintech firms. Furthermore, bank liquidity is included as the ratio of cash and short-term investment over total assets ($Liquidity$). As shown by Kwon et al. (2024), banks with greater liquidity are more capable of entering a fintech acquisition deal, supported by their excess liquidity. As a result, we predict a positive relationship between bank liquidity and the possibility of acquiring Fintech companies.

Additionally, two measures are used to gauge the extent of technological advancement within the bank: (1) the ratio of intangible assets and (2) the ratio of IT expenditure. First, we follow Collevecchio et al. (2023) and Ayadi et al. (2021) in using the intangible assets to total assets ratio ($Intangible$) to measure bank internal fintech development. Second, We follow Kwon et al. (2024) and Beccalli (2007) and use bank IT expenditure. Specifically, we use the ratio of data processing costs to non-interest expenses ($IT\_Expenditure$) since it is the most straightforward accounting measure for analyzing bank technological investment (Sedunov, 2017). Data processing expenses is an item often used in the US banking literature to assess bank IT capabilities (Sefried and Riepe 2023; Sedunov 2017). The expected sign for the two variables can be either positive or negative with fintech acquisitions. On the one hand, banks that are developing their internal technological capabilities might consider acquiring fintech companies as a growth opportunity, whereas other banks may prioritize internal investment related to fintech projects such as research and development (R&D) initiatives. On the other hand, banks with a low intangible asset ratio or IT expenditure may view fintech acquisitions as a profitable option to avoid the costs and complications of setting up departments and utilizing resources while quickly exploiting the potential benefits of financial innovations.

Finally, to account for macroeconomic variables, we add the growth of real gross domestic product (GDP_Growth), and the real interest rate ($Interest\_Rate$) to our model. First, GDP_Growth proxies the country's overall health and future prospect of profit and growth. Kwon et al. (2024) outline that banks located in a country with higher GDP growth are more likely to conduct fintech acquisitions. Therefore, we expect it to be positively correlated with bank-fintech acquisition. The data is collected from US Bureau of Economic Analysis (BEA). Second, we use the nominal lending rate adjusted for inflation ($Interest\_Rate$). The expected sign can be either positive or negative. Rising interest rates may lead to more fintech acquisitions as banks improve their net interest margins and capital reserves. Conversely, banks may be discouraged from acquiring fintech firms due to increased interest rates, which might signal stricter monetary conditions and slower economic growth. We collect the data from the Federal Reserve Board. Table 12 provides a summary of research variables' definitions.

Table 12: Variable Definitions

Variable	**Definition**
FintechAcquisition	A dummy variable that equals 1 if a bank participated in an acquisition deal with a fintech company in a given quarter, or equals 0 otherwise.
Size	The natural logarithm of total bank assets.
Bank Loans Ratio	The sum of industrial loans, loans to depository institutions and bank acceptances divided by total assets.
Consumer Loans Ratio	The sum of consumer loans for home, family, and other personal expenses divided by total assets.
Total Investments Ratio	The sum of all securities, interest-bearing bank balances, federal funds sold, and trading account assets divided by total assets.
Intangible Assets Ratio	Intangible assets divided by total assets.
CDA Ratio	Core deposits are the total of all time deposits under \$100,000 (\$250,000 from 2010 and onward), interest-bearing transaction accounts, non-transaction savings deposits, and demand deposits, scaled by total assets.
Efficiency Ratio	Non-interest expenses over total assets.
Non-performing Loans Ratio	Nonperforming loans divided by total loans.
Liquidity Ratio	The sum of cash + short-term investment over total assets.
Capitalization Ratio	Total equity over total assets.
Return on Equity	Net income divided by total equity.
Non-Interest Income Ratio	The net income from non-interest-bearing assets and bank services such as fees and commissions on deposits, assets held in trading accounts, foreign exchange market gains and losses, other foreign transactions, and other non-interest income divided by the adjusted operating income.
IT Expenditure Ratio	Data processing expenses divided by non-interest expenses.
GDP Growth	The inflation adjusted percentage change in GDP.
Interest Rate	The natural logarithm form of bank nominal lending rate adjusted for inflation.

Prior to conducting the main and additional regression analyses, we perform a preliminary analysis in Table 13 to compare the main characteristics of acquiring banks and non-acquiring banks. We provide the regression estimation sample instead of the full sample due to missing data on some variables. We start by providing a summary of the data for all banks. The sample is then split into two groups: acquiring banks (banks that acquired a fintech company at least once during the sample period) and non-acquiring banks (banks that did not acquire any fintech companies). The mean and standard deviation (SD) of variables utilized in the baseline regression analysis are displayed. These two metrics are supplemented by the mean difference (MD), which demonstrates the difference between both groups of banks in terms of absolute value (Abs) and statistical significance determined based on p-value.

Table 13: Summary Statistics

	All banks		Acquiring banks		Non-acquiring banks		Mean Difference (MD)
	Mean	SD	Mean	SD	Mean	SD	Abs
Size (ln)	12.20	1.35	15.90	1.60	12.18	1.32	-3.72***
ROE (%)	4.84	6.52	5.97	4.74	4.83	6.53	-1.14***
NPL (%)	1.27	1.95	1.03	1.18	1.27	1.95	0.24***
Efficiency (%)	1.91	1.41	1.85	1.09	1.91	1.41	0.06*
Liquidity (%)	12.51	10.08	11.38	10.21	12.51	10.07	1.13***
Intangible (%)	0.46	1.14	2.24	1.98	0.45	1.13	-1.78***
Capitalization (%)	11.48	5.02	10.80	2.79	11.49	5.03	0.68***
IT Expenditure (%)	4.62	4.32	3.25	3.43	4.62	4.32	1.38***
Number of Banks	9280		30		9250		

Note: This table presents the summary statistics in the period under study (2005Q1-2021Q4) for three groups of banks; the first group contains all banks in the regression estimation sample (All banks), the second group contains banks who acquired at least one fintech firm (Acquiring banks), and the third group contains statistics for banks that did not participate in any acquisition deal with a fintech firm (Non-acquiring banks). Mean and standard deviation (SD) values are calculated as the average cross-sectional mean and SD of the individual time-series bank values. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the findings. Table 12 shows the definition of all variables. MD in the last column refers to the mean difference between acquiring banks and non-acquiring banks in absolute (Abs) values and its statistical significance which is denoted by the following symbols: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 13 shows that acquiring banks are statistically different from non-acquiring banks in terms of all variables: $Size$, ROE, NPL, $Efficiency$, $Liquidity$, $Intangible$, $Capitalization$ and $ITExpenditure$. First, in terms of $Size$, our results show that acquiring banks are larger than non-acquiring banks (15.90 vs 12.18), suggesting that larger banks are more likely to acquire fintech firms. This result is in line with previous literature (Beccalli and Frantz, 2013). Next, the return on equity (ROE) ratio result shows that acquiring banks (5.97%) are generally more profitable than non-acquiring banks (4.83%). This is consistent with what Pasiouras et al. (2011) and Focarelli et al. (2002) find. While non-acquiring banks have higher non-performing loans (NPL) ratio than acquiring banks (1.27% vs 1.03%), suggesting that banks who are more burdened with non-performing loans are less likely to acquire fintech firms. This is consistent with Kwon et al. (2024) findings. Similarly, non-acquiring banks are a slightly less efficient with a higher non-interest expense to total asset ratio ($Efficiency$) of 1.91% versus 1.85% for acquiring banks, and have held more cash and short-term investments ($Liquidity$) with a ratio of 12.51% versus 11.38% for acquiring banks.

Moreover, our results show that intangible assets ratio ($Intangible$) is statistically different in acquiring banks (2.24%) than non-acquiring banks (0.45%), suggesting that fintech acquiring banks are more involved in technological advancement and research and development (R&D) initiatives. Furthermore, non-acquiring banks have a higher capitalization ratio ($Capitalization$) than acquiring banks (11.49% vs 10.80%), indicating that well-capitalized banks favor a cautious risk management approach, abstaining from acquisition activities associated with uncertainties. Lastly, non-acquiring banks are investing more in electronic data processing (EDP) equipment as can be seen in their IT expenditure ratio ($ITExpenditure$) of 4.62% compared with 3.25% ratio of fintech acquiring banks.

3.3.7 Econometric Model

We use a logistic regression model to investigate whether banks with a certain business model are more likely to participate in acquisitions of fintech firms. Logit regression model has been extensively used in numerous settings involving bank merger and acquisition activities (Akhigbe et al. 2004; Correa 2009; Beccalli and Frantz 2013), banking business models (Ayadi et al., 2021), and bank-fintech partnerships (Del Gaudio et al. 2024; Kwon et al. 2024). As such, the following logistic regression model is used to evaluate the likelihood of a bank-fintech acquisition:

$$
\begin{aligned}
Z_{it} = \beta_0 + \beta_1 BM_{it-1} + \beta_2 Size_{it-1} + \beta_3 ROE_{it-1} + \beta_4 NPL_{it-1} + \beta_5 Efficiency_{it-1} \\
+\beta_6 Liquidity_{it-1} + \beta_7 Intangible_{it-1} + \beta_8 Capitalization_{it-1} + \beta_9 ITExpenditure_{it-1} \\
\beta_{10} Macroeconomic_{it-1} + \gamma_t + \epsilon_i
\end{aligned} \tag{3}
$$

where Z_{it} denotes the likelihood that a bank will acquire a fintech company. We use $FintechAcquisition$ as the binary outcome variable that takes 1 if a bank acquired a fintech company in a given quarter and 0 otherwise. β_0 is an intercept term. β_1 is the main coefficient of interest. BM refers to one of the four business models: $Diversified$, $Wholesale$, $Traditional$, and $Investment$. Depending on the regression specification, the business model indicator takes the value 1 if the bank follows the respective business model and 0 otherwise.[16] $Size$ is the natural logarithm form of total assets. ROE is the bank's net income divided by its equity capital. NPL is the ratio of the bank's nonperforming loans over its total loans. $Efficiency$ is calculated as the non-interest expenses over total assets. $Liquidity$ is the sum of cash and short-term investment over total assets. $Intangible$ is intangible assets over total assets. $Capitalization$ is the bank total equity over total assets. $IT\_Expenditure$ is calculated as the ratio of data processing expenses scaled by non-interest expenses. $Macroeconomic$ includes GDP_Growth and $Interest\_Rate$. γ_t is the time fixed effects. Banks and times are denoted by the sub-indices i and t, respectively. All explanatory variables are lagged by one period to mitigate potential concerns about endogeneity and reverse causality. ϵ_i is an error term.

[16]Since each of the four dummy variables included in the variable BM corresponds to one of the identified business models, we follow the extant literature in the analysis of banking business models and estimate our model with random effects given that using fixed effects estimates would cause time-invariant variables to be omitted due to collinearity (Galletta and Mazzù, 2019).

3.4 Results and Discussion

This section discusses the baseline results, robustness checks, and additional analysis.

3.4.1 Impact of Banking Business Model on Fintech Acquisitions

Our baseline analysis uses a logistic regression to investigate whether banks with a certain business model are more likely to acquire a fintech firm. Table 14 presents the results of this logistic regression.[17] We find a significant and positive relationship between the diversified banking business model and the likelihood of acquiring fintech companies as shown in column (1). This indicates that banks with a diversified business model (i.e., more variety of bank asset compositions and revenue sources) are more likely to be active in acquiring financial technology firms. This finding supports the argument that being diversified does not necessarily make the bank safer; rather, it may enable the bank to seek expansion strategies via riskier projects such as fintech acquisitions. Given the characteristics of diversified banks, our results supplement the findings of Demsetz and Strahan (1997) who demonstrate that banks with larger leverage, supported by greater asset, financing, and income diversification, may take on more lending risks than other banks. In addition, Wu et al. (2020) indicate that greater bank diversification can indirectly increase bank risk-taking through lower efficiency since greater diversification reduces efficiency through higher monitoring costs and the problem of being too complex to manage.

Furthermore, we find a significant negative relationship between having a wholesale banking business model and fintech acquisitions as shown in column (2). The results indicate

[17] The sample size decreases to include 9280 banks and 406,675 bank-quarter observations in the regression estimation due to missing data on regression variables.

Table 14: Main Results: Impact of Banking Business Model on Fintech Acquisitions

	(1)	(2)	(3)	(4)
Diversified Banking	0.884***			
	(0.282)			
Wholesale Banking		-1.187***		
		(0.383)		
Traditional Banking			-1.263**	
			(0.525)	
Investment Banking				1.355***
				(0.421)
Size (ln)	1.896***	1.851***	1.814***	1.753***
	(0.161)	(0.156)	(0.157)	(0.156)
ROE (%)	0.022	0.029	0.012	0.015
	(0.026)	(0.027)	(0.026)	(0.027)
NPL (%)	-0.182	-0.112	-0.164	-0.090
	(0.153)	(0.136)	(0.146)	(0.129)
Efficiency (%)	-0.014	-0.023	-0.005	-0.042
	(0.091)	(0.093)	(0.089)	(0.095)
Liquidity (%)	0.048***	0.034***	0.035***	0.011
	(0.009)	(0.008)	(0.008)	(0.012)
Intangible (%)	0.118*	0.121*	0.130**	0.122*
	(0.068)	(0.065)	(0.066)	(0.063)
Capitalization (%)	-0.099**	-0.077*	-0.115***	-0.090**
	(0.045)	(0.043)	(0.049)	(0.041)
IT_Expenditure (%)	0.008	0.021	0.010	0.027
	(0.033)	(0.032)	(0.031)	(0.031)
GDP_Growth (%)	-0.047	-0.045	-0.044	-0.044
	(0.052)	(0.052)	(0.052)	(0.052)
Interest_Rate (ln)	-2.869	-2.920	-2.905	-3.032
	(2.387)	(2.380)	(2.397)	(2.407)
Bank-quarter Observations	406,675	406,675	406,675	406,675
Number of Banks	9280	9280	9280	9280
Wald Chi2	220.4	231.5	230.5	253.2
VIF	1.15	1.16	1.16	1.17

Note: This table shows the logit regression results for the dependent variable *FintechAcquisition*, which is a binary variable that equals 1 if a bank acquired a fintech company in a given quarter and equals 0 otherwise. The results are presented for four models, each of which relates to one of the four banking business models identified—diversified banking (BM1), wholesale banking (BM2), traditional banking (BM3), and investment banking (BM4) in the period under study (2005Q1-2021Q4). Table 12 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. Variance inflation factor (VIF) scores are reported as mean values of independent variables and are used to check for multicollinearity. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

that banks with a greater level of activity in the interbank market are less likely to acquire fintech companies. Wholesale banks have a lower risk-taking appetite, hence less interest in acquiring venture fintech firms, than banks with other business models. This might be because their target clientele is large financial institutions and governmental agencies that may not demand cutting-edge technology. Huang and Ratnovski (2011) argue that wholesale banks have a reduced risk appetite as they mostly cooperate with large financial institutions which closely monitor their counterparties activities and have the ability to punish the wholesale bank by withdrawing funding.

As for traditional banking business model, the results in column (3) show a negative and statistically significant relationship at the 5% level, indicating that these business models, relative to the others, are not more likely to acquire fintech firms. One probable explanation for this result is that strategic acquisitions of fintech firms may not be in line with the bank's vision, since they mainly depend on conventional means of conducting business, including accepting deposits and providing loans, to generate profits. Additionally, they may choose safer alternatives to acquisition deals in the form of collaboration with fintech businesses. This cautious attitude may have enabled conventional banks to remain the surviving group during times of crisis, as shown in Chiorazzo et al. (2018).

The findings of investment banking business model in column (4) indicate a statistically significant and positive relationship at the 1% level with fintech firms acquisition. It suggests that banks with an investment business model are more inclined to engage in fintech acquisition agreements compared to other business models. However, with a total of 24 fintech deals, investment banks may be more selective in their fintech acquisition due to their advancement over other business models. Furthermore, Hryckiewicz and Kozłowski (2017) highlight the increased systemic risk associated with the investment banking business models. This may potentially influence investment banks' risk-taking decisions.

External factors can significantly influence the strategic decisions of banks regarding fintech acquisitions. As highlighted by Hornuf et al. (2021), market regulatory conditions can shape the scope and nature of bank-fintech alliances, including the types of products developed. Additionally, competition within the banking industry plays a crucial role. Diversified and investment banks, facing increasing pressure to meet the evolving demands of their customers, may be more inclined to seek innovative solutions through fintech partnerships. In contrast, wholesale and traditional banks, often prioritizing risk aversion, may opt for less risky collaborations to acquire necessary technology.

Next, we analyze the role of bank-specific characteristics in fintech acquisitions. In all four models, we find that the coefficient on bank size, as measured by the natural logarithm form of its total assets, is positively and statistically significant at the 1%. This indicates that larger banks in the sample are more likely to conduct fintech acquisitions. The result is consistent with the findings of Beccalli and Frantz (2013) who show that larger banks with higher growth prospects are more capable of conducting acquisition deals. Furthermore, in models (1), (2), and (3), we show that more liquid banks are more likely to acquire fintech companies, with a positive and significant coefficient value (at the 1% level). Consistent with the findings of Kwon et al. (2024), this indicates that more liquidity encourages the bank to take more risk and may lead to the acquisition of financial technology companies.

Moreover, we document a significantly positive association between a bank's intangible assets ratio and its likelihood of acquiring fintech firms. Bank intangibles include technological capabilities within the bank that can act as a facilitator of innovation (Collevecchio et al., 2023). The findings highlight the significance of strategic alignment between the bank's internal technological advancement and the fintech firm. In addition, results show a statistically significant negative relationship between bank capitalization, measured as total equity divided by total assets, and the probability of fintech acquisitions. A possible explanation for this result is that well-capitalized banks might prioritize prudent risk management practices to improve their stability during times of uncertainty. Additionally, Delis et al. (2017) show that highly capitalized banks are more likely to have an efficient risk management strategy that ensures a lower risk-taking. Finally, we do not find significant effects of macroeconomic factors (GDP growth and interest rate) or bank-specific variables (profitability, NPL and IT expenditure) on the likelihood of fintech acquisitions.

Overall, the empirical results confirm that business model structures have a significant influence on banks' decisions to acquire FinTech firms. We show that diversified and investment banking business models are more likely than other business models to acquire financial technology firms. Conversely, wholesale and traditional banking business models exhibit a cautious attitude towards FinTech acquisitions compared with other business models. These results highlight the inherent structural differences between banks that can explain their inclination for risk-taking. Consequently, policymakers must consider these variations to design effective policies that promote innovation and protect the stability of the financial system.

3.4.2 Robustness Checks

We conduct a number of tests to check the robustness of our main results. First, we use an alternative method to evaluate the role of banking business models in bank-fintech acquisitions. Second, we use the propensity score matching technique to avoid any potential bias in sample selection. Third and finally, we convert our quarterly sample to annual to examine whether our findings are consistent in different data forms.[18]

[18] We further analyze in Table B.2 in Appendix B the impact of banking business model on the geographic location of fintech firms acquired by US banks. We categorize fintech firms into domestic (US) or cross-border (foreign). The results are broadly similar to that shown in the main analysis of this chapter.

