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The Role of Banks' Business Models in their FinTech Acquisitions

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Abstract
In this paper, we examine the role of banks' business models on their decisions to acquire FinTech firms and how they do so. We find that banks with diverse assets, funds, and income structures are more inclined to engage in FinTech acquisitions. Investment banks display selectivity in FinTech acquisitions while wholesale and traditional banks appear more wary, possibly because of the limited need for FinTech in their business models or the externalities in their existing business models.

Keywords Banks · Fintech · Business model · Mergers and acquisitions

JEL Classification G21 · G34 · O31 · O33

1 Introduction

Banks can drive technological innovation by developing new 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 firms that already provide innovative services as a more viable option.

FinTech firms combine financial expertise with technological advancements to create innovative financial products (Thakor 2020). The mergers and acquisitions (M&As) of Fin-

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Tech firms open up opportunities for banks to explore new markets and expand their service offerings beyond traditional boundaries. For instance, collaborations with FinTech firms can enable banks to offer products such as mobile banking apps, digital wallets, robo-advisors, and personalized financial solutions.

In this paper, we empirically examine the role of the business models in driving banks' decisions to acquire FinTech firms. We add to the research on banks' business models and financial crises (Hryckiewicz and Kozłowski 2017; Altunbas et al. 2011; Ayadi et al. 2011), bank performances (Lagasio and Quaranta 2022; Ayadi et al. 2021; Mergaerts and Vander Vennet 2016; Roengpitya et al. 2014), stability (Köhler 2015), interest margins (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 business models of US banks. To achieve this identification, 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 types of business models: diversified, wholesale, traditional, and investment. These four business models have varying characteristics in terms of asset composition, funding sources, and income streams. Next, we employ a textual analysis technique to classify the FinTech acquisitions in our sample based on two dimensions: the type of firm and the motivation of the bank to acquire that firm. Our results show that, within our sample of FinTech acquisitions, the acquired firms can be categorized into five types: payment and settlements, data analytics, lending, financial services software, and investment services. Furthermore, the acquisitions under consideration can be classified into four categories in terms of the bank's motivation to acquire a 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 their diverse assets, funds, and income mixes inherent to them that afford them the flexibility to undertake additional risks. This flexibility aligns with the early findings in the literature (Berger et al. 1999) as well as with more recent papers (Cappa et al. 2022; Zheng and Mao 2024) that indicate technological innovation is one of the most important external motivating factors for banks to engage in M&As.

We also provide novel insights concerning the specific types of FinTech firms that banks target for acquisition. The empirical evidence indicates that diversified banks have a propensity to acquire 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 paper is as follows: In Sect. 2, we examine FinTech development. In Sect. 3, we discus the sample selection, outline our approach to identifying banks' business models, and provide an initial examination of banks' FinTech acquisitions. Section 4 presents our method. Section 5 presents the empirical findings. Section 6 contains the conclusion.

2 Overview of the US FinTech industry

Bank-FinTech relationships date back to the late nineteenth century and have developed through three major periods (Arner et al. 2015). FinTech 1.0 (1866-1967) witnessed the rise of digital financial transactions through the introduction of credit cards and the establishment of double-entry bookkeeping. These two developments laid the groundwork for future innovations. FinTech 2.0 (1967-2008) saw 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 FinTech 3.0 (2008-present) was the global financial crisis (GFC) of 2008. This event significantly affected the public's trust in banks, creating opportunities for new innovative firms 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. The emergence of new firms that offer innovative financial services has placed banks under competitive pressure to adopt technology-driven solutions (Navaretti et al. 2017).

This growth in delivering innovative financial services and the relative maturity of FinTech firms may have sparked investors' interest in the 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 acquisitions globally by 2021. However, global FinTech investment experienced a substantial decline in 2022 and 2023; it dropped to 78.6 billion US dollars in 2022 that represented a 56% decrease year-over-year, and dropped to 39.2 billion US dollars in 2023 that represented another 50% decrease (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.