3.4.2.1 Alternative Regression Method

First, we use an alternative regression method to evaluate the likelihood of acquiring fintech firms by banks. We adopt the probit model and show in Table 15 that the results are broadly similar to the results presented in the baseline analysis. While banks with a diversified or investment business models are more likely to acquire fintech firms than other banks, banks with a wholesale or traditional business models are less likely to acquire fintech firms relative to other banks. Still, bank size, liquidity and intangible assets have a positive and statistically significant relationship with fintech acquisition. On the other hand, bank capitalization shows a negative and statistically significant relationship with fintech acquisition.

3.4.2.2 Sample Selection Bias

Second, to check for any potential sample selection bias in our main results, we use the propensity score matching (PSM) technique (Rosenbaum and Rubin, 1983). This technique is particularly useful in our context as it balances the sample size between fintech-acquiring banks and non-acquiring banks. Prior literature on bank-fintech partnerships recommends using the PSM approach to overcome the challenge of having a limited number of fintech-acquiring banks in comparison to non-acquiring banks (Del Gaudio et al. 2024; Kwon et al. 2024).

We use $FintechAcquisition$ as a treatment variable to run the matching technique and construct two groups of banks with similar characteristics. In particular, banks in the treated group (have acquired fintech firm) are matched with a control group of banks (have not acquired fintech firm) based on bank capitalization ratio (Kwon et al., 2024) and bank

Table 15: Robustness Check: Probit Regression

	(1)	(2)	(3)	(4)
Diversified Banking	0.272***			
	(0.100)			
Wholesale Banking		-0.370***		
		(0.126)		
Traditional Banking			-0.430**	
			(0.174)	
Investment Banking				0.539***
				(0.157)
Size (ln)	0.548***	0.535***	0.524***	0.496***
	(0.045)	(0.043)	(0.043)	(0.043)
ROE (%)	0.008	0.009	0.006	0.006
	(0.009)	(0.009)	(0.009)	(0.009)
NPL (%)	-0.064	-0.046	-0.066	-0.040
	(0.051)	(0.047)	(0.051)	(0.046)
Efficiency (%)	0.001	-0.001	0.001	-0.009
	(0.031)	(0.031)	(0.030)	(0.031)
Liquidity (%)	0.018***	0.014***	0.015***	0.006
	(0.004)	(0.003)	(0.003)	(0.004)
Intangible (%)	0.050**	0.052**	0.057**	0.060**
	(0.025)	(0.024)	(0.024)	(0.024)
Capitalization (%)	-0.041**	-0.035**	-0.049***	-0.041***
	(0.017)	(0.016)	(0.017)	(0.016)
IT_Expenditure (%)	0.003	0.006	0.004	0.010
	(0.012)	(0.012)	(0.012)	(0.011)
GDP_Growth (%)	-0.021	-0.020	-0.020	-0.019
	(0.020)	(0.020)	(0.020)	(0.020)
Interest_Rate (ln)	-1.326	-1.340	-1.338	-1.369
	(0.843)	(0.844)	(0.850)	(0.857)
Bank-quarter Observations	406,675	406,675	406,675	406,675
Number of Banks	9280	9280	9280	9280
Wald Chi2	223.5	230.4	234.9	253.1
VIF	1.15	1.15	1.17	1.18

Note: This table shows the probit regression results for the dependent variable $FintechAcquisition$, which is a binary variable that equals 1 if a bank acquired a fintech company in a given quarter and equals 0 otherwise. The results are presented in four models, each of which relates to one of the four banking business models identified—diversified banking (BM1), wholesale banking (BM2), traditional banking (BM3), and investment banking (BM4) in the period under study (2005Q1-2021Q4). Table 12 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. Variance inflation factor (VIF) scores are reported as mean values of independent variables and are used to check for multicollinearity. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

size (Del Gaudio et al., 2024) as it is found in the literature to be significant factors for bank-fintech partnerships. We apply one-to-one nearest neighbor matching method without replacement, with a maximum acceptable difference in propensity score (caliper) of 0.01 between fintech-acquiring banks and non-acquiring banks (Del Gaudio et al. 2024; Kwon et al. 2024). The differences in bank capitalization ratio and bank size between acquiring and non-acquiring banks before and after matching are shown in Table 16. Before matching, the mean difference in absolute terms between the two groups for bank capitalization was 0.515 with a significance of 0.346. Bank size showed a statistically significant difference of -4.329 between the two groups. However, the difference between the two groups becomes nearly non-existent when the PSM technique is used.

Table 16: Robustness Check: Results of the Propensity Score Matching

	Before Matching				After Matching			
	Acquiring banks	Non-acquiring banks	MD (Abs)	p-value	Acquiring banks	Non-acquiring banks	MD (Abs)	p-value
Capitalization (%)	10.967	11.483	0.515	0.346	10.967	10.910	-0.057	0.897
Size (ln)	16.525	12.196	-4.329	0.000	16.525	16.522	-0.003	0.985

Note: This table shows the results of using the Propensity Score Matching technique to match two samples: Banks who acquired a fintech firm (Acquiring banks), and banks that did not acquire a fintech firm (Non-acquiring banks). The variables used for matching are *Capitalization* (bank equity over total assets) and *Size* (natural logarithm of bank total assets). MD is the mean difference between acquiring banks and non-acquiring banks in absolute (Abs) values and its statistical significance (p-value).

Similar to our main results, Table 17 shows that the diversified banking business model has a positive and significant coefficient, while wholesale business model shows a negative coefficient of the same magnitude. However, traditional and investment banking business models lost their significance. Regarding bank-specific variables, we find that the coefficients for liquidity is positive and statistically significant. Consequently, the results suggest that sample selection bias has no effect on the results of the main analysis.

Table 17: Robustness Check: Logit Regression - PSM Sample

	(1)	(2)	(3)	(4)
Diversified Banking	1.851***			
	(0.565)			
Wholesale Banking		-2.087***		
		(0.625)		
Traditional Banking			0.188	
			(0.754)	
Investment Banking				0.0638
				(0.809)
ROE (%)	0.042	0.054	0.045	0.042
	(0.058)	(0.059)	(0.058)	(0.057)
NPL (%)	0.035	0.039	0.049	0.053
	(0.311)	(0.312)	(0.282)	(0.283)
Efficiency (%)	-0.203	-0.184	-0.146	-0.143
	(0.217)	(0.243)	(0.197)	(0.199)
Liquidity (%)	0.110***	0.069***	0.069***	0.067**
	(0.029)	(0.025)	(0.023)	(0.030)
Intangible (%)	-0.086	0.060	0.092	0.082
	(0.125)	(0.114)	(0.117)	(0.109)
IT Expenditure (%)	0.005	0.070	0.027	0.028
	(0.061)	(0.064)	(0.058)	(0.062)
GDP_Growth (%)	-0.251	-0.315*	-0.218	-0.217
	(0.171)	(0.172)	(0.158)	(0.159)
Interest_Rate (ln)	-3.133	-3.349	-2.443	-2.376
	(3.053)	(3.169)	(2.918)	(2.914)
Bank-quarter Observations	158	158	158	158
Number of Banks	75	75	75	75
Wald Chi2	36.96	36.23	34.85	34.93

Note: This table shows the results of repeating the main analysis based on a matched sample of acquiring and non-acquiring banks. It shows the logistic regression results for the dependent variable $FintechAcquisition$, which is a binary variable that equals 1 if a bank acquires a fintech company in a given quarter, and equals 0 otherwise. Both $Size$ and $Capitalization$ variables were not included in the estimation as they were used as matching variables. The results are presented in four models, each of which relates to one of the four banking business models identified—diversified banking (BM1), wholesale banking (BM2), traditional banking (BM3), and investment banking (BM4) in the period under study (2005Q1-2021Q4). Table 12 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

3.4.2.3 Using Annual Data

Third, since US bank-level data is officially reported on a quarterly basis, the annual frequency is sometimes used in the literature in the main analysis or for robustness checks (van Ewijk and Arnold, 2014). As such, we repeat our main analysis using an annualized US bank-level dataset. To do this, we calculate the annual mean of variables used in the regression by averaging each bank's quarterly values for each year under study. The total number of bank-year observations decreases to 96,622. Furthermore, we account for duplicates by counting all bank-fintech acquisitions that take place in any calendar year as one for the purpose of creating the annual dataset. This results in reducing the total number of fintech acquisitions to 69.

The empirical results are reported in Table 18. Similar to the main analysis, diversified and investment banking business model indicators have significantly positive coefficients. While both wholesale and traditional banking business models have a negative and statistically significant relationship with fintech acquisitions. The results also show evidence that bank size and liquidity positively affect the likelihood of fintech acquisitions, while bank capitalization has a negative impact on fintech acquisitions.

3.4.3 Further Analysis: What Type of Fintech Firms Do Banks Acquire?

We have discussed in section 3.3.5 the type of fintech firms in detail, and in this subsection we empirically investigate the likelihood of banks acquiring fintech firms based on the services they provide. We contribute to a limited literature aimed at understanding the dynamics of fintech firms and their interactions with financial institutions. Haddad and Hornuf (2019) are among the first to investigate the economic and technological factors affecting the creation of nine types of fintech firms across the globe. Among other factors, they find positive evidence for the impact of a developed economy on the formation of innovative firms. Additionally, Cappa et al. (2022) analyze a sample of fintech companies

Table 18: Robustness Check: Logit Regression - Annual Sample

	(1)	(2)	(3)	(4)
Diversified Banking	0.971***			
	(0.330)			
Wholesale Banking		-1.230***		
		(0.443)		
Traditional Banking			-1.022*	
			(0.536)	
Investment Banking				1.219**
				(0.515)
Size (ln)	1.764***	1.721***	1.675***	1.630***
	(0.157)	(0.151)	(0.152)	(0.151)
ROE (%)	0.022	0.021	0.011	0.008
	(0.032)	(0.033)	(0.030)	(0.031)
NPL (%)	-0.183	-0.120	-0.161	-0.111
	(0.164)	(0.146)	(0.152)	(0.139)
Efficiency (%)	0.046	0.047	0.052	0.026
	(0.108)	(0.108)	(0.104)	(0.111)
Liquidity (%)	0.050***	0.033***	0.035***	0.013
	(0.011)	(0.010)	(0.010)	(0.014)
Intangible (%)	0.116	0.120	0.137*	0.128*
	(0.079)	(0.075)	(0.076)	(0.075)
Capitalization (%)	-0.119**	-0.095*	-0.134***	-0.111**
	(0.053)	(0.050)	(0.051)	(0.048)
IT_Expenditure (%)	-0.009	0.005	-0.007	0.008
	(0.042)	(0.041)	(0.041)	(0.040)
GDP_Growth (%)	-5.833	-4.684	-5.040	-3.642
	(16.01)	(15.48)	(15.89)	(14.88)
Interest_Rate (ln)	-24.30	-22.22	-24.07	-21.38
	(84.28)	(95.89)	(86.84)	(105.8)
Bank-year Observations	96,622	96,622	96,622	96,622
Number of Banks	9047	9047	9047	9047
Wald Chi2	193.4	202.5	199.6	212.8

Note: This table shows the results of repeating the main analysis based on the annualized sample. It shows the logistic regression results for the dependent variable *FintechAcquisition*, which is a binary variable that equals 1 if a bank participated in an acquisition deal with a fintech company in a given quarter, and equals 0 otherwise. The results are presented in four models, each of which relates to one of the four banking business models identified—diversified banking (BM1), wholesale banking (BM2), traditional banking (BM3), and investment banking (BM4) in the period under study (2005Q1-2021Q4). Table 12 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables are lagged by one period to mitigate potential concerns about endogeneity and reverse causality. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

operating in the USA and Europe for the purpose of measuring the effect of acquiring them on the acquirers' profit. They find a distinction between the effect of partial and full fintech acquisitions by banks. For example, personal finance and fundraising fintech companies have a positive impact on banks' future earnings only if the acquisition is partial. While banks' full acquisitions of fintech firms in the payment, personal finance, or fundraising sectors had negative effects.

We use Equation 3 to examine the likelihood of banks acquiring fintech firms based on the services they provide. In particular, we estimate five models each with a dependent dummy variable representing one type of fintech firms acquired by banks. As explained earlier, we identify five types of fintech firms in our sample including: payment & settlements, data analytics, lending, investment services, and financial services software.[19] Tables 19, 20 and 21 present the regression results in five panels each representing one type of fintech firms.

The findings of the regression analysis for the payment and settlement fintech firms (paytech) are shown in Panel A of Table 19. Rapid payment sector innovation may have incentivized US banks to buy out paytech firms. Investment banks, in particular, appear to be more likely than other business models to acquire paytechs (at the %5 significance level), possibly owing to the strategic alignment between the disruptive nature of payment technology firms and the focus on innovation-driven initiatives of investment banks. Although the results do not indicate any significant differences among other banking business models in terms of acquiring paytech firms, the coefficients are mostly as anticipated. In particular, the coefficient is positive for diversified banks, the most active payment technology firm acquirers with a total of 12 deals. Wholesale and traditional banks are less likely, compared with other business models, to acquire paytech firms. With regards to bank-specific metrics, while bank size has significant and positive coefficients, indicating that larger banks

[19] Please see subsection 3.3.4 for further information on the methodology used to classify bank-fintech acquisitions in our sample. In addition, Table 9 presents the types of fintech firms and their main characteristics.

are more likely to acquire paytech firms, bank capitalization ratio is negatively associated with the likelihood of acquiring payment firms.

Table 19: Further Analysis: Types of Fintech Firms (1)

	Panel A: Payment Firms				Panel B: Data Analytics Firms			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Diversified Banking	0.839				2.827***			
	(0.561)				(0.947)			
Wholesale Banking		-1.061				0		
		(0.768)				(0)		
Traditional Banking			-1.553				0	
			(1.063)				(0)	
Investment Banking				1.865**				-0.136
				(0.880)				(0.968)
Size (ln)	1.960***	1.903***	1.900***	1.813***	4.904***	4.481***	4.073***	4.366**
	(0.352)	(0.341)	(0.345)	(0.344)	(1.712)	(1.701)	(1.556)	(1.711)
ROE (%)	0.024	0.029	0.017	0.026	0.026	0.014	-0.005	0.012
	(0.050)	(0.051)	(0.049)	(0.052)	(0.050)	(0.047)	(0.044)	(0.046)
NPL (%)	-0.233	-0.160	-0.255	-0.138	0.0753	0.151	0.203	0.158
	(0.353)	(0.304)	(0.362)	(0.294)	(0.330)	(0.237)	(0.221)	(0.212)
Efficiency (%)	0.065	0.047	0.068	-0.018	0.252*	0.243	0.310**	0.282*
	(0.199)	(0.200)	(0.190)	(0.204)	(0.150)	(0.149)	(0.147)	(0.146)
Liquidity (%)	0.020	0.007	0.007	-0.026	0.122***	0.066***	0.063***	0.064**
	(0.020)	(0.019)	(0.019)	(0.027)	(0.027)	(0.020)	(0.019)	(0.026)
Intangible (%)	0.293	0.297*	0.293*	0.271	0.548***	0.495***	0.522***	0.548***
	(0.181)	(0.180)	(0.178)	(0.177)	(0.169)	(0.150)	(0.160)	(0.168)
Capitalization (%)	-0.457***	-0.410***	-0.466***	-0.390**	-0.165	-0.085	-0.174	-0.163
	(0.160)	(0.157)	(0.157)	(0.152)	(0.109)	(0.097)	(0.108)	(0.114)
IT_Expenditure (%)	0.053	0.060	0.052	0.069	0.122*	0.132**	0.106*	0.089
	(0.060)	(0.059)	(0.059)	(0.058)	(0.074)	(0.063)	(0.061)	(0.060)
GDP_Growth (%)	0.011	0.012	0.013	0.012	-0.234	-0.226	-0.209	-0.218
	(0.086)	(0.086)	(0.086)	(0.086)	(0.169)	(0.169)	(0.166)	(0.167)
Interest_Rate (ln)	-4.005	-4.035	-4.048	-4.276	0.634	-0.067	0.240	0.111
	(4.696)	(4.694)	(4.705)	(4.765)	(6.653)	(6.596)	(6.556)	(6.576)
N	250,182	250,182	250,182	250,182	185,645	170,240	132,759	185,645
Number of banks	9273	9273	9273	9273	7304	6556	5293	7304

Note: This table shows the logistic regression results for the two dependent dummy variables: *Payment&Settlements* and *DataAnalytics*, which are shown in two panels: A and B. Each dummy variable takes the value 1 if the bank acquired a fintech firm of the corresponding type, and 0 otherwise. The analysis period is from 2005Q1 to 2021Q4. Table 12 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

Panel B of the same table shows the findings pertaining to data analytics fintech firms. The results demonstrate that diversified banks exhibit a greater propensity to acquire data analytics firms when compared to other business models, as indicated by a positive and statistically significant coefficient. This outcome underscores the significance attributed by diversified banks to integrating technology-enabled perks, such as cashback, loyalty, rewards, and benefits applications, into their financial products. These additions are anticipated to create opportunities for customer retention and attraction. Notably, the study omits the results for wholesale and traditional banking entities since they did not engage in any data analytics deals during the research period. Consistent with previous observations, we ascertain that larger banks are more inclined to engage in transactions involving data analytics fintech firms. Similarly, banks with higher liquidity, lower efficiency, and advanced technology (as measured by both bank intangibles and IT expenditure) exhibit an increased likelihood of acquiring data analytics firms.

Panel C of Table 20 displays the outcome related to lending fintech firms. Diversified banks exhibit positive and statistically significant coefficient at the 5% level, indicating a higher likelihood of acquiring lending firms compared to other business models. This inclination is attributed to their position as the second largest issuers of loans to consumers and banks, motivating them to consider lending technology acquisitions, such as digital lending platforms and financing/leasing services, as a means to stay relevant in the dynamic lending industry. Conversely, wholesale banks show a negative coefficient, indicating a lower propensity for acquiring lending firms compared to other business models. This can be attributed to their focus on major financial institutions and governmental organizations, which may not find digital lending beneficial. Surprisingly, traditional banks did not engage in any acquisitions of lending firms. This seemingly counter-intuitive observation may be explained by their preference for collaborating with fintech companies instead of outright acquisitions, as it is perceived as a less risky strategy, allowing them to swiftly and easily harness the advantages offered by fintech firms, as opposed to internal development (Klus et al., 2019). The positive coefficient for the investment banking business model can be attributed to certain investment banks viewing the online consumer lending market as a promising opportunity for revenue diversification, as noted by one of the investment banks in our sample following the acquisition of an online lending fintech firm. Additionally, we find that larger, more profitable, and more liquid banks are more disposed towards conducting fintech acquisitions of lending firms.

Table 20: Further Analysis: Types of Fintech Firms (2)

	Panel C: Lending Firms				Panel D: Investment Services Firms			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Diversified Banking	1.438**				-0.525			
	(0.658)				(0.866)			
Wholesale Banking		-0.895				-0.838		
		(0.685)				(0.916)		
Traditional Banking			0				-0.793	
			(0)				(1.232)	
Investment Banking				1.038				3.320***
				(1.024)				(0.963)
Size (ln)	2.127***	1.986***	1.970***	1.896***	0	0	0	0
	(0.399)	(0.378)	(0.388)	(0.378)	(0)	(0)	(0)	(0)
ROE (%)	0.133**	0.127**	0.106**	0.114**	-0.066	-0.058	-0.069	-0.075
	(0.054)	(0.057)	(0.052)	(0.055)	(0.052)	(0.053)	(0.052)	(0.063)
NPL (%)	0.089	0.096	0.106	0.105	-0.453	-0.538	-0.619	-0.447
	(0.171)	(0.151)	(0.174)	(0.151)	(0.499)	(0.532)	(0.550)	(0.476)
Efficiency (%)	-0.246	-0.218	-0.197	-0.218	-0.074	-0.102	-0.138	-0.275
	(0.213)	(0.209)	(0.209)	(0.216)	(0.226)	(0.231)	(0.236)	(0.267)
Liquidity (%)	0.043**	0.024	0.025	0.008	0.034**	0.035**	0.034**	-0.036
	(0.021)	(0.020)	(0.020)	(0.027)	(0.016)	(0.016)	(0.015)	(0.027)
Intangible (%)	-0.003	0.059	0.054	0.081	0.035	0.007	-0.037	-0.128
	(0.153)	(0.141)	(0.143)	(0.136)	(0.134)	(0.134)	(0.140)	(0.132)
Capitalization (%)	0.025	0.027	-0.019	0.005	-0.087	-0.071	-0.089	-0.055
	(0.082)	(0.076)	(0.081)	(0.073)	(0.076)	(0.078)	(0.076)	(0.071)
IT_Expenditure (%)	0.016	0.028	0.021	0.035	-0.196	-0.211	-0.229	-0.147
	(0.069)	(0.064)	(0.065)	(0.064)	(0.153)	(0.159)	(0.160)	(0.161)
GDP_Growth (%)	-0.045	-0.038	-0.040	-0.037	0.089	0.076	0.080	0.075
	(0.112)	(0.111)	(0.111)	(0.111)	(0.124)	(0.124)	(0.124)	(0.127)
Interest_Rate (ln)	-3.851	-3.733	-3.837	-3.801	2.909	2.726	2.947	2.507
	(6.236)	(6.223)	(6.292)	(6.268)	(4.695)	(4.702)	(4.752)	(4.850)
N	216,620	216,620	155,371	216,620	2890	2890	2890	2890
Number of banks	7537	7537	5496	7537	133	133	133	133

Note: This table shows the logistic regression results for the two dependent dummy variables: *Lending*, and *InvestmentServices*, which are shown in two panels: C and D. Each dummy variable takes the value 1 if the bank acquired a fintech firm of the corresponding type, and 0 otherwise. The analysis period is from 2005Q1 to 2021Q4. Table 12 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

Panel D findings of the same table indicate that investment banking business models exhibit a higher propensity to acquire fintech companies offering investment services, in contrast to other banking business models. Acquiring firms specializing in investment advisory services, wealth management, and trading platforms appears to be a strategic move, commonly pursued by specialist business models like investment banks. This assertion is reinforced by the negative coefficients observed for other business models, implying their lower likelihood of acquiring investment fintech firms. It is plausible that alternative business models may opt for collaborations with such fintech firms, accessing the required technology through financial investments instead.[20] Also, results suggest that more liquid banks are more likely to conduct acquisition of investment services firms.

Finally, in Panel E of Table 21, we present the regression results for financial services software fintech firms. Diversified banks exhibit a positive and significant relationship, possibly owing to the diverse nature of their clientele. With 12 deals, diversified banks integrate financial software technology, such as financial security and safety applications, along with consumer online banking services, into their financial products. Conversely, wholesale banks engaged in only 1 deal for financial software showing limited interest in this type of fintech firms, as indicated by the negative and significant coefficient. Upon checking the details of this deal we find that it is specifically related to money transfer technology. Furthermore, the negative coefficient observed for traditional banking may reflect their risk-averse acquisition strategy, as they prefer collaborating with venture fintech companies as a less risky alternative. For investment banks, the negative coefficient suggests a lack of interest in acquiring financial technology software companies; instead, they may be more

[20]Bank size was omitted from the regression due to the application of our winsorizing method, which resulted in similar size levels for all banks acquiring 16 investment services firms (all classified as large banks above the 99% level). As a consequence, the variable *Size* was omitted from the regression, as positive values (i.e., 16.85) perfectly predicted failure. However, upon replacing the winsorized data with the original dataset and rerunning the regression, consistent with Panel D results, positive and significant coefficients were observed for bank size.

inclined to acquire other fintech firms offering distinct technological advances in different business areas. Additionally, we find that larger and more liquid banks are more likely to engage in acquisitions of these types of fintech firms.

Table 21: Further Analysis: Types of Fintech Firms (3)

	Panel E: Financial Services Software Firms			
	(1)	(2)	(3)	(4)
Diversified Banking	1.500** (0.684)			
Wholesale Banking		-1.803* (1.044)		
Traditional Banking			-0.400 (0.779)	
Investment Banking				-0.00820 (1.035)
Size (ln)	1.391*** (0.211)	1.329*** (0.199)	1.263*** (0.199)	1.265*** (0.199)
ROE (%)	-0.003 (0.063)	-0.005 (0.063)	-0.013 (0.057)	-0.013 (0.056)
NPL (%)	-0.443 (0.362)	-0.323 (0.330)	-0.364 (0.324)	-0.347 (0.318)
Efficiency (%)	-0.449 (0.334)	-0.430 (0.324)	-0.376 (0.307)	-0.358 (0.305)
Liquidity (%)	0.047** (0.020)	0.026 (0.018)	0.030* (0.018)	0.030 (0.022)
Intangible (%)	-0.009 (0.147)	0.029 (0.136)	0.055 (0.138)	0.065 (0.137)
Capitalization (%)	-0.002 (0.078)	-0.001 (0.074)	-0.027 (0.076)	-0.025 (0.076)
IT_Expenditure (%)	-0.006 (0.076)	0.011 (0.074)	-0.001 (0.070)	-0.001 (0.070)
GDP_Growth (%)	-0.119 (0.149)	-0.116 (0.148)	-0.113 (0.147)	-0.112 (0.147)
Interest_Rate (ln)	-8.209 (5.617)	-8.045 (5.577)	-8.019 (5.546)	-7.954 (5.524)
N	300,961	300,961	300,961	300,961
Number of banks	9196	9196	9196	9196

Note: This table shows the logistic regression results for the dependent dummy variable: $FinancialServicesSoftware$ which takes the value of 1 if the bank acquired a fintech firm that provides financial services software, and 0 otherwise. The analysis period is from 2005Q1 to 2021Q4. Table 12 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

3.4.4 Further Analysis: Why Do Banks Acquire Fintech Firms?

We further provide an empirical analysis of the motives of banks to acquire fintech firms. Little research has been conducted to investigate the motivations of alliance between both fintech firms and banks (e.g., Klus et al., 2019). On the one hand, fintech firms earn public trust, expand their client base, and exploit synergies. Banks, on the other hand, view collaboration with fintech firms as a method to increase innovation, promote digitalization, and gain a competitive edge. Bömer and Maxin (2018) analyze the motives of fintech firms to cooperate with banks in the German market. They find that fintech firms gain easier market entry, increased revenue, and broader innovative products. In this analysis, we aim to empirically examine the influence of banking business models on bank motivation to acquire fintech firms. To this end, we use Equation 3 to examine the likelihood of banks acquiring fintech firms based on the bank motive behind the acquisition deal. In particular, we estimate four models each with a dependent dummy variable representing one of the four motives fintech firms acquired by banks.[21]

The regression results are presented in Tables 22 and 23. Panel A of Table 22 presents some notable observations regarding the effects of banking business models on fintech acquisitions with the motive to provide new products. The results indicate that investment banks are more inclined than other business models to utilize fintech acquisitions for the purpose of introducing innovative products to the market. The positive and statistically significant coefficient highlights the relevance of fintech acquisitions in supporting investment banks toward the creation of innovative products. Although not statistically significant, diversified banks show a positive coefficient. 20 deals were conducted by diversified banks, potentially owing to the capacity of investment and diversified business models to tolerate

[21] Please see 3.3.4 for further information on the methodology used to classify bank-fintech acquisitions in our sample. In addition, Table 10 presents the motives of banks to acquire fintech firms.

the additional risks associated with acquiring fintech firms and launching new products, both of which are regarded as risky strategies. During the sample period, wholesale banks completed four transactions aimed at introducing new products, indicating limited interest in fintech acquisitions for this purpose. Traditional banks, meanwhile, did not utilize fintech acquisitions to introduce new products. Additionally, the findings indicate that larger banks with higher liquidity are more likely to acquire fintech firms to launch new products.

Moreover, panel B of Table 22 show positive coefficients for both diversified banks and investment banks, albeit statistically insignificant. This highlights the relevance of fintech acquisitions in fostering in-house fintech capabilities for diversified and investment banks. Conversely, wholesale and traditional banking display negative coefficients, suggesting their lower likelihood, compared to other business models, of acquiring fintech firms to enhance internal technological capabilities. This finding supports the argument that wholesale and traditional banks are hesitant to undertake additional risk through fintech acquisitions if it does not align with their core business, which may not heavily rely on the latest technological advancements. As for the control variables, we find that larger and more liquid banks are more inclined to acquire fintech firms to enhance their technical capabilities, while higher capitalized banks have a lower propensity to acquire fintech firms for the same purpose.

The results for business scalability motivation are presented in Panel C of Table 23. It should be noted that the targeted market of each business model influences both the growth strategy and its execution. Similar to Panel B of Table 22, no banking business model exhibits statistically significant indications. However, diversified banks show positive coefficient. This suggests that banks with this business model are attracted to expansion strategies that involve the risky acquisition of financial technology firms. This inclination may be supported by their capacity to undertake additional risks, as evidenced by diversified banks completing 14 deals for growth purposes in the period under study. On the contrary,

Table 22: Further Analysis: Motives of Banks (1)

	Panel A: Introducing New Products				Panel B: Enhancing Capabilities			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Diversified Banking	0.678				1.195			
	(0.452)				(0.524)			
Wholesale Banking		-0.838				-2.168		
		(0.555)				(1.023)		
Traditional Banking			0				-0.928	
			(0)				0.763	
Investment Banking				1.747***				1.308
				(0.613)				0.812
Size (ln)	1.740***	1.708***	1.688***	1.598***	1.790***	1.786***	1.715***	1.740***
	(0.227)	(0.220)	(0.224)	(0.221)	(0.250)	(0.246)	(0.250)	(0.265)
ROE (%)	-0.001	0.001	-0.013	-0.008	-0.038	-0.040	-0.041	-0.044
	(0.040)	(0.040)	(0.040)	(0.042)	(0.041)	(0.042)	(0.039)	(0.040)
NPL (%)	-0.516	-0.421	-0.529	-0.317	-0.051	0.002	-0.045	-0.010
	(0.351)	(0.331)	(0.349)	(0.310)	(0.187)	(0.160)	(0.176)	(0.161)
Efficiency (%)	0.069	0.066	0.071	0.029	-0.214	-0.207	-0.170	-0.180
	(0.113)	(0.114)	(0.113)	(0.124)	(0.203)	(0.196)	(0.197)	(0.198)
Liquidity (%)	0.058***	0.048***	0.048***	0.018	0.050**	0.032**	0.032**	0.008
	(0.013)	(0.019)	(0.011)	(0.017)	(0.016)	(0.015)	(0.015)	(0.023)
Intangible (%)	0.135	0.135	0.113	0.108	0.160	0.186	0.150	0.153
	(0.099)	(0.096)	(0.097)	(0.092)	(0.138)	(0.127)	(0.131)	(0.127)
Capitalization (%)	-0.067	-0.059	-0.085	-0.055	-0.231**	-0.174*	-0.228**	-0.182**
	(0.060)	(0.058)	(0.058)	(0.054)	(0.104)	(0.093)	(0.099)	(0.092)
IT_Expenditure (%)	0.039	0.049	0.037	0.062	0.035	0.054	0.034	0.052
	(0.047)	(0.047)	(0.046)	(0.046)	(0.055)	(0.051)	(0.052)	(0.052)
GDP_Growth (%)	-0.001	-0.001	0.001	0.001	-0.119	-0.114	-0.112	-0.109
	(0.079)	(0.079)	(0.079)	(0.079)	(0.108)	(0.107)	(0.107)	(0.107)
Interest_Rate (ln)	0.030	0.017	-0.021	-0.047	-6.029	-5.880	-5.587	-5.680
	(3.538)	(3.547)	(3.567)	(3.619)	(5.646)	(5.556)	(5.568)	(5.575)
N	250,672	250,672	181,638	250,672	265,927	265,927	265,927	265,927
Number of banks	9278	9278	6939	9278	9272	9272	9272	9272

Note: This table shows the logistic regression results for the two dependent dummy variables: *NewProducts* and *EnhancingCapabilities*, which are shown in two panels: A and B. Each dummy variable takes the value 1 if the bank's strategic aim behind the fintech acquisition is the corresponding motivation, and 0 otherwise. The analysis period is from 2005Q1 to 2021Q4. Table 12 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

wholesale, traditional and investment banking business models are less likely to employ fintech acquisitions as a means of expanding their businesses. This does not necessarily imply a lack of interest in business growth for these models, but rather a greater propensity to adopt alternative methods to achieve the same objective. Furthermore, we find that larger banks, more profitable and more active in technology development are more inclined to seek fintech acquisitions for the purpose of growth. Moreover, our results show a negative and statistically significant (at the 10% level) relationship between interest rates and fintech acquisitions. Higher interest rates may indicate tighter monetary conditions and lower economic growth, which deter banks from acquiring financial technology firms for expansion purposes.

Finally, Panel D of Table 23 presents the regression results of bank-fintech acquisitions with the aim of entering new markets. Banks pursue entry into new markets for various reasons, such as seeking higher profits, diversifying risks, and exploring growth opportunities. Among the four banking business models, investment banking displays a positive and significant coefficient, indicating that fintech acquisitions serve as an effective tool for investment banks to expand into new markets. Notably, investment banks that acquired fintech firms are the largest in terms of total assets ($Size$), which may explain their inclination towards exploring new markets. While not statistically significant, the positive coefficient observed for diversified banking suggests that fintech acquisition serves as a risk diversification strategy for these banks, introducing them to new markets with the potential for growth and attracting new clients. Conversely, both wholesale and traditional business models did not engage in fintech acquisitions to enter new markets. Consistent with previous findings, larger banks are more likely to acquire fintech companies as a means of expanding into new markets.

Table 23: Further Analysis: Motives of Banks (2)

	Panel C: Business Scalability				Panel D: Entering New Markets			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Diversified Banking	0.770				0.648			
	(0.547)				(1.316)			
Wholesale Banking		-0.807				0		
		(0.670)				(0)		
Traditional Banking			-0.316				0	
			(0.770)				(0)	
Investment Banking				-0.023				4.630**
				(1.035)				(2.018)
Size (ln)	1.497***	1.472***	1.419***	1.419***	1.443***	1.422***	1.386***	1.189**
	(0.248)	(0.242)	(0.239)	(0.239)	(0.519)	(0.480)	(0.521)	(0.523)
ROE (%)	0.110**	0.113**	0.099**	0.099**	0.088	0.143	0.084	0.163
	(0.051)	(0.051)	(0.048)	(0.049)	(0.108)	(0.128)	(0.109)	(0.140)
NPL (%)	-0.203	-0.148	-0.168	-0.154	0.020	0.056	0.089	0.117
	(0.297)	(0.271)	(0.274)	(0.266)	(0.488)	(0.395)	(0.539)	(0.337)
Efficiency (%)	-0.119	-0.138	-0.096	-0.089	-0.104	-0.209	-0.121	-0.493
	(0.204)	(0.206)	(0.193)	(0.198)	(0.366)	(0.396)	(0.380)	(0.527)
Liquidity (%)	0.013	0.001	0.004	0.004	0.054	0.044	0.045	-0.042
	(0.022)	(0.021)	(0.021)	(0.026)	(0.036)	(0.036)	(0.033)	(0.062)
Intangible (%)	0.270*	0.268*	0.305**	0.310**	0.085	0.086	0.085	0.029
	(0.151)	(0.145)	(0.145)	(0.145)	(0.295)	(0.287)	(0.286)	(0.251)
Capitalization (%)	-0.149	-0.131	-0.170	-0.166	0.025	0.067	0.002	0.052
	(0.114)	(0.110)	(0.110)	(0.109)	(0.149)	(0.109)	(0.151)	(0.070)
IT_Expenditure (%)	-0.0805	-0.0731	-0.0722	-0.0720	-0.0866	-0.0726	-0.0830	0.0150
	(0.086)	(0.084)	(0.083)	(0.083)	(0.177)	(0.179)	(0.175)	(0.169)
GDP_Growth (%)	-0.046	-0.044	-0.042	-0.041	-3.057	-3.234	-2.983	-2.938
	(0.092)	(0.092)	(0.091)	(0.091)	(3.673)	(3.751)	(3.650)	(3.645)
Interest_Rate (ln)	-11.72*	-11.72*	-11.73*	-11.71*	-7.023	-6.120	-6.972	-6.546
	(6.371)	(6.353)	(6.379)	(6.370)	(14.77)	(14.36)	(14.78)	(14.81)
N	332,446	332,446	332,446	332,446	43,819	40,411	31,212	43,819
Number of banks	9279	9279	9279	9279	5837	5366	4169	5837

Note: This table shows the logistic regression results for the two dependent dummy variables: $BusinessScalability$ and $NewMarkets$, which are shown in two panels: C and D. Each dummy variable takes the value 1 if the bank's strategic aim behind the fintech acquisition is the corresponding motivation, and 0 otherwise. The analysis period is from 2005Q1 to 2021Q4. Table 12 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

3.5 Conclusion

In this chapter, we empirically examine the role of the banking business models in the bank decisions related to fintech acquisitions. We employ a unique sample of US bank-fintech acquisitions over a period of 17 years between 2005Q1 and 2021Q4.