Figure 1 shows that a significant portion of the worldwide FinTech investment, around 610 billion US dollars, is located within the US. This total represents 51% of the total amount raised, and around 38% of the approximately 15,000 FinTech equity investment acquisitions.

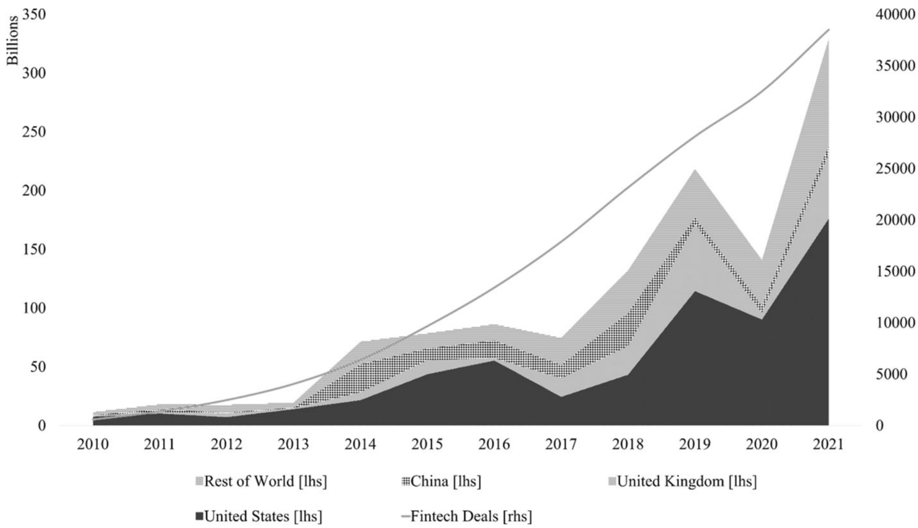

Fig. 1 Amount of worldwide fintech funding and number of deals (2010-2021). Source: Authors' calculations based on data from Cornelli et al. (2021)

2.1 Banks' business models and FinTech

Banks' business models have come under increased scrutiny in academic research following the GFC of 2008. The consensus in this line of literature is that the business models determined how banks fared during the GFC. For instance, Ayadi et al. (2011) examine 26 major banks in Europe during the period from 2006 to 2009 and find that banks with a retail business model had superior performance to those with wholesale and investment business models due to their reliance on stable funding sources. Similarly, Roengpitya et al. (2014) use a global sample of banks to identify the varying responses to the GFC of banks based on their business models. Hryckiewicz and Kozłowski (2017) use a sample of banks from 65 countries during the period from 2000 to 2012 to identify the significant differences among banks' 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 to 2009. They find that during the GFC, banks' credit supply varied depending on their business model.

Altunbas et al. (2011) examine the role of the business model in explaining banks' risk exposure. They show that, in contrast to retail and diversified banks that 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 bank's greater assets, funding, and income diversification, supported by its higher leverage, incentivizes it 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 greater 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 is related to its capacity (or mindset) to take on risk and manage it.

Banks may be wary of the risks in undertaking FinTech acquisitions for multiple reasons. Some of the risks stem from the fundamental instability of the non-deposit liabilities of FinTech firms. Others may stem from regulatory risks that are particularly salient as they may threaten the core culture of "boring stability" on which banks are predicated. For example, Navaretti et al. (2017) argue that many lending FinTech firms are likely to have riskier assets and liabilities than those of banks. This is primarily owing to their adoption of an agency model in which they do not assume the risk of the loans they make, potentially attracting riskier borrowers. In addition, these firms charge commission-based fees, collecting from both parties involved in the transaction that promotes volume over stability. Therefore, many FinTech firms lack diversity in their assets and liabilities compared with incumbents. Furthermore, banks may be reluctant to undertake M&As 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 use of innovative products in the financial industry. Moreover, Del Gaudio et al. (2024) suggest that acquiring FinTech firms is a fast but riskier approach for banks to obtain the necessary technology. This higher risk is due to the potentially high valuation of FinTech firms and their increased risk of bankruptcy.