We present four main findings. Firstly, our analysis reveals that US banks can be classified into four distinct business models: diversified, wholesale, traditional, and investment. Among these, slightly more than half of the US bank sample falls under the category of diversified business models, characterized by a mixed asset structure with features from both traditional banking and investment activities. Additionally, we demonstrate that US banks adopting a wholesale business model actively participate in the interbank market, as evidenced by their higher average bank loan ratio compared to other business models. The second most prevalent business model among US banks in our sample is the traditional banking model, comprising banks primarily reliant on core deposits and loans offered to consumers. Lastly, the investment business model encompasses banks with significant involvement in investment activities and a dependence on short-term deposits and repurchase agreements.

Secondly, we find evidence on the significant role of banking business models in explaining bank-fintech acquisitions. For instance, we demonstrate that diversified banks are more inclined to acquire fintech firms compared to other banks indicating that the adoption of a diversified banking business model does not necessarily lower bank risk-taking (i.e., fintech acquisitions). We contend that diversified banks derive benefits from their diverse asset, funding, and income structures, providing them with the flexibility to embrace greater risks in the form of fintech acquisitions. Furthermore, our empirical analysis reveals that banks with a wholesale business model are less likely to engage in fintech acquisitions. We posit that wholesale banking exhibits lower risk-taking tendencies compared to other business models, possibly influenced by the monitoring activities of large financiers, which in turn have significant power to influence bank decisions. Moreover, our findings indicate that banks with traditional banking business models are less likely to acquire fintech companies. This is likely a result of their risk-averse strategy, which favors collaboration with fintech firms as a safer alternative. Conversely, the investment banking business model exhibits a selective approach in acquiring fintech firms. This selectivity may be attributed to the maturity and development of banks in this group relative to banks operating under other business models.

Thirdly, we contribute novel insights concerning the specific types of fintech firms that banks target for acquisition. Through our analysis, we identify five distinct categories of fintech firms: payment & settlements, data analytics, lending, financial services software, and investment services. Notably, empirical evidence highlights the propensity of diversified banks to engage in acquisitions of fintech firms specializing in data analytics, lending, and financial software services, setting them apart from other banking business models. This underscores diversified banks' strategic approach toward income and investment diversification. On the other hand, wholesale bank exhibit a lack of interest in acquiring fintech firms of any kind which is likely due to their pronounced focus on large financial institutions and governmental entities. Furthermore, the preferences of traditional banks indicate that they are less likely to venture into fintech acquisitions which are aligned with the proposition that they favor less risky alternatives to acquisitions. Interestingly, the results pertaining to the investment banking business model demonstrate their keen interest in acquiring fintech firms specializing in investment services. This inclination may be attributed to the nature of innovative investment services, which aligns with the core expertise and capabilities of investment banks, making them particularly suited to provide such niche services. Investment banks are also more likely to acquire paytech firms, which might be attributed to the strategic alignment between the disruptive nature of payment technology firms and investment banks' focus on innovation-driven initiatives.

Our fourth and final main result delves into the motivations driving banks to acquire fintech firms. We categorize bank motivations into four distinct areas: introducing new products, enhancing capabilities, pursuing business scalability, and entering new markets. Our empirical analysis reveals compelling evidence of investment banks' tendency to employ fintech acquisitions strategically to both introducing new products and facilitating their entry into new markets. This strategic inclination aligns with their larger size and extensive experience in navigating diverse market landscapes and creation of innovative products. Moreover, our analysis uncovers that diversified banks show no statistically significant inclination towards a specific aim. Conversely, our findings demonstrate that banks adopting a wholesale banking business model exhibit a reduced likelihood of acquiring fintech firms to enhance in-house fintech capabilities. This hesitation is likely to be stemmed from their reluctance to undertake additional risks if such acquisitions do not directly align with their core business activities. Their cautious approach reflects a preference for maintaining stability and preserving the status quo. Furthermore, the results pertaining to traditional banks reaffirm their risk-averse strategy regarding fintech acquisitions. Traditional banks, accustomed to more conservative practices, may prefer alternative approaches to accessing fintech expertise rather than direct acquisitions.

Overall, the outcomes of this chapter bear significant relevance to policymakers and supervisors, offering valuable insights into the role of banking business models in explaining bank-fintech partnerships. The research sheds light on the factors influencing banks' decisions to acquire various types of fintech firms, providing crucial knowledge for designing policies that facilitate mutually beneficial collaborations between banks and fintech entities. Our findings regarding the diverse impact of banking business models on the decision to acquire fintech firms underscore the necessity for a comprehensive evaluation of banks' strategic choices by banking supervisors rather than relying on isolated indicators that may yield misleading conclusions. It is essential to recognize that banks' risk-taking behavior and their propensity to acquire and collaborate with innovative firms are intricately influenced by the complexity of their structures, encompassing asset composition, funding sources, and income streams. In light of these findings, formulating efficient and targeted policies and regulations demands a nuanced understanding of bank structures to effectively address the dynamics of bank-fintech partnerships. An in-depth comprehension of banks' motivations and preferences for specific types of fintech firms can foster a more informed regulatory approach that supports innovation while safeguarding financial stability.

Chapter 4: Examining the Impact of Bank-Fintech Equity Investment on Bank Innovation

Examining the Impact of Bank-Fintech Equity Investment on Bank Innovation

Abstract

By analyzing a unique dataset on bank-fintech equity funding rounds, we find that greater bank investments in fintech firms are associated with more bank innovation capabilities. The positive impact on bank innovation holds even when considering only the initial bank-fintech investment. Furthermore, our analysis shows a tendency among US banks to invest more in US fintech firms compared with foreign ones. Such inclination to invest in domestic fintech ventures might be warranted as evident by the increased bank innovation output. Our findings carry significant implications for policymakers, bank executives, and entrepreneurs alike.

JEL Classification: G21, G34, O31

Keywords: Banks, Fintech, Investment, Innovation

4 Examining the Impact of Bank-Fintech Equity Investment on Bank Innovation

4.1 Introduction

Financial technology (fintech) startups provide innovative ways to perform traditional financial services. As a result, many banks have actively participated, either directly or indirectly, in recent years in the equity funding rounds of fintech firms. In 2021, U.S. Bank announced its ownership stake in two venture capital firms that specialize in fintech startups (U.S. Bank, 2021). The bank has noted in its announcement that these partnerships enable it to obtain necessary innovations without undergoing the lengthy, risky, and challenging process of creating technology from scratch. Additionally, Live Oak Bank has established a venture capital company named Canapi Inc., which aims to invest in and collaborate with fintech startups that provide banks with innovative platforms (Callison, 2019). Many banks are also seeking to foster their innovation with larger capital injections through equity ownership in fintech firms (Drasch et al., 2018). Such investment in innovation, whether done directly by the bank or indirectly through a venture capital firm that the bank owns, might also help to modernize the bank's product suite. For example, in a recent study, Babina et al. (2024) highlight how JP Morgan's investment in innovation has enabled it to integrate artificial intelligence (AI) technologies in its core product line. Perhaps most importantly, such investments enable banks to establish partnerships with competitors that may have contributed to the debranching of these banks (Yuan et al., 2023).

Bank investments in fintech firms can have far-reaching economic significance. As Navaretti et al. (2017) note, fintech firms have the technological innovation required to perform bank's traditional activities in a more efficient way. For example, payment Fintech firms can support banks in managing their non-interest expenses by implementing new payroll and payment processing solutions. Kwon et al. (2024) provide additional evidence to this argument as they empirically show that less efficient banks may improve their cost efficiency through the acquisition of new technologies facilitated by the acquisition/investment of fintech firms. Furthermore, fintech solutions can foster financial inclusion. For example, Demir et al. (2022) highlight that fintech firms, particularly those in the mobile financial services sector, have the necessary technological advancement to develop products that effectively reach underserved populations, ultimately increasing financial inclusion. We argue that partnering with banks through equity investment can further strengthen this impact. By combining the technological advancement of fintech firms with the financial resources, financial infrastructure, and regulatory expertise of traditional banks, such collaboration can ensure that financial products are more accessible to unbanked and underbanked populations.

Against this background, we examine the effect of banks' participation in equity investment rounds conducted by fintech startups on bank innovation. Although there has been increased attention in recent years to analyzing bank-fintech collaboration (Kwon et al. 2024; Li et al. 2023; Bellardini et al. 2022; Hornuf et al. 2021; Del Gaudio et al. 2024), little is known regarding the impact of such collaboration on bank innovation. Zheng and Mao (2024) briefly consider this issue. However, they mainly focus on the short-term market reaction to fintech mergers and acquisitions (M&As) for three types of acquirers including U.S. public banks, nonbank financial institutions, and tech companies, with a sample that includes 14 banks only. Little attention is paid to the effect of investing in fintech funding rounds on bank innovation. In contrast, this chapter offers a more focused analysis by using a comprehensive sample of banks to investigate the impact of bank investment (both minority and majority) in fintech equity funding rounds on bank innovation.

Bank-fintech collaboration happens in several forms including acquisitions, alliances, incubation, and joint ventures (Drasch et al., 2018). Carlini et al. (2022) argue that the most effective type of collaboration between banks and fintech firms is equity investment, which may be regarded as a control-oriented innovation strategy. Such strategic initiative enables banks to align the services and products of fintech firms with their own through board position (Hornuf et al., 2021). However, scholars have identified several challenges that prevent banks from effectively exploiting collaboration with fintech firms. These include strategic misalignment (Riikkinen and Pihlajamaa, 2022), regulatory landscape (Hornuf et al., 2021), considering fintech firms as vendors (Meinert, 2017), and agency costs (Stulz, 2019).

In this chapter, we regard bank innovation as financial innovation and use both concepts interchangeably (Pi and Yang, 2023). We measure bank innovation through two indicators: trademark and patent applications filed by the bank. We then link these measures to Crunchbase database, which offers details on the investment activity of US banks in equity funding rounds of fintech startups from 2005Q1 to 2023Q4. A dynamic system GMM framework is used to conduct this analysis, enabling us to effectively address numerous econometric issues including endogeneity. Our result provides compelling evidence that participating in fintech equity investment rounds positively impacts the number of trademark and patent applications by banks. This result holds when we limit the involvement of banks to the initial investment done in every fintech funding round.

The findings pass a battery of robustness checks. First, we conduct a falsification test to provide validity to our main result. Through swapping the chapter's main explanatory variables with the dependent variables, we are able to empirically eliminate the possible alternative explanation that banks with more innovative capabilities may be more motivated to participate in investment rounds conducted by fintech firms. Second, we use bank intangible assets as an alternative measure of bank innovation. Similarly, the results of this test provide additional support to our main finding.

This chapter offers several noteworthy contributions to the existing literature. Through the analysis of a comprehensive data from Crunchbase, this chapter provides valuable insights by identifying US banks' strategic equity investment in fintech firms. We then link these investment activities to bank innovation, as measured by the number of trademark and patent applications. By collecting and analyzing this data, we are able to make another significant contribution through enriching the literature on bank financial innovation (Beck et al. 2016; Wu et al. 2024; Zhang et al. 2023; Wu et al. 2023) from the unique perspective of bank-fintech collaboration. We provide empirical evidence to support the argument that through equity investment, banks may exert influence on the direction of fintech firm's innovation business that aligns with that of the bank (Hornuf et al., 2021). Furthermore, Carlini et al. (2022) argue that bank-fintech equity investment can be considered as a control-oriented innovation strategy for banks, which enable them to be involved in modern financial technology developments. Our result differs from that of Zheng and Mao (2024) who find that the acquisition of fintech firms by banks does not significantly affect bank innovation. The discrepancies might be attributed to variations in the study's empirical design, as well as its focus on the effects of bank-fintech acquisitions. Moreover, their study is based on a small sample size of 14 US banks, which limits the ability to generalize the findings to a wide range of various banking institutions.

Furthermore, we make a contribution to the home bias literature (Solnik and Zuo 2017; Levis et al. 2016). Our analysis indicates the tendency of US banks to participate more in funding rounds conducted by domestic fintech firms. This in turn has exerted a positive impact on bank innovation through an increased number of trademark and patent applications. Our result may provide a rationale for banks' inclination to prioritize investments in domestic fintech firms, while potentially missing out on several advantages. For example, prior research focusing on bank-fintech home bias behavior indicates that a bank's tendency to favor local investments may limit its ability to innovate and result in missed opportunities (Del Gaudio et al., 2024).

The rest of this chapter proceeds as follows: Section 4.2 overviews the chapter's theoretical background and introduces its hypothesis. Section 4.3 discusses the sample selection process, analyzes the bank-fintech investment rounds, previews the chapter's variables, and presents the econometric model used for the main analysis. Section 4.4 presents the chapter's results, robustness checks, and additional analysis. Section 4.5 concludes the chapter and provides the implications for stakeholders in light of chapter's findings, and highlights avenues for future academic inquiries.

4.2 Theoretical Background and Hypothesis Development

This section sets the conceptual foundation for this chapter. First, it provides an overview of innovation, with an emphasis on financial innovation within banking institutions. Second, it narrows the focus on banks' interactions with financial technology firms. Third and finally, it presents the chapter's hypothesis.

4.2.1 Bank Innovation

Innovation is the creative application of technologies, processes, or ideas to achieve objectives (Horn, 2015). Previous research has contributed to the development of a theoretical framework for understanding the dynamics of firm innovation and its interaction with acquisition activities (Hitt et al. 1996; Ahuja and Katila 2001), organizational structure (Koberg et al., 1996), technological strategy (Beneito, 2003), and external cooperation (Freel, 2003), among other factors. At its core, tangible innovation requires a series of internal research and development (R&D) commitment, together with the use of external knowledge sources (Roper et al., 2008).

Although banks have recently increased their involvement in financial technology, either through the acquisition of fintech firms (Kwon et al. 2024; Collevecchio et al. 2023; Zheng and Mao 2024; Cappa et al. 2022; Kueschnig and Schertler 2024), or equity investment in fintech firms (Del Gaudio et al. 2024; Li et al. 2023; Bellardini et al. 2022; Carlini et al. 2022), the empirical research conducted to examine the impact of this engagement on banks' innovation capabilities remains sparse. Part of this might be attributed to difficulties in quantifying bank financial innovation, which has posed significant challenges to scholars attempting to measure it, particularly because of the ambiguity surrounding its definition and lack of available data (Frame and White, 2004).

For the purpose of this study, we follow Pi and Yang (2023) and refer to bank innovation as financial innovation. Frame and White (2004) defines financial innovation as the combination of several activities that include the introduction of new products, new production processes, and new organizational structures. Researchers in the banking literature have creatively used various metrics to quantify bank innovation. These include, bank off-balance sheet activities (Beck et al. 2016; Chortareas et al. 2009; Lozano-Vivas and Pasiouras 2014; Lee et al. 2020), research and development (R&D) expenses (Beck et al. 2016; Lee et al. 2020), IT expenditure (Kwon et al. 2024; Beccalli 2007; Shu and Strassmann 2005; Licht and Moch 1999), intangible assets (Collevecchio et al. 2023; Ayadi et al. 2021; Cao et al. 2022), trademarks (Duygun et al. 2013; González-Pedraz and Mayordomo 2012), patents (Zheng and Mao 2024; Liu and Li 2024; Zhao et al. 2022; Tan et al. 2023), securitization (Beck et al. 2016; González et al. 2016; Allen and Carletti 2006), and textual analysis of bank annual reports (Wu et al. 2023; Guo and Zhang 2023; Zhang et al. 2023). Moreover, Bos et al. (2013) provide an excellent overview of early empirical works that aimed to investigate innovation within the US banking sector.

In this chapter, we measure bank financial innovation through trademarks and patents. Even though trademarks and patents are examples of intellectual property programs that may promote innovation by providing innovators with protection against unauthorized copying by competitors in the market (Frame and White, 2004), they serve a slightly different purposes. Trademarks are associated with the commercialization of a developed product or service, while patents typically applied for in the early stages of the innovation process (Hsu et al., 2022). We argue that the combination of these two indicators provide us with the unique advantage of capturing bank financial innovation. This includes bank product innovation through the expansion of bank financial products, as captured by bank trademarks, as well as the initial development of bank innovative service/product, as captured by bank patents.

A trademark is "any word, phrase, symbol, design, or a combination of these things that identifies your goods or services. It's how customers recognize you in the marketplace and distinguish you from your competitors" (United States Patent and Trademark Office, 2024b). In the US banking industry, Goldman Sachs's digital consumer loan platform, Marcus, is an example of a registered trademark associated with their brand. JP Morgan has recently launched Partior, a new product that provides a blockchain-based wholesale payment network. The bank has also officially registered Partior as a trademark. In related literature, Duygun et al. (2013) and González-Pedraz and Mayordomo (2012) support the notion that trademarks are linked to bank innovation as they represent the commercial aspect of innovation. In light of this, we contend that bank trademarks can be a reliable indicator of bank innovation in this chapter, particularly from the perspective of bank product expansion.

A patent is a legally granted exclusive right that allows the holder to prevent others from producing, using, marketing, or selling an innovation (United States Patent and Trademark Office, 2024a). Wells Fargo's recent filing for a smart contract patent titled "Smart contract blockchain abstraction API" is an example of a patent.[22] Our use of patents as a proxy of bank financial innovation is primarily motivated by the literature. In particular, Lerner et al. (2024) provide compelling evidence through three investigations, each designed to test whether patenting may serve as a reliable indicator of financial innovation. The first test explores the value significance of financial patents, the second test examines the correlation between major financial innovations and patents, and the third test measures the consistency of patenting with the investments in new technologies. Together, these tests support the validity of patents as a measure of bank financial innovation.

4.2.2 Bank-Fintech Collaboration

According to the Schumpeterian theory of innovation, bank funding is essential for innovative entrepreneurs, enabling them the ability to realize their innovation (Akdere and Benli, 2018).[23] In light of this, banks have the capability to not only provide finance to financial entrepreneurs, but also to build partnerships. Bank-fintech collaboration includes several forms of cooperation, including acquisitions, alliances, incubation, and joint ventures (Drasch et al., 2018).[24] Although the existing literature thoroughly examines the

[22]Smart contracts are blockchain-based contractual agreements that eliminate the need for a trusted intermediary (Thakor, 2020).

[23]Bircan and De Haas (2020) present further evidence that bank funding increases a firm's propensity to apply for a patent or trademark in emerging markets, indicating greater firm innovation capabilities.

[24]Drasch et al. (2018) define acquisition as the purchase of a majority stake in the target firm. An alliance is a contractual agreement between the two parties to share resources to achieve common goals. Incubation is the fostering of early-stage startups. A joint venture is a business arrangement in which partners create an independent firm.

influence of fintech development on bank performance (Haddad and Hornuf 2023; Hodula 2024; Zhao et al. 2022; Phan et al. 2020; Scott et al. 2017), bank risk-taking (Banna et al. 2021; Wang et al. 2021a; Cheng and Qu 2020), bank efficiency (Lee et al. 2023; Lee et al. 2021; Wang et al. 2021b), financial inclusion (Demir et al. 2022; Senyo et al. 2022), and economic growth (Bu et al. 2023; Laeven et al. 2015). A significant knowledge gap exists in our understanding of the effects of collaboration between banking institutions and financial technology firms (Choudhary and Thenmozhi 2024; Chernoff and Jagtiani 2023).

Despite the lack of comprehensive documentation on bank-fintech relationship, a limited number of papers have shed light on the two parties' motives to collaborate. For example, Hornuf et al. (2021) find that banks may modernize their product offerings and gain a competitive edge by forming alliances with fintech firms, which allow them to acquire exclusive rights to use specific applications. However, fintech firms pursue collaboration with banks in order to gain easier market access, enhance profitability, and develop new products (Bömer and Maxin, 2018).

The market reaction to bank-fintech collaboration has suggested multiple views. On the one hand, Kueschnig and Schertler (2024) argue that banks have a higher abnormal returns following their first bank-fintech deal, as it may signal the bank's commitment to financial technology. On the other hand, Zheng and Mao (2024) find evidence of a negative reaction, possibly driven by the bank's overestimation of the benefits of collaboration and overlooking the associated costs involved with integration. Similarly, Carlini et al. (2022) document a negative effect and attribute it to market participants perceiving bank-fintech investments as risky and time-consuming in order to turn the investments into profit. Another group of papers have found that market's reaction to bank-fintech M&As depends on specific characteristics such as the type of acquisition or services provided by the fintech firm (Collevecchio et al. 2023; Cappa et al. 2022).

A few other contributions have investigated the determinants of bank-fintech collaboration. Del Gaudio et al. (2024) analyze the composition of banks' board of directors, and find that banks' boards characterized with a high network connections, a female dominance, and younger directors are more inclined to invest in fintech firms' funding rounds. Moreover, Bellardini et al. (2022) show that larger amounts are invested in the bank-fintech collaboration through equity investment if the fintech firm specializes in financial services (fin-native), the funding round is in a later stage, the deal includes other investors, and the bank is large in size. Furthermore, Hornuf et al. (2021) provide findings indicating that fintech firms requiring financial assistance may find larger banks more appropriate to partner with, since these banks have greater interest in investing in financial innovation. While fintech firms seeking growth are encouraged to collaborate with smaller banks that prioritize product collaboration with fintech firms. Additionally, they show that banks that adopt a clear digital strategy and/or appoint a chief digital officer are more inclined to build partnerships with fintech firms.

To sum up, banks have shown growing interest in fintech innovation in recent years, as evident from their involvement in activities such as acquiring fintech firms or participating in investment rounds of fintech startups. However, little is known regarding the impact of bank-fintech collaboration on bank innovation. To fill this significant knowledge gap, we investigate US banks' participation in fintech firms' funding rounds and examine its influence on bank innovation output as measured by the number of bank trademarks and patents.

4.2.3 Hypothesis Development

This chapter analyzes the impact of bank-fintech collaboration, specifically through equity investment channel, on bank innovation capabilities. Two points of views are discussed in this regard. On the one hand, Carlini et al. (2022) argue that bank-fintech equity investment can be regarded as a control-oriented innovation strategy formulated by banks to get involved with the latest technology. They further outline that the closest connection between the two parties is formed through equity investment. Such investment by banks may grant them with unique advantages. For example, through equity investment in fintech firms, banks may have a representation on the fintech firm's board, enabling them the distinct ability of aligning the fintech firm's services with their own (Hornuf et al., 2021). Therefore, several banks might find collaborating with fintech firms is an effective approach to enhance their innovation capabilities, rather than attempting to establish fintech innovation internally, which could be both costly and risky endeavours (Li et al., 2023).

On the other hand, several complications hinder the bank from fully capitalizing on the advantages of collaborating with a fintech firm. Strategic misalignment between the two parties may limit the bank's pursuit of an effective technological advancement (Riikkinen and Pihlajamaa, 2022). Furthermore, the financial industry has come under great regulatory scrutiny after the 2008 global financial crisis (GFC) in order to ensure the stability and safeguarding of participants in the financial sector. Regulatory conditions not only dictate the scope of bank-fintech collaboration, but also the type of products affected by such an alliance (Hornuf et al., 2021). In addition, viewing fintech firms as a mere service vendors to the bank undermines the partnership that should be based on recognizing the fintech firm as a business partner (Meinert, 2017). In a recent study, Zheng and Mao (2024) find limited evidence supporting the bank's long term innovation performance, as measured by the number and quality of bank patents filed, following the announcement of acquisition of fintech firms. They document that banks may overestimate the advantages of such deals, neglecting the associated costs of integrating advanced technology into the their operations. According to Stulz (2019), the agency costs is another contributing factor that hinders bank innovation. The process of introducing new products that could compete with existing ones may face internal resistance from bank management, who earn incentives based on the success of existing products. Therefore, minimizing the desired innovation benefits of collaborating with fintech firms.

In light of the aforementioned discussions, we propose hypothesis (H1).

H1*: Bank-fintech equity investment significantly enhances bank innovation.*

4.3 Data and Methodology

This section discusses sample selection process and addresses potential sample selection bias. It details our approach to identifying fintech firms in the sample, and provides initial analysis to fintech funding rounds involving US banks. It also previews the variables used in the analysis. Finally, it outlines the econometric model of the baseline analysis.

4.3.1 Sample Selection

To construct our sample, Crunchbase (CB) database (www.crunchbase.com) is used to retrieve data on US banks' investments in fintech financing rounds from the start of 2005 until the end of 2023. We choose to start our investigation from 2005 since Prosper, one of the top US fintech firms, was founded and the fintech industry boomed shortly afterward with the introduction of GreenSky. Crunchbase is an online database that provides updated data on companies, investment rounds, and mergers and acquisitions (M&As) deals. It is often used in related literature (Li et al. 2023; Hornuf et al. 2021; Butticè et al. 2020; Cumming et al. 2019), and it offers a comprehensive view of fintech firms' funding rounds. This includes deal characteristics such as the funding date, funding amount, cumulative funding amount, funding type, and funding status. Additionally, it provides relevant information about the fintech firm, including its name, location, business description, revenue range, number of employees, and website. Furthermore, it offers insights into the investors involved, including their names, the names of lead investors, and the number of partner investors.

To identify US banks in Crunchbase database, we limit the location of investors to be in "United States". We include banks by adding their two main industries in CB; these are: "Financial Services" and "Banking". We also follow Li et al. (2023) and include the investment arm or venture capital firm that belong to the bank and have the speciality to undertake investment in funding rounds of startups on behalf of the bank. Norwest Venture Partners (Wells Fargo), One Equity Partners (JP Morgan), Citi Impact Fund (Citibank), and American Express Ventures (American Express) are examples of such companies. As such, to identify these firms, we include the term "Venture Capital" as one of the main firm industries in CB.

Our identification process of fintech firms in CB database is of two folds. First, we include fintech firm if it integrates technology into its financial products offerings. To do this, we follow Li et al. (2023) and include firms that work in "Financial Services" industry as categorized by Crunchbase, which includes firms in sub-industries such as "FinTech", "Lending" and "Payments". It also includes firms in "InsurTech", "Asset Management", "Mobile Payments", "Trading Platform", "Accounting", "Banking", "Cryptocurrency", and "Blockchain" sub-industries. Second, we include possible firms that were not captured in our first step by adding firms in technological industries as per CB which use at least one of these keywords in their description: "financial", "banking", "fintech". These industries are: "Software", "Data and Analytics", "Information Technology", "Internet Services", and "Privacy and Security".

To assess the level of commitment that banks have towards financial innovation, we limit our sample to deals where banks invest in fintech firms in exchange for equity. As such, we exclude deals that include these investment types in CB database: “Debt Financing”, “Grant”, “Non-equity Assistance”, “Product Crowdfunding” and “Post-IPO Debt”.

The final bank-fintech equity investment sample includes 81 US banks that invested in 512 fintech ventures through the participation of 772 fundraising rounds in the period under study.[25] We supplement it with bank-level US banks’ financials retrieved from the Federal Financial Institutions Examination Council’s (FFIEC) Reports of Condition and Income (Call Reports).

Furthermore, we conduct a propensity score matching (PSM) technique for the purpose of addressing possible sample selection bias, and the difficulties in generalizing study’s main findings to a larger population. Specifically, we create a sample of non-investing banks that are similar in size, as measured by the natural logarithm of bank total assets (Del Gaudio et al., 2024). We choose to match on bank size as it incorporates a range of characteristics that affect the bank’s propensity to innovate. As innovation may be a result of bank research and development (R&D) initiatives, larger institutions leverage economies of scale inherent in such activities to innovate (Frame and White, 2004). We argue that financial innovation is a complex phenomenon that requires the availability of adequate financial resources to mitigate the costs associated with innovation, necessitates a highly skilled human capital that are capable of driving innovation, and requires the availability of advanced technological infrastructure. The argument is supported by Pi and Yang (2023)’s findings in the Chinese banking market, which show that larger banks are more inclined to conduct innovative strategies, supported by their higher human, material,

[25]Please see Table C.1 in Appendix C for the list of fintech-investing banks.

and financial resources. Therefore, large banks are best suited to innovate due to the availability of necessary tools that distinguishes them from smaller banks. This is further supported by the statistically significant difference in mean value between investing banks and non-investing banks as shown in Table 24.

Table 24: Propensity Score Matching

	Before Matching				After Matching			
	Investing banks	Non-investing banks	MD (Abs)	p-value	Investing banks	Non-investing banks	MD (Abs)	p-value
Size (ln)	15.423	12.111	-3.312	0.000	15.423	15.424	0.001	0.999

Note: This table shows the propensity score matching results. Investing banks are banks that have invested in a fintech funding round at least once in the period 2005Q1 to 2023Q4. Non-investing banks are banks that did not partake in any fintech investment rounds. Bank total assets in logarithmic form (*Size*) was used as a matching variable. Mean values are shown, along with the statistical significance difference (p-value).

To implement the PSM technique, we follow Kwon et al. (2024) and Del Gaudio et al. (2024) and apply a one-to-one nearest neighbor matching with a caliper of 0.01 to ensure that the most similar banks are paired together. Following the matching process, we are able to create a control group that closely matches the treatment group in terms of bank size. As indicated in Table 24, no statistically significant difference in mean value between the two groups is observed, which enables us to capture the impact of bank-fintech investment behaviour on bank innovation more effectively. The final regression sample includes 9,734 bank-level observations.

Despite the fact that our sample size is small, it is comparable to that found in bank-fintech literature. For example, Carlini et al. (2022) analyze the bank-fintech collaboration in the period 2013-2018, utilizing 80 banks that invested in 334 fintech firms in 581 investment rounds across North America and EU regions. Bellardini et al. (2022) use a global sample of 236 banks that invested in 623 fintech firms through 803 investment rounds during the period between 2008 to 2018. Similarly, Del Gaudio et al. (2024) use the data of 140 banks across the US, EU, and UK during 2008-2018. While Li et al. (2023) investigate

117 banks and 840 fintech firms in the US market during 2000 until 2018.

4.3.2 Classifying Bank-Fintech Equity Investment Rounds

We use the qualitative content analysis (QCA) approach to classify each fintech company in the sample according to the specific sub-industry it belongs to, based on the services it offers. Fintech is an interdisciplinary field where firms may use their innovative capabilities to provide a wide variety of products across multiple sub-industries. Bellardini et al. (2022) investigate a global sample of fintech funding rounds between 2008 and 2018. They find that their sample of fintech firms can be classified in the following industries: open banking, deposit and lending, investment management, capital raising, market provisioning, digital wallets and payments, insurtech, blockchain, artificial intelligence, cryptocurrency, and software and services. Similarly, Li et al. (2023) find 11 sub-industries of fintech firms, these are: online banking, payment, lending, investment, capital raising, trading platforms, personal finance, insurtech, blockchain, cybersecurity, and enterprise software and services.

In this chapter, we follow Collevecchio et al. (2023)'s approach and assign the fintech company to the sub-industry that is most frequently highlighted in its business description in Crunchbase. In our sample, we have identified 10 sub-industries: PayTech, Software and services, Investment Services, Digital Lending, Data Analytics, Personal Finance, InsurTech, Blockchain, RegTech, and Neobank. Table 25 lists the characteristics of identified fintech firms' sub-industries in our sample.

Table 25: Sub-Industries of Fintech Firms

Sub-Industry	Characteristics
PayTech	An abbreviation for "payment technology," it refers to providing innovative payment solutions including digital wallets and mobile and contactless payments.
Software and Services	Specializing in software services such as financial APIs, SaaS, and BaaS models.
Investment Services	The use of technology to provide cutting-edge investing services. These include robo-advisors, foreign exchange trading, and digital wealth management.
Digital Lending	A type of credit that is issued using online methods. For example, P2P lending, cloud-based credit, POS financing.
Data Analytics	Firms that use cutting-edge data analysis techniques to offer innovative financial products. It includes credit scoring capital market analytics services.
Personal Finance	It refers to the management of all financial aspects related to individuals. This include tools for financial planning, expense management, and debt control.
InsurTech	Short for "insurance technology", InsurTech firms provide digital insurance solutions such as income protection plans and virtual evaluation and claim services.
Blockchain	The use of distributed ledger technology in order to offer decentralized financial products and services. Decentralized crypto-trading, cryptocurrency, and tokenization of financial assets are examples of blockchain services.

Continued on next page

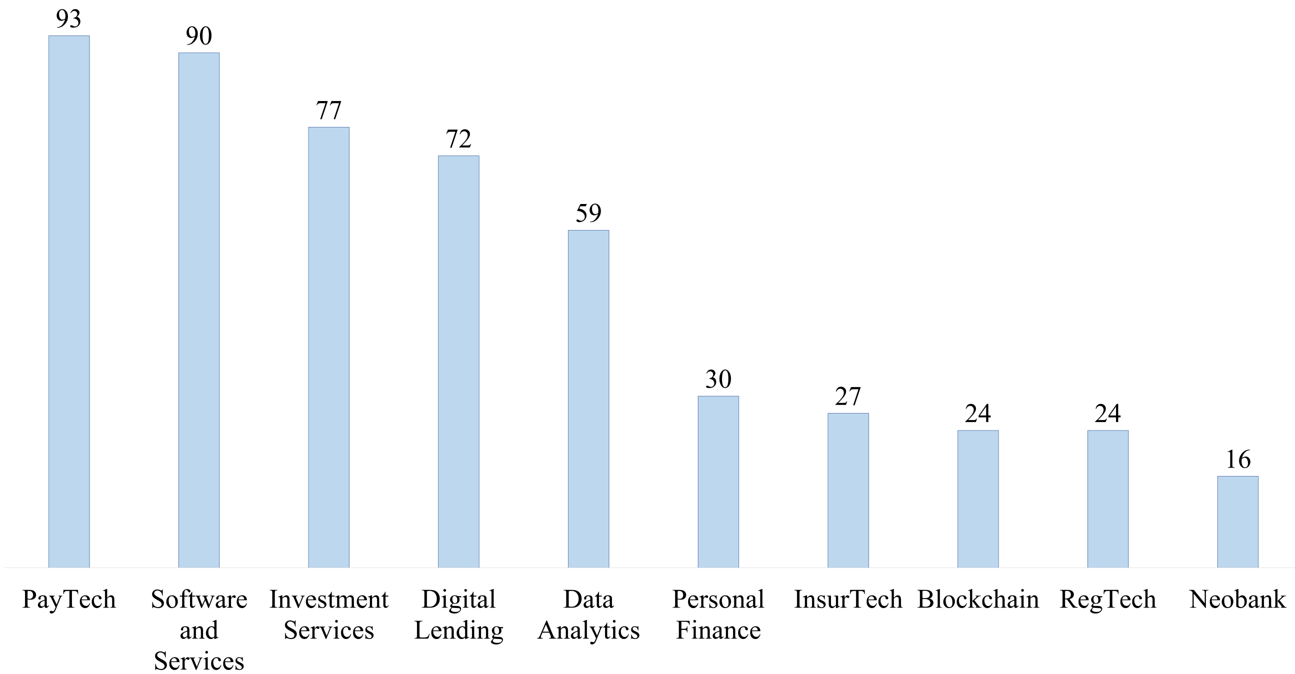
Table 25 – *Continued from previous page*

Sub-Industry	Characteristics
RegTech	The abbreviation for "regulation technology", which refers to the use of technology to facilitate compliance requirements. It includes financial crime, fraud detection and AML services.
Neobank	Digital-only banks that provide exclusively online financial services and products to consumers.

Figure 10 outlines the number of fintech firms categorized into the identified sub-industries in our sample. With 93 firms specializing in providing innovative payment technology (PayTech) services, this sub-industry has the highest number of firms that secured equity investment during the sample period. With a market size of $240 trillion USD, the potential growth for PayTechs is unlimited with the increasing demands from consumers and merchants (Gancz et al., 2022). Firms under this category have a wide range of niche innovation, including mobile payments, digital wallets, and contactless payments. Through equity investments, banks are forming alliances with innovative paytech ventures in order to maintain their competitiveness and relevance in a rapidly evolving payment industry.

The second highest number of investments were made in fintech startups specializing in software services, with a total of 90 firms. It involves companies that provide financial and banking application programming interfaces (APIs) which enable the use of third-party features. Additionally, It covers software-as-a-service (SaaS) and banking-as-a-service (BaaS) models, which enable the use of software and banking services to a third party via APIs, such as utilizing robo-advisors or opening savings accounts. It also include companies that offer cloud accounting and credit card software.

Figure 10: Sub-Industries of Fintech Firms (2005Q1-2023Q4)



Investment services firms accounts for 77 of the total fintech firms in the sample. These firms have introduced innovative digital investment tools such as digital wealth management solutions. Moreover, digital lending come next with 72 firms that use cutting-edge technology in the domain of loans. Services include peer-to-peer (P2P) lending, credit software based on cloud technology, and financing solutions available through point of sale (POS).

The data analytics sub-industry consists of 59 firms that leverage their innovative data analysis approaches to provide unique financial solutions. It includes risk management companies that specialize in using innovation to deliver services such as credit score and worthiness services. In addition, this sub-industry include capital market analytics, which involve the use of financial charts and visualization services. Furthermore, there are a total of 30 companies that fall under the Personal Finance category. These companies provide customers tools and services to facilitate the management of their finances. For example, companies that manage expenses, debt, and financial planning are included. In addition to cutting-edge retirement plans and income intelligence services.

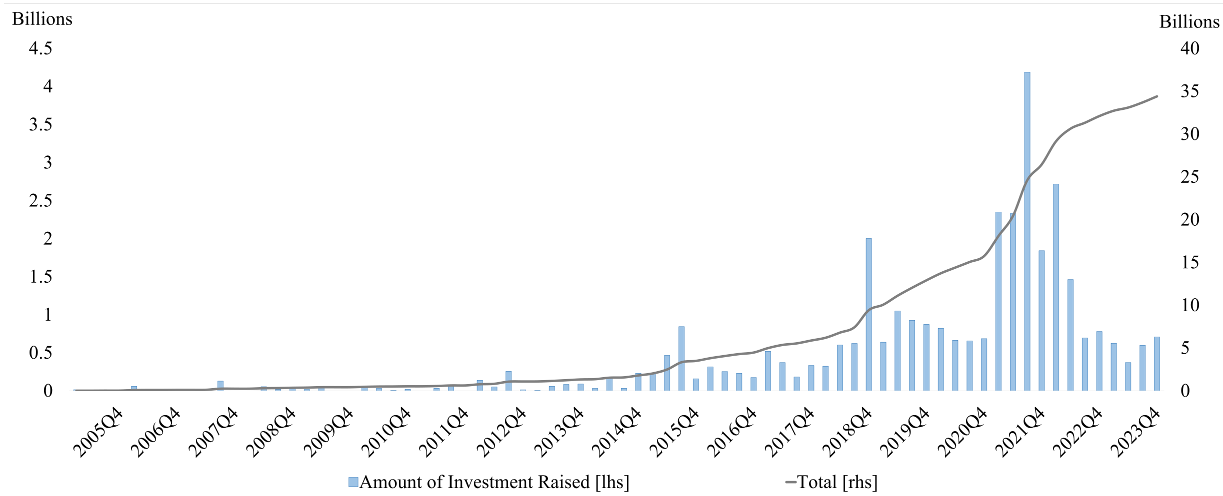
InsurTech is the term used to describe the use of technology in the insurance sector. 27 firms are under this category, and it covers several innovative solutions to provide unique insurance services. Companies within this sub-industry provide online platforms that allow consumers to apply for income protection plans, as well as virtual evaluation and claim services. The following category consists of blockchain firms that use distributed ledger technology to provide decentralized solutions (Goldstein et al., 2019). DeFi (Decentralized Finance), decentralized crypto-trading, cryptocurrency, and tokenized issuance of financial securities are among the services offered by 24 blockchain firms.

Next, regulatory technology, or RegTech, is the application of technology to facilitate the compliance requirements. In our sample, 24 firms are labeled as RegTech firms that provide financial crime and fraud detection tools, anti-money laundering (AML) and client verification services. Finally, 16 companies are classified as neobanks, which are digital-only banks with no physical presence. It provides its customers with a broad range of financial solutions via digital platforms.

4.3.3 Preliminary Insights into Fintech Funding Rounds

Our objective is to investigate the impact of bank equity involvement in fintech financing rounds on bank innovation. To achieve this, we first analyze the fintech investment rounds which at least one US bank participated in as an equity investor. Initially, we examine the total funds received by fintech companies throughout their fundraising campaigns. Figure 11 illustrates the growth of investments in fintech firms during funding rounds in the sample period (2005Q1-2023Q4). The cumulative amount of investments raised by fintech firms during funding rounds involving US banks reaches $34.3 billion USD over the entire study period.

Figure 11: Fintech Equity Fundraising in Rounds Involving US Banks (in USD) (2005Q1-2023Q4)



The graph may be divided into three distinct periods based on investment activity: from 2005Q1 to 2011Q4, from 2012Q1 to 2019Q4, and from 2020Q1 to 2023Q4. The period from 2005Q1 to 2011Q4 is characterized by the small and infrequent equity financing, which amount to $0.6 billion USD. This may be attributed to issues related to the early emergence of fintech innovation, which was both new and unproven. Furthermore, at this time, the world witnessed the 2008 global financial crisis (GFC), which had a significant impact on many investors. Banks, in particular, have become risk-averse and faced severe liquidity crunch, along with tighter financial regulations that might have limited their ability to make investments. In the aftermath of the GFC, Haddad and Hornuf (2019) highlight the potential of fintech ventures to take advantage of the ongoing distrust towards financially stressed incumbents.

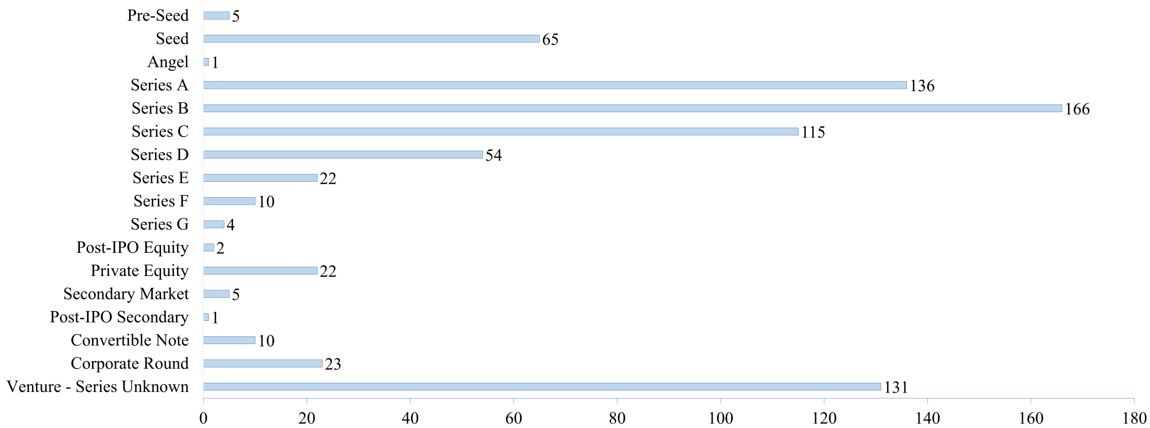
However, from 2012Q1 to 2019Q4, there was a significant increase in financing round investment activity. US banks have consistently participated in each quarter, resulting in a substantial accumulation of $12.2 billion USD. Multiple factors have influenced the significant increase in investment throughout this period. Consumers started using digital platforms to conduct their financial operations, possibly driving banks to fulfill and meet new market expectations. Cornelli et al. (2023) also point out that in this period, several innovative intermediaries have disrupted the financial landscape through the lending channel by offering state-of-the-art alternative credit solutions to consumers.

Interestingly, despite that fintech firms initially experienced a decline in equity investments received during the COVID-19 pandemic period due to economic uncertainty and operational challenges, Fu and Mishra (2022) demonstrate the surge in the use of finance-related mobile apps in reaction to the pandemic, particularly in the areas of payment, lending, and investment. The rise in consumer demands for online financial services during the pandemic has pushed banks to quickly adapt to the rapid advancement of financial digitalization prompted by the pandemic. This adaptation has had a positive effect on the amount raised by fintech firms in fundraising campaigns, resulting in a total of $21.5 billion USD in equity investment rounds involving US banks in the period (2020Q1 - 2023Q4), averaging higher than pre-pandemic levels.

We further conduct an in-depth examination of the fundraising stages in which fintech firms have received funding in. Figure 12 outlines the funding types of all 772 rounds included in this chapter. According to Crunchbase, it may be divided into two primary types according to the investment stage: early-stage funding and late-stage funding.

Early-stage funding include the Pre-seed, Seed, Angel investment, Series A, and Series B funding stages. In our sample, slightly less than half of the rounds (373, or 48%), were classified as early-stage. This implies that banks prefer to invest in riskier startups that have yet to prove their business plan and market presence. Hornuf et al. (2021) find that banks tend to invest in smaller fintech firms, which may provide them the ability to control the strategy of the fintech firm, ensuring that it aligns with banks' interests.

Figure 12: Fintech Firms Funding Types (2005Q1-2023Q4)



Additionally, late-stage funding include Series C to G, private equity, and post-IPO equity investment rounds. These rounds, representing 229 (or 30%) of the total rounds, are at the advanced stage of development, indicating that they have successfully demonstrated the effectiveness of their products and are now seeking additional market share. Finally, the funding stage of 170 (or 22%) investment rounds were either not applicable to the categorization or unidentified due to lack of available data. These include Secondary Market, Post-IPO Secondary, Convertible Note, Corporate Round, and unknown funding rounds.

4.3.4 Variables

In this chapter, we proxy bank innovation using two variables: the number of trademark and patent applications filed to the United States Patent and Trademark Office (USPTO). In the empirical setting of this chapter, we include bank trademarks as the natural logarithm of one plus the number of trademark applications filed by the bank, while patents as the natural logarithm of one plus the number of patent applications filed by the bank.[26]

[26]We use the natural logarithm of one plus to account for the presence of zero values for some banks in different temporal periods.

We use The Lens (www.lens.org) and Onscope (www.onscope.com) databases to collect data on banks' trademark and patent applications. In this chapter, the two databases complement each other as we use the Lens for bank patent applications and Onscope primarily for retrieving information on bank trademark activity. Choosing Lens and Onscope as our data sources provide us with several advantages. By combining the two datasets, we are able to capture a more comprehensive insights into bank innovation from different perspectives. Furthermore, the two databases allow us the ability to track down the activity of US banks' trademark and patent submitted applications over a period of 19 years, specifically from 1/1/2005 until 31/12/2023. A drawback to these databases is that the data was hand-collected for individual banks since bulk data for an industry is unavailable at the time of collecting data.[27] Nevertheless, several studies have utilized one of these databases in various academic investigations (de Boyrie and Pavlova 2024; Yalcin and Daim 2022).

In addition, we include a set of control variables that could explain bank innovation activities. Table 26 presents the definition of all this chapter's variables. For starters, we account for the bank's profitability through the use of return on equity (ROE) ratio, calculated by dividing net income by total bank equity. The process of bank innovation often involves a high level of uncertainty, which requires the availability of funds and profitability to endure possible failures. As such, we expect bank profit to be positively correlated with its innovation activity. Furthermore, we consider the level of bank capitalization, as measured by bank's total equity scaled by its total assets. We expect a positive sign as highly capitalized banks have a larger cushion against possible losses, which may enable them to undertake innovative initiatives that result in legally protected intellectual rights. Additionally, we add the ratio of bank liquid assets scaled by total assets to our empirical model. We expect the liquidity ratio of be positively associated with bank innovation

[27]We provide further validity to the main results obtained through the use of an alternative measure of bank innovation in subsection 4.4.3.

activities. Banks with higher liquid assets such as cash and short-term investment have the necessary financial resources to allocate it to innovative initiatives. Moreover, the model incorporates bank non-performing loans (NPLs). We argue that banks with high levels of NPLs may be discouraged from pursuing costly and uncertain innovation trials, thus increasing their risk and cost burden. Cheng and Qu (2020) find a negative correlation between bank NPL levels and its fintech development. As such, we expect a negative correlation. Finally, as a macroeconomic indicator, we include the bank nominal lending rate. We expect higher interest rates to be positively associated with bank innovation through the channel of profitability. Related literature found a positive relationship between interest rates and the profitability of banks (Alessandri and Nelson, 2015).

Table 26: Variable Definitions

Variable	**Definition**
Trademarks (ln)	The natural logarithm of one plus the number of trademark applications filed by the bank.
Patents (ln)	The natural logarithm of one plus the number of patent applications filed by the bank.
Multiple_Investment (ln)	The natural logarithm of one plus the total number of bank investment in fintech firms' funding rounds.
Initial_Investment (ln)	The natural logarithm of one plus the number of initial bank investment in fintech firms' funding rounds.
Size (ln)	The natural logarithm form of bank total assets.
ROE (%)	The ratio of net income / total equity.
Capitalization (%)	The ratio of total equity / total assets.
Liquidity (%)	The ratio of cash and short-term investment / total assets.
NPL (%)	The ratio of total loans on non-accrual status / total loans.
Interest_Rate (%)	The quarterly bank nominal lending rate.
Intangible Assets (ln)	The natural logarithm of one plus the total amount of bank intangible assets.
Domestic (dummy)	A dummy variable that takes the value of 1 if the headquarters of the fintech firm is located in the United States, and 0 otherwise.
Cross_border (dummy)	A dummy variable that takes the value of 1 if the headquarters of the fintech firm is located outside the United States, and 0 otherwise.

Table 27 shows the summary statistics of variables used in the baseline regression analysis categorized in three groups: (1) All banks, (2) Investing banks (banks that have invested in the equity shares of at least one fintech firm), and (3) Non-investing banks (banks that did not participate in any equity funding round conducted by a fintech firm).

Table 27: Summary Statistics

	All banks		Investing banks		Non-investing banks		Mean Difference (MD)
	Mean	SD	Mean	SD	Mean	SD	Abs
Trademarks (ln)	0.12	0.37	0.18	0.44	0.04	0.22	-0.14***
Patent (ln)	0.22	0.77	0.37	0.97	0.01	0.14	-0.36***
Multiple_Investment (ln)	0.04	0.21	0.08	0.27	0	0	-0.08***
Initial_Investment (ln)	0.03	0.17	0.06	0.23	0	0	-0.06***
ROE (%)	5.42	7.05	5.53	7.09	5.27	7.01	-0.26*
Capitalization (%)	11.44	3.82	11.06	3.45	11.98	4.22	0.92***
Liquidity (%)	10.45	10.52	11.24	10.55	9.35	10.39	-1.89***
NPL (%)	1.19	1.73	1.13	1.54	1.28	1.95	0.15***
Interest_Rate (%)	4.62	1.80	-	-	-	-	-
Number of Banks	162		81		81		

Note: This table presents the summary statistics of regression variables in the period under study (2005Q1-2023Q4) for three groups of banks; the first group contains all banks in the regression estimation sample (All banks), the second group contains banks who invested in the equity shares of at least one fintech firm (Investing banks), and the third group contains statistics for banks that did not participate in any equity funding round conducted by a fintech firm (Non-investing banks). Mean and standard deviation (SD) values are calculated as the average cross-sectional mean and SD of the individual time-series bank values. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the findings. Table 26 shows the definition of all variables. MD in the last column refers to the mean difference between acquiring banks and non-acquiring banks in absolute (Abs) values and its statistical significance which is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

We note some interesting results. For starters, we find that investing banks have a higher number of bank trademark and patent applications than non-investing banks, and this difference is statistically significant. Specifically, investing banks filed for a total of 2,409 trademarks and 32,386 patents in the period under study, while non-investing banks applied for 385 trademarks and 138 patents within the same period. This result may provide a supporting evidence that bank involvement in fintech equity activities can be significantly beneficial to its innovation capabilities. Furthermore, the summary statistics analysis has revealed that banks that invest in fintech firms' funding rounds have a higher profitability margins as indicated in their return on equity (ROE) ratio of 5.53% compared with 5.27% for non-investing banks. This suggests that bank profitability may facilitate the involvement of banks in legally protected products and innovation activities such as equity investment in startups. In addition, results show that investing banks have a lower capitalization ratio (11.06%) than non-investing banks (11.98%). This indicates that non-investing banks might prioritize prudent risk management framework in order to protect their capital position. Moreover, we find that with 11.24%, investing banks have a higher cash and short-term investment ratio than non-investing banks (9.35%). Lastly, the results show that investing banks have a lower non-performing loan ratio (1.13%) than non-investing banks (1.28%).

4.3.5 Econometric Model

To empirically investigate the effect of bank-fintech investment on bank innovation, we use the system generalized method of moments (SYS-GMM) to estimate the parameters of our baseline model. The SYS-GMM technique, an extension of the regular GMM method, has been developed to improve its performance when dealing with dynamic panel data (Blundell et al., 2001). This method was initially proposed by Arellano and Bond (1991) and consists of two equations, one for first differences and one for levels, to address certain biases such as omitted variables bias. It has been extensively used in the literature of bank-fintech (Wu et al. 2024; Wu et al. 2023; Yao and Song 2023; Lee et al. 2021).

Choosing the system GMM as our model estimator is helpful in many ways to address econometric issues. Since bank innovation levels might be influenced by previous periods, system GMM allows for the designing of dynamic panel models through its inclusion as lagged explanatory variable. Furthermore, it is capable of effectively dealing with the problem of endogeneity, which refers to the correlation between independent variables and the error term. It also handles the presence of unobserved bank-specific effects, as well as variations between banks. Another advantage of using system GMM estimator as mentioned in Blundell et al. (2001) is that it significantly increases the precision while reducing finite sample bias. To ensure the consistency of system GMM estimations, we report two tests in all regression tables. First, we use Hansen J statistics to verify our selection of instruments. It evaluates the suitability of our endogenous and instrumental variables, determining whether they appear exogenous. Second, we examine the presence of first-order AR(1) and second-order AR(2) autocorrelation.

To examine the impact of bank equity investment in fintech firms on bank innovation, the following dynamic model is used:

$$\begin{aligned} Bank\_Innovation_{i,t} = \alpha_i + \beta_1 Bank\_Innovation_{i,t-1} + \beta_2 Fintech\_Investment_{i,t-1} \\ + \theta X_{i,t-1} + \gamma_i + \epsilon_{i,t} \end{aligned} \tag{4}$$

Where $Bank\_Innovation_{i,t}$ is the bank-level fintech innovation measure for bank i in time t. We measure bank innovation through two indicators: (1) trademark applications; and (2) patent applications. $Fintech\_Investment_{i,t-1}$ is the chapter's main coefficient of interest which represents the investment of banks in fintech firms' funding rounds. Two indicators are used to measure bank-fintech equity investment: (1) multiple investment; and (2) initial investment. $X_{i,t-1}$ includes a set of bank-level and macroeconomic characteristics that might influence the innovation capabilities of banks. These are: profitability (net income/total equity), capitalization (total equity/total assets), bank liquidity as measured by the sum of cash and short-term investment over total assets, bank non-performing loans over total loans, and the bank nominal lending rate. γ_i is the time-specific fixed effects. $\epsilon_{i,t}$ is the error term.

4.4 Results and Discussion

This section discusses the baseline results, robustness checks, and additional analysis.

4.4.1 Impact of Bank-Fintech Equity Investment on Bank Innovation

Before presenting the results, we distinguish between two types of bank-fintech investment strategies: a single occurrence of equity investment in a unique fintech firm financing round, and multiple investment made in several equity fundraising rounds for the same firm by the same US bank. By using this approach, we follow Li et al. (2023) and mitigate some concerns relating to the possible inaccuracies in reporting of funding rounds (Aragon et al. 2023; Lerner 1995), or giving more weight to banks that have invested in subsequent fintech equity funding rounds as some investors may prefer to split their investment across successive funding rounds in order to monitor the development of invested firm (Aragon et al. 2023; Gompers 1995). Our objective is to examine the impact of bank initial and multiple fintech equity investments on its innovation capabilities.

Table 28 shows the chapter's main findings. When banks participate in multiple fintech equity investment rounds, it has a positive and statistically significant effect on the number of trademark applications submitted by the bank at a 1% significance level. Similarly, it has a positive effect on the number of patent applications submitted by the bank at a 1% significance level. By restricting the bank's equity involvement in fintech startups only to the first investment, or first "hand-shake" (Li et al., 2023), we still observe a similar significantly positive impact on the number of bank's trademark and patent applications at 1% level. Our results challenge the findings of Zheng and Mao (2024) who find that banks may overestimate the associated benefits. We show that banks that invested in fintech firms' equity funding rounds (indicating a greater level of involvement in financial technology) between 2005Q1 and 2023Q4 are associated with higher bank innovation capabilities, as shown by a higher number of legally protected intellectual rights in the form of bank trademarks and patents. Interestingly, our findings reveal that even when considering only the initial equity investment by banks, it continues to have a positive impact on bank innovation, emphasizing the significance of bank-fintech alliance. We argue that new technological developments brought about by financial technology companies may enhance the innovation capabilities of banks via the equity investment channel. Hornuf et al. (2021) suggest that through equity investment, banks may better control fintech startups, overseeing the development of services that align with the bank's strategy and engineering them for easier integration into the banks' existing functions. Our findings offer empirical support for this argument and confirm our proposed hypothesis (H1) that bank-fintech equity investment collaboration enhances bank innovation. Regarding the bank-specific control variables, we find that banks that engage in innovative experiments which result in more trademark and patent applications have easier access to cash, as shown by the positive and statistically significant coefficients of bank liquidity.

4.4.2 Falsification Test

To provide validity to our main findings, we conduct a falsification test. Specifically, we test for the alternative explanation that banks with higher innovative capabilities, as indicated by a larger number of trademark and patent applications, are inherently more motivated to participate in fintech equity investment rounds. To do this test, we use equation 4 and swap the dependent variable $Bank\_Innovation$ with explanatory variable $Fintech\_Investment$. Table 29 shows a statistically insignificant coefficients for bank trademark and patent filings, suggesting that bank innovation is not affecting the investment in fintech firms.

Table 28: Main Results: Impact of Bank-Fintech Equity Investment on Bank Innovation

	Dependent: Trademarks (ln)		Dependent: Patents (ln)	
	(1)	(2)	(3)	(4)
$\text{Trademarks}_{t-1}(ln)$	-0.014	-0.017		
	(0.027)	(0.028)		
$\text{Patents}_{t-1}(ln)$			0.198***	0.179***
			(0.058)	(0.058)
$\text{Multiple\_Investment}_{t-1}(ln)$	0.240***		0.590***	
	(0.078)		(0.144)	
$\text{Initial\_Investment}_{t-1}(ln)$		0.298***		0.739***
		(0.104)		(0.199)
$\text{ROE}_{t-1}(\%)$	-0.017	-0.017	-0.022	-0.024
	(0.013)	(0.013)	(0.014)	(0.015)
$\text{Capitalization}_{t-1}(\%)$	-0.003	-0.002	0.007	0.008
	(0.006)	(0.007)	(0.013)	(0.013)
$\text{Liquidity}_{t-1}(\%)$	0.004*	0.004*	0.008**	0.009**
	(0.002)	(0.002)	(0.004)	(0.004)
$\text{NPL}_{t-1}(\%)$	-0.297	-0.303	-0.366	-0.413
	(0.211)	(0.211)	(0.307)	(0.329)
$\text{Interest\_Rate}_{t-1}(\%)$	0.385	0.377	-0.130	-0.164
	(0.245)	(0.249)	(0.500)	(0.487)
Constant	-0.586	-0.553	1.244	1.449
	(0.631)	(0.632)	(1.919)	(1.931)
Number of Observations	9,491	9,491	9,491	9,491
Number of Groups	161	161	161	161
Number of Instruments	30	30	30	30
AR(1)	0.000	0.000	0.000	0.000
AR(2)	0.586	0.613	0.533	0.803
Hansen Test	0.269	0.267	0.075	0.087

Note: This table shows the two-step system GMM regression results for equation 4 during the period 2005Q1 - 2023Q4. Columns (1) and (2) were estimated using the natural logarithm of the one plus the number of trademarks filed by a bank as a dependent variable. Columns (3) and (4) represent the results with the natural logarithm form of one plus the number of bank patent applications as dependent variable. Table 26 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. We also test for the presence of first and second order serial correlation through AR(1) and AR(2), and we use the Hansen test to check the validity of instruments used. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

Table 29: Robustness Check: Falsification Test

	Dependent: Multiple Investment (ln)		Dependent: Initial Investment (ln)	
	(1)	(2)	(3)	(4)
Multiple_Investment$_{t-1}(ln)$	0.004	0.022		
	(0.117)	(0.036)		
Initial_Investment$_{t-1}(ln)$			0.037	0.053
			(0.045)	(0.036)
Trademarks$_{t-1}(ln)$	0.789		0.175	
	(1.246)		(0.321)	
Patents$_{t-1}(ln)$		0.056		0.044
		(0.060)		(0.073)
ROE$_{t-1}$(%)	-0.001	0.002	0.001	0.001
	(0.008)	(0.001)	(0.001)	(0.001)
Capitalization$_{t-1}$(%)	0.000	-0.002	-0.001	-0.002
	(0.008)	(0.002)	(0.003)	(0.003)
Liquidity$_{t-1}$(%)	-0.000	0.001	0.001	0.001
	(0.004)	(0.001)	(0.001)	(0.001)
NPL$_{t-1}$(%)	0.122	-0.019	0.001	-0.007
	(0.341)	(0.052)	(0.079)	(0.061)
Interest_Rate$_{t-1}$(%)	-0.082	-0.026	-0.049*	-0.042**
	(0.089)	(0.017)	(0.029)	(0.016)
Constant	0.013	0.160	0.133	0.175
	(0.402)	(0.108)	(0.100)	(0.156)
Number of Observations	9,491	9,491	9,491	9,491
Number of Groups	161	161	161	161
Number of Instruments	30	30	30	30
AR(1)	0.355	0.001	0.000	0.000
AR(2)	0.246	0.168	0.120	0.115
Hansen Test	0.574	0.155	0.407	0.397

Note: This table shows the two-step system GMM regression results during the period 2005Q1 - 2023Q4. Columns (1) and (2) were estimated using the natural logarithm of one plus the total number of bank investment in fintech firms' funding rounds as a dependent variable. Columns (3) and (4) represent the results with the natural logarithm form of one plus the number of initial bank investment in fintech firms' funding rounds as dependent variable. Table 26 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. We also test for the presence of first and second order serial correlation through AR(1) and AR(2), and we use the Hansen test to check the validity of instruments used. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

4.4.3 Alternative Measure of Bank Innovation

To provide further validity to our main findings, an alternative measure of bank innovation is utilized. We follow extant literature (Collevecchio et al. 2023; Ayadi et al. 2021; Cao et al. 2022) and use bank intangible assets to quantify the innovation capabilities within banks. We argue that intangible assets is a relevant indicator that is worth investigating. Primarily due to its relevance to bank intellectual properties, which include trademarks and patents within its calculations according to the generally accepted accounting principles (GAAP) that is mandated when banks present their financial statements (Federal Deposit Insurance Corporation, 2024). In this subsection, we replicate the main analysis outlined in equation 4 and include the natural logarithm of one plus the total amount of bank intangible assets as a dependent variable.

Table 30 presents the regression results of the alternative measure analysis. We still observe a significantly positive relationship between the total number of bank investments in the funding rounds of fintech startups and the level of bank innovation, as measured by bank intangible assets. The initial bank investment in fintech funding rounds continues to have a significantly positive impact. Overall, our alternative measure analysis has resulted in broadly similar findings to those found in the main analysis. This provides additional reliability to our main results.

Table 30: Robustness Check: Impact of Bank-Fintech Equity Investment on Bank Innovation

	Dependent: Intangible Assets (ln)	
	(1)	(2)
Intangible_Assets$_{t-1}(ln)$	0.994***	0.994***
	(0.008)	(0.008)
Multiple_Investment$_{t-1}(ln)$	0.081**	
	(0.035)	
Initial_Investment$_{t-1}(ln)$		0.101**
		(0.043)
ROE$_{t-1}$(%)	0.003	0.003
	(0.006)	(0.006)
Capitalization$_{t-1}$(%)	-0.003	-0.003
	(0.005)	(0.005)
Liquidity$_{t-1}$(%)	0.000	0.000
	(0.001)	(0.001)
NPL$_{t-1}$(%)	-0.105	-0.106
	(0.107)	(0.108)
Interest_Rate$_{t-1}$(%)	-0.018	-0.019
	(0.049)	(0.049)
Constant	0.366	0.371
	(0.247)	(0.248)
Number of Observations	9,492	9,492
Number of Groups	161	161
Number of Instruments	30	30
AR(1)	0.000	0.000
AR(2)	0.299	0.304
Hansen Test	0.420	0.424

Note: This table shows the two-step system GMM regression results for equation 4 during the period 2005Q1 - 2023Q4. The dependent variable used in this table is the natural logarithm of one plus the total amount of bank intangible assets. Table 26 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. We also test for the presence of first and second order serial correlation through AR(1) and AR(2), and we use the Hansen test to check the validity of instruments used. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

4.4.4 Additional Analysis: Home Bias in Bank-Fintech Investment

We further broaden and enrich the scope of the chapter by exploring home bias in bank-fintech investment. Home bias in the field of financial economics is the tendency of investors to allocate a larger share of their portfolio to assets in their home country (French and Poterba, 1991). A stronger form of this bias is known as local bias, where investors show a preference for investing in firms that are geographically close to them, such as within their state or city, also known as home bias at home (Coval and Moskowitz, 1999). Extant literature has extensively explored the phenomenon of home bias and provided several reasons for its presence. These include information asymmetry (Van Nieuwerburgh and Veldkamp, 2009), the availability of home-based alternatives (Errunza et al., 1999), cultural and institutional similarities (Levis et al., 2016), and investors' optimism towards domestic assets (Solnik and Zuo, 2017). Our analysis in this subsection adds to this strand of literature through the unique perspective of US bank equity investment in innovative financial technology startups.

Table 31 shows that in our sample, out of the 772 investment rounds, 556 rounds (or 72%) were bank investment in domestic US fintech firms, while 216 rounds were cross-border (or 28%). Given that our sample of US banks seem to exhibit home bias in their investment behavior, we aim to investigate the impact of investing in domestic and overseas fintech companies on bank innovation output. For this reason, we use model equation 4 and introduce two location-based dummy variables. Specifically, we rely on CB database's "Organization Location" and construct a dummy variable *Domestic*, that takes the value of 1 if the fintech firm is located in the US, and 0 otherwise. Also, we construct another dummy variable *Cross_border* that takes 1 if the fintech firm is located in a foreign country outside the US, 0 otherwise.

Table 31: Breakdown of Fintech Firm Investment Rounds

Fintech Investment Round	**Number of Rounds**	**Percentage (%)**
Domestic	556	72%
Cross-border	216	28%

Note: This table shows a breakdown of sample's fintech investment rounds, categorized based on the geographic location of the fintech firm as indicated in Crunchbase database, divided into domestic (US) and cross-border fintech firms.

The estimate results of equation 4 with the inclusion of dummy variables for domestic and cross-border fintech firms are shown in Table 32. The findings indicate that investing in domestic fintech ventures is correlated with an increase in bank trademark applications, as seen in column (1) with a positive and statistically significant relationship at a 5% confidence level. A similar positive and statistically significant (at 5% level) relationship is shown if we use the number of patent applications as a measure of bank innovation, as shown in column (3). For cross-border firms, no statistically significant coefficients are found in columns (2) and (4). Our initial sample analysis found a tendency for US banks to invest in domestic fintech startups, and our empirical analysis has revealed findings that suggest that such propensity may be warranted, as evident by increased bank innovation output. However, Del Gaudio et al. (2024) find empirical evidence supporting the argument that banks' innovative potential can be significantly constrained by their tendency to invest in and collaborate with fintech firms that are located in close proximity to them.

A policy intervention is recommended to promote healthy environment for domestic bank-fintech collaboration. Existing literature suggest that such bank-fintech collaboration help banks develop innovative products that support its competitive position in a rapidly digitalized market, and meet the growing demands of consumers (Hornuf et al., 2021). Although international collaboration may pose challenges in integration, its diverse nature enables firms to introduce more novel products to domestic market compared to those launched through domestic alliances (Rodríguez et al., 2022). As such, bank executives are advised to mitigate their home bias investment behavior and explore international innovation collaborations as they may miss out on opportunities (Del Gaudio et al., 2024).

Table 32: Additional Analysis: Impact of Domestic and Cross-border Bank-Fintech Equity Investment on Bank Innovation

	Dependent: Trademarks (ln)		Dependent: Patents (ln)	
	(1)	(2)	(3)	(4)
Trademarks$_{t-1}(ln)$	-0.002	-0.022		
	(0.023)	(0.092)		
Patents$_{t-1}(ln)$			0.168**	0.241*
			(0.074)	(0.137)
Domestic (dummy)	1.742**		3.592**	
	(0.871)		(1.711)	
Cross_border (dummy)		0.958		4.791
		(4.015)		(7.318)
Multiple_Investment$_{t-1}(ln)$	0.211**	0.075	0.520***	-0.038
	(0.089)	(0.164)	(0.175)	(0.427)
ROE$_{t-1}$(%)	-0.003	-0.010	0.013	-0.009
	(0.005)	(0.011)	(0.010)	(0.015)
Capitalization$_{t-1}$(%)	0.002	-0.003	0.015	-0.001
	(0.004)	(0.008)	(0.011)	(0.016)
Liquidity$_{t-1}$(%)	-0.001	0.007	-0.008	0.004
	(0.007)	(0.019)	(0.016)	(0.030)
NPL$_{t-1}$(%)	-0.052	-0.265	0.268	-0.270
	(0.176)	(0.321)	(0.388)	(0.497)
Interest_Rate$_{t-1}$(%)	0.289	0.504*	-0.891	0.381
	(0.179)	(0.280)	(0.545)	(0.433)
Constant	-1.590***	-3.851***	-0.019	-0.628
	(0.621)	(1.419)	(1.423)	(0.975)
Number of Observations	9,492	9,492	9,492	9,492
Number of Groups	161	161	161	161
Number of Instruments	31	31	31	31
AR(1)	0.002	0.000	0.036	0.333
AR(2)	0.874	0.617	0.023	0.740
Hansen Test	0.922	0.431	0.304	0.663

Note: This table shows the two-step system GMM regression results for equation 4 with the inclusion of two dummy variables *Domestic* and *Cross_border*. Columns (1) and (2) were estimated using the natural logarithm of one plus the number of trademarks filed by a bank as a dependent variable. Columns (3) and (4) represent the results with the natural logarithm form of one plus the number of bank patent applications as dependent variable. Table 26 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. We also test for the presence of first and second order serial correlation through AR(1) and AR(2), and we use the Hansen test to check the validity of instruments used. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

4.5 Conclusion

Several studies in the domain of bank-fintech have highlighted the positive effects of banks partnering with fintech firms, emphasizing the significance of this collaboration in fostering both financial market growth and financial innovation (Kwon et al. 2024; Li et al. 2023; Bellardini et al. 2022; Hornuf et al. 2021; Del Gaudio et al. 2024). However, little is known about the effect of such partnerships on bank innovation. To fill this knowledge gap, this chapter aimed to investigate the impact of bank investment in the equity funding rounds of fintech firms on bank innovation. To the best of our knowledge, this chapter is among the first to conduct bank-fintech collaboration analysis from the perspective of bank innovation. We provide empirical evidence suggesting that the greater involvement of banks in fintech equity funding rounds as investors has a positive effect on the level of bank innovation, as measured by the number of trademark and patent applications. We argue that via the equity investment channel, banks may improve their innovation capabilities, supported by the new technological development of fintech firms. Our findings highlight the significance of bank-fintech collaboration and provide empirical support to the argument that through equity investments in fintech firms, banks are able to have representation on the fintech firms' board of directors, which allows banks to influence the services developed that cater to the bank's existing infrastructure, thereby enhancing their innovation capabilities (Hornuf et al., 2021). Furthermore, we find that bank investment in domestic firms' funding rounds enhances its innovation output, compared with foreign fintech firms. This result may serve as a justification for banks' tendency to favor the investment in domestic and local firms, while at the same time missing out on overseas opportunities.

The findings of this chapter have interesting implications for policymakers, bank executives, and entrepreneurs. We have outlined how significant bank-fintech collaborations can be from the perspective of bank innovation capabilities. In light of it, we take this opportunity to provide three recommendations targeted to each stakeholder. (1) Macroprudential supervisors should ensure that the regulatory framework promotes innovative collaboration between banks and fintech firms, while also safeguarding the stability of financial markets. (2) Fintech firms have brought a disruptive wave of technology to the banking sector, which has made a significant impact on consumer demands. A key strategy for banks to capitalize on the development of financial innovation is to cooperate with the newcomers. This collaboration should not only aim to design innovative products, but also establish an environment that promotes financial innovation. (3) Fintech firms have suffered significantly from the lack of financing in 2022 and 2023 due to various macroeconomic conditions (CCAF, 2024). To overcome this adversity, entrepreneurs are encouraged to seek cooperation with incumbents that have the necessary financial resources to ensure their continuity and success.

Our work is subject to certain limitations that could act as a door for intriguing future academic inquiries. First, data on bank trademark and patent applications was collected individually for each bank in the sample. Future work may enrich the empirical investigations through the use of an extensive database that allows the inclusion of all banks when it becomes available. Second, our analysis was conducted in a single country, and future work can test the proposed results in other geographic settings.

Chapter 5: Conclusions

5 Conclusions

5.1 Introduction

The final chapter offers a concluding remarks for each of the core chapters of the thesis, as well as the policy implications in light of results. Additionally, it presents the the limitations of these chapters and offers several potential research ideas for future investigations.

5.2 Summary of Contributions and Policy Implications

This thesis offers several valuable contributions to the bank-fintech literature. It has utilized various econometric approaches, including fixed effects, logistic regression, propensity score matching, and system generalized method of moments, to analyze the development of fintech and collaboration between banks and financial technology firms. Different samples, which include global digital credit, US bank-fintech acquisitions, and US bank-fintech equity rounds investment, were employed for this purpose.

Chapter 2 presents our initial empirical investigation in the bank-fintech relationship. Using fixed effects model, we find that digital credit complements that of traditional credit. This result contributes to the ongoing debate on whether digital lending complements or substitutes bank credit (Tang 2019; Hodula 2021; Cornaggia et al. 2018). The finding corroborates those of de Roure et al. (2022), which show that digital credit and bank credit have a complimentary relationship. Our empirical analysis adds to this discussion through linking the expansion of global digital credit with the growth of financial institutions. The results bear significant relevance to policymakers. Chapter 2 presents results suggesting that fintech ventures and traditional banks can co-exist within the same lending market.

Financial inclusion is directly impacted by this, since digital lending may serve individuals who are unbanked or have been rejected by banks due to their low credit scores. A regulatory intervention is critical for developing frameworks that ensure the protection of consumers and safeguarding financial stability, especially given that fintech ventures are subject to lower regulatory scrutiny compared to banks (Buchak et al., 2018).

Chapter 3 focuses on analyzing the role of banking business model structure in banks' acquisition of fintech firms. It contributes to a growing literature that aims to analyze banking business model structures following the 2008 financial crisis (Ayadi et al. 2011; Altunbas et al. 2011; Hryckiewicz and Kozłowski 2017; Vinas 2021). Also, it adds to the recent bank-fintech acquisition strand of literature (Kwon et al. 2024; Kueschnig and Schertler 2024; Zheng and Mao 2024; Collevecchio et al. 2023). We extend the current knowledge in these two areas by adding a new dimension to the bank-fintech relationship. Specifically, our empirical analysis presents evidence of the significant role of banking business models on three aspects: bank-fintech acquisitions, the types of fintech firms acquired, and the motivations driving bank-fintech acquisitions. These results should be dealt with adequate policy responses. When designing a policy that aims to benefit both banks and fintech startups, it is crucial to consider the complexity of banks' business model structures. Policymakers should take into account the banking business model structure as an important factor that may influence the risk-taking behavior of banks and their motives to acquire fintech ventures.

Chapter 4 examines the impact of bank-fintech equity investment on bank innovation. Our empirical analysis relates to literature that investigates bank financial innovation (Beck et al. 2016; Wu et al. 2024; Zhang et al. 2023; Wu et al. 2023) and bank-fintech equity funding rounds (Del Gaudio et al. 2024; Li et al. 2023; Bellardini et al. 2022). We contribute to these two lines of literature by finding that bank investments in fintech firms' equity increases their financial innovation output, as captured by bank trademark and patent applications. The positive impact of fintech investment on bank innovation holds when we limit the equity funding round participation to the initial investment. Chapter 4 provides the following recommendations to policymakers, bank executives, and entrepreneurs. In March 2023, the Office of the Comptroller of the Currency (OCC) established the Office of Financial Technology (OFT) to supervise bank-fintech partnerships (Office of the Comptroller of the Currency, 2023). Given the bank innovation benefits documented in this chapter, the OCC may scale up its bank-fintech innovation experiments. Such initiative ensures that financial innovation resulting from bank-fintech collaboration may be more fostered through a controlled environment while effectively managing its associated risks. Bank executives are encouraged to actively explore collaboration with fintech ventures, as these newcomers possess the necessary technical capabilities to help banks meet shifting consumer demands (Fu and Mishra, 2022). While fintech entrepreneurs should consider collaboration with incumbents. Global fintech investment experienced a substantial decline in 2022 and 2023, dropping to 78.6 billion US dollars in 2022, a 56% decrease year-on-year, followed by a further 50% decrease to reach 39.2 billion US dollars in 2023 (CB Insights, 2024). According to an industry report (CCAF, 2024), fintech firms identified macroeconomic and funding conditions as the main obstacles that have slowed the flow of capital in recent years. Thus, collaborating with banks may be a viable strategic initiative to ensure their survival.

To summarize, this thesis provides valuable contributions to the bank-fintech literature. Specifically, Chapter 2 analyzes the key drivers of global digital credit and adds to the ongoing debate on whether digital credit is a complement or a substitute to traditional lending. We find that traditional banks and fintech ventures can co-exist within the same lending market. Chapter 3 introduces a new dimension to the bank-fintech literature through exploring the role of banking business models, highlighting the significance of bank's internal structure in evaluating strategic fintech acquisitions. Lastly, Chapter 4 explores how bank innovation is affected following the bank-fintech equity investment strategic decision. We find that bank investments in the equity of fintech firms increases the financial innovation of banks, as captured by bank trademark and patent applications. Collectively, these empirical analyses offer a significant contribution to the field and deepen our understanding of the relationship between banking and fintech.

5.3 Limitations

This thesis presents a unique perspective on the fintech industry and its interaction with the banking sector. Nevertheless, its findings are subject to some limitations as described in this section.

In chapter 2, due to confidentiality concerns, the dataset only gives a year-end data without stating the percentage or number of firms that contributed to the overall credit volume. This restriction, to some degree, limits our ability to investigate the country-specific factors driving an increase or decrease in digital credit adoption levels. Furthermore, the sample size of the dataset covers credit activities over a period of six years, from 2013 to 2018. This may imply that the chapter's findings should be treated with care because it is difficult to generalize a conclusion based on such a small sample period. The aforementioned limitations should not be interpreted as implying that the dataset is less trustworthy; rather, it is an interesting dataset that contains valuable data that could aid scholars and policymakers in understanding the disruptive and innovative nature of new types of digital lending channels.

Regarding chapter 3, the sample included in the analysis focuses on US banks only. Although the US banking sector offers valuable insights into its interaction with fintech firms, it is vital to include other financial institutions in other jurisdictions to avoid limiting the generalizability of the results to other countries around the world. In addition, the sample consists of 30 US banks that acquire fintech companies. Although a representativeness test was conducted, there is a potential that the results may not be relevant to all banks in the US banking sector.

Chapter 4 raises a concern regarding the individually collected data on trademark and patent applications for banks. Due to the unavailability of a comprehensive database for the US banking industry, data on bank trademark and patent applications was hand collected for each fintech-investing banks. Consequently, it is necessary to treat the obtained results with care, as it may not be applicable to all banks. Furthermore, the analysis was conducted on a single country, which may further affect the applicability of the results obtained through the analysis shown in this chapter.

5.4 Avenues for Future Research

Building on previous knowledge to advance current understanding is the essence of academic research. To facilitate this ambitious aim, this section outlines avenues for future research. Some of the presented ideas in this section is on the author's future research agenda.

In chapter 2, we document that higher financial development within a country's banking sector can influence higher activities in alternative credit market. Future research can further investigate the impact of digital credit volumes on the traditional credit provided by banks. Such analysis would deepen our understanding of the interaction between two types of credits within the financial market.

In chapter 3, we have focused our analysis on the banking business model structures of the US banking institutions. Future work may conduct a broader investigation that includes banking sectors of other developed and emerging countries, in order to have a nuanced understanding of the role of banking business models play in the interaction of banks and fintech firms. Furthermore, there is a pressing need to investigate the impact of regulatory policies on the development of the bank-fintech relationship (Choudhary and Thenmozhi, 2024). This will enhance our understanding of this relationship, ultimately guiding the development of effective regulatory policies that promote the growth of both banks and fintech in the financial industry.

Finally, Chapter 4 examines the influence of banks' participation in equity investment rounds conducted by fintech startups on bank innovation. Future work may explore the effect of bank-fintech collaboration on bank competition. Analyzing the bank-fintech relationship from the perspective of market power can provide insightful knowledge for bank executives seeking to maximize profits, as well as policymakers aiming to address the issue of market monopoly through promoting innovative collaboration between banks and fintech firms.

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Appendices

Appendix A

Table A.1: List of countries with their classifications

Argentina	(0)	Estonia	(1)	Malaysia	(0)	Senegal	(0)
Australia	(1)	Finland	(1)	Mali	(0)	Sierra Leone	(0)
Austria	(1)	France	(1)	Mexico	(0)	Singapore	(1)
Belgium	(1)	Germany	(1)	Morocco	(0)	Slovakia	(1)
Brazil	(0)	Ghana	(0)	Mozambique	(0)	Slovenia	(1)
Bulgaria	(0)	Guatemala	(0)	Netherlands	(1)	South Africa	(0)
Burkina Faso	(0)	Hong Kong	(1)	New Zealand	(1)	Spain	(1)
Burundi	(0)	Indonesia	(0)	Nigeria	(0)	Sweden	(1)
Cambodia	(0)	Ireland	(1)	Norway	(1)	Switzerland	(1)
Canada	(1)	Italy	(1)	Pakistan	(0)	Tanzania	(0)
Chile	(0)	Japan	(1)	Palestine	(0)	Thailand	(0)
China	(0)	Jordan	(0)	Panama	(0)	Togo	(0)
Colombia	(0)	Kenya	(0)	Paraguay	(0)	Turkey	(0)
Czech Republic	(1)	Korea	(1)	Peru	(0)	Uganda	(0)
Côte d'Ivoire	(0)	Laos	(0)	Philippines	(0)	UAE	(0)
DR Congo	(0)	Latvia	(1)	Poland	(0)	UK	(1)
Denmark	(1)	Lebanon	(0)	Portugal	(1)	USA	(1)
Ecuador	(0)	Lithuania	(1)	Russia	(0)	Uruguay	(0)
Egypt	(0)	Madagascar	(0)	Rwanda	(0)	Viet Nam	(0)
El Salvador	(0)	Malawi	(0)	Saudi Arabia	(0)		

Note: This table lists the 79 countries included in the regression analysis of Chapter 2. Developed economies are noted (1), whereas developing/emerging ones are noted (0).

Table A.2: Summary Statistics of Log-transformed Variables

Variable	**Obs**	**Mean**	**SD**	**Min**	**Max**	**Skewness**	**Kurtosis**
Digital credit per capita	492	9.32	24.54	0.13	165.47	4.19	21.41
Financial institutions access (0-1)	472	0.41	0.29	0.1	1	0.33	1.88
Financial institutions depth (0-1)	472	0.36	0.30	0.20	1	0.76	2.14
Financial institutions efficiency (0-1)	472	0.59	0.12	0.21	0.79	-0.79	3.08
Financial institutions index (0-1)	472	0.48	0.24	0.07	1	0.24	1.86
Economic freedom (0-100)	484	63.54	10.33	28.50	90.01	0.10	2.96
Economic globalization (0-100)	458	59.95	16.44	29.96	90.01	0.10	1.75
Human development index (0-1)	484	0.73	0.16	0.40	0.96	-0.40	1.81

Source: Author's preparation.
Note: This table presents the summary statistics for original variables of eight variables, which were log-transformed in Table 1. It covers the period 2013-2018. It contains information about the number of observations, mean, standard deviation (SD), minimum and maximum indicators.

Table A.3: Determinants of Digital Credit (Using Normalized Depth of Credit Information Variable)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial institution access	0.324***								2.132***
	(0.099)								(0.746)
Financial institution depth		0.277***							-1.143
		(0.093)							(0.954)
Financial institution efficiency			0.252						1.002
			(0.387)						(0.679)
Financial institution development				0.486***					-3.421**
				(0.157)					(1.362)
Economic freedom					0.931				-1.532
					(0.604)				(1.344)
Economic globalization						0.846			1.173
						(0.865)			(0.813)
Public debt							-2.556***		-2.730***
							(0.778)		(0.794)
Human development								1.350***	-9.430
								(0.335)	(8.386)
GDP growth	0.040*	0.040*	0.041**	0.039*	0.042**	0.045**	0.030*	0.041**	0.044***
	(0.021)	(0.020)	(0.020)	(0.021)	(0.020)	(0.021)	(0.017)	(0.020)	(0.015)
Fintech regulation	0..920***	0.918***	0.928***	0.909***	0.921***	0.785***	0.799***	0.794***	0.881***
	(0.183)	(0.182)	(0.181)	(0.181)	(0.188)	(0.198)	(0.197)	(0.199)	(0.155)
Normalized depth of credit information	-0.343	-0.316	-0.356	-0.340	-0.299	-0.188	-0.221	-0.346	-0.001
	(0.366)	(0.357)	(0.360)	(0.364)	(0.383)	(0.369)	(0.379)	(0.359)	(0.307)
Mobile phone subscriptions	0.004	0.003	0.003	0.003	0.004	0.002	0.002	0.003	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	392	392	392	392	398	377	401	402	363
R^2	0.390	0.386	0.374	0.386	0.378	0.372	0.377	0.367	0.486
Hausman Test	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004

Notes: Analysis period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significance at the 1/5/10%. The dependent variable is digital credit and it has been winsorized at the 1% and 99% levels. Independent variables were lagged by one period. Control variables include the following: GDP growth; normalized depth of credit information; mobile phone subscriptions; fintech regulation dummy that takes the value of 1 if a country is explicitly implementing fintech regulation within its jurisdictions, and 0 otherwise.

Table A.4: Robustness Check: Determinants of Digital Credit (Reverse Causality Analysis)

	(1) Access	(2) Depth	(3) Efficiency	(4) Development	(5) Freedom	(6) Globalisation	(7) Public debt	(8) Human development
Digital Credit	-0.016	-0.017**	0.011	0.002	-0.005	0.001	-0.016**	-0.002***
	(0.010)	(0.007)	(0.011)	(0.007)	(0.004)	(0.004)	(0.006)	(0.001)
GDP growth	-0.001	-0.003**	-0.001	-0.001	-0.001	0.001	-0.005***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fintech regulation	-0.056*	0.001	0.007	-0.022	-0.004	-0.001	-0.009	0.001
	(0.030)	(0.017)	(0.022)	(0.015)	(0.013)	(0.010)	(0.018)	(0.001)
Depth of credit information	-0.005	0.003	-0.006	-0.005***	0.001	-0.003	0.004	0.001*
	(0.006)	(0.004)	(0.004)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)
Mobile phone subscriptions	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	395	395	395	395	400	405	400	405
R^2	0.106	0.255	0.070	0.133	0.058	0.031	0.209	0.625

Notes: Analysis period 2013-2018. Robust standard errors in parentheses. ***/**/* denotes results significance at the 1/5/10%. This regression analysis tests for reverse causality by using the independent variables from the main analysis in Table 4 as the dependent variables. All variables are winsorized at the 1% and 99% levels. Independent variables were lagged by one period. Control variables include the following: GDP growth; depth of credit information; mobile phone subscriptions; fintech regulation dummy that takes the value of 1 if a country is explicitly implementing fintech regulation within its jurisdictions, and 0 otherwise.

Appendix B

Table B.1: List of Fintech-Acquiring Banks

Ally Financial	First National Bank Corp	Regions Financial Corp
Bank Of America	First Republic Bank	SVB Financial Group
Capital One Financial Corp	Goldman Sachs	Simmons First National Corp
Citigroup	Huntington Bancshares	State Street Corp
City National Bank	JPMorgan Chase & Co	SunTrust Banks
Commerce Bancorp	KeyCorp	TBK Bank
CRB Group	Live Oak Bancshares	UMB Financial
Evans Bancorp	MB Financial	US Bancorp
Fifth Third Bancorp	MVB Financial Corp	Wells Fargo & Co
First Colebrook Bancorp	People's United Financial	Regions Financial Group

Note: This table lists the 30 fintech-acquiring banks of Chapter 3.

Table B.2: Impact of Banking Business Model on Fintech Acquisitions (Using Geographic Location Variable)

	(1)	(2)	(3)	(4)
Diversified Banking	0.924***			
	(0.289)			
Wholesale Banking		-1.139***		
		(0.384)		
Traditional Banking			-1.216**	
			(0.526)	
Investment Banking				1.194***
				(0.438)
Size (ln)	1.881***	1.833***	1.796***	1.742***
	(0.161)	(0.156)	(0.157)	(0.155)
ROE (%)	0.021	0.022	0.012	0.014
	(0.027)	(0.027)	(0.026)	(0.027)
NPL (%)	-0.178	-0.110	-0.159	-0.093
	(0.158)	(0.139)	(0.149)	(0.133)
Efficiency (%)	0.001	-0.004	0.011	-0.018
	(0.091)	(0.092)	(0.089)	(0.094)
Liquidity (%)	0.046***	0.031***	0.032***	0.011
	(0.009)	(0.008)	(0.008)	(0.012)
Intangible (%)	0.111	0.117*	0.129*	0.124*
	(0.070)	(0.067)	(0.068)	(0.066)
Capitalization (%)	-0.104**	-0.082*	-0.122***	-0.097**
	(0.047)	(0.045)	(0.046)	(0.043)
IT_Expenditure (%)	0.014	0.025	0.015	0.029
	(0.032)	(0.032)	(0.031)	(0.031)
GDP_Growth (%)	-0.043	-0.041	-0.040	-0.040
	(0.054)	(0.054)	(0.054)	(0.054)
Interest_Rate (ln)	-2.318	-2.358	-2.347	-2.435
	(2.423)	(2.419)	(2.433)	(2.442)
Bank-quarter Observations	406,675	406,675	406,675	406,675
Number of Banks	9280	9280	9280	9280
Wald Chi2	212.0	221.8	220.3	237.0
VIF	1.15	1.16	1.16	1.17

Note: This table shows the logit regression results using the geographic location of fintech firms as a dependent binary variable which equals 1 if a bank acquired a US fintech company in a given quarter, and equals 0 if a bank acquired a foreign fintech firm. The results are presented for four models, each of which relates to one of the four banking business models identified—diversified banking (BM1), wholesale banking (BM2), traditional banking (BM3), and investment banking (BM4) in the period under study (2005Q1-2021Q4). Table 12 shows the definition of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables have been winsorized at the 1% and 99% levels to avoid outliers from skewing the chapter's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. Variance inflation factor (VIF) scores are reported as mean values of independent variables and are used to check for multicollinearity. The statistical significance is denoted by the following symbols: *** p<0.01, ** p<0.05, * p<0.1.

Appendix C

Table C.1: List of Fintech-Investing Banks

Ally Financial	East West Bank	PeoplesBank
Amerant Bank	Emigrant Bank	PNC Bank
American Express	FFB Bank	Popular
Atlantic Union Bank	Fifth Third Bank	Regions Financial Corp
Avidbank	First American Bank	Republic Bank
Banc of California	First Financial Bank	Santander Bank
Bank of America	First National Bank Of Omaha	Seattle Bank
Bank of St. Elizabeth	First Republic Bank, California	SVB Financial Group
BankProv	First Southern National Bank	State Street Corp
BankSouth	Goldman Sachs	Sterling National Bank
Blue Ridge Bank	Grasshopper Bank	SunTrust Banks
Bridge Bank	HSBC North America	Sunwest Bank
Bruning Bank	Huntington Bancshares	Synchrony Bank
Capital One Financial Corp	JPMorgan Chase & Co	TD Bank
Central Pacific Bank	Kearny Bank	BNY Mellon
Choice Financial Group	KeyCorp	Truist Financial
Citigroup	Leader Bank	US Bancorp
Citizens Bank	Live Oak Bancshares	UMB Financial
Citizens National Bank	Midland States Bank	Unity Bank
City National Bank	Morgan Stanley	USAA Federal Savings Bank
Coastal Community Bank	NBH Bank	Valley National Bank
Cogent Bank	Needham Bank	Veritex Community Bank
Commerce Bank, Missouri	Northern Trust	Washington Federal Bank
Compass Bank	OceanFirst Bank	Washington Trust Bank
Congressional Bank	Pacific Mercantile Bank	Webster Bank
ConnectOne Bank	Pacific Western Bank	Wells Fargo & Co
Cross River Bank	Pathward	Woodforest National Bank

Note: This table lists the 81 fintech-investing banks of Chapter 4.