Although the mainstream literature on bank M&As provides a good understanding of what motivates banks to engage in M&As (DeYoung et al. 2009), less attention is paid to the FinTech M&As. For example, Austin and Dunham (2022) show that the acquirers' risk profiles improve after the FinTech acquisitions. A related strand of literature has an analyzation of the operating performance of banks after the M&As 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) have investigated the motivations behind the acquisitions of FinTech firms 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 effect from banks' FinTech M&As on their profitability in the US.

However, studies have mixed results when the effect of banks' FinTech acquisitions are measured by the market reaction. Kueschnig and Schertler (2024) show that banks have higher abnormal returns following their first FinTech acquisitions, as they may signal the commitment of banks to financial technology. While Cappa et al. (2022) argue that the effects of bank FinTech M&As depend on the type of service provided by the FinTech firms. Collevecchio et al. (2023) find that the market reaction to a bank's stock 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 that could be due to investors believing that banks are overestimating the advantages of acquiring a FinTech firm.

3 Data

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 paper, we first identify banks' business models within our data and use clustering variables to perform the cluster analysis on 9,558 banks and 452,375 bank-quarter observations. Our sample period spans from 2005Q1 to 2021Q4. We investigate this period because it covers the introduction of new innovative financial firms. For example, 2005 marks the introduction of Prosper that was 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 banks' FinTech M&As from the Zephyr and Refinitiv databases that are powered by Bureau van Dijk and Thomson Reuters, respectively. We follow specific criteria for each database in order to include target firms 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.[1] These codes result in the identification of 1545 acquisitions from the Zephyr database. While in the Refinitiv database, we search for acquisitions in the following industries: high technology, financials, consumer goods and services, healthcare, and real estate. We identified 4,190 acquisitions in the Refinitiv database. We supplement these two databases with announced acquisitions that were not captured by either database.

[1] The following are the names of each SIC code: 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 services; 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.

To identify our final sample of FinTech acquisitions, we apply the following criteria. First, we limit our sample to only include those involving banks with headquarters in the US as acquirers. Second, we only include completed or announced acquisitions in which the acquirer controls at least 51% of the target firm's shares. Third, we review the business description 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 Bank) acquired FirstAgain LLC that is 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 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 press release on an acquisition to confirm that the target firm is a FinTech firm, investigate the type of target, and explore the bank's motivation for the acquisition.[2] Finally, we remove duplicates. Due to the fact that we use multiple databases, it is important to double-check each acquisition included to avoid counting the same one twice.

As a result of applying the above criteria, we obtain 39 banks' FinTech acquisitions from the Zephyr database, 36 from the Refinitiv database, and 16 manually added from banks' official websites. All identified acquisitions of FinTech firms were made by banks. This criteria results in a total of 91 FinTech acquisitions done by 30 banks. The sample size is similar to those in other studies. For example, de Boyrie and Pavlova (2024) find 155 FinTech acquisitions done by 55 US banks in the period from 2010-2022. Kwon et al. (2024) use 105 international FinTech acquisitions done by 80 banks in 15 OECD countries during the period from 2010-2018. Collevecchio et al. (2023) investigate 107 international banks' FinTech acquisitions and use a total of 60 observations spanning from 2010-2020. Akhtar and Nosheen (2022) identify a sample of 81 banks' FinTech acquisitions in the US, UK, Canada, and France in the period from 2010-2020. Zheng and Mao (2024) use 196 acquisitions between FinTech and US public banks, nonbank financial institutions, and tech firms (US banks had full control over 22 FinTech firms) in the period from 2010 to 2021. We note that our strict inclusion criteria based on our definition of a FinTech firm is another contributing factor that limits the number of banks' FinTech acquisitions in the sample (Kwon et al. 2024). We specifically focus on target firms that embody both financial and technological expertise, excluding acquisitions involving target firms that solely offer either technology or financial services. Figure 2 shows the number of acquisitions in each quarter under investigation, as well as the cumulative number of acquisitions over time.

In Fig. 3, we compare the total assets of acquiring banks to the industry's in each quarter throughout the paper. Although the number of acquiring banks in our sample is small, they did account for 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 constitute a higher portion of industry's total assets than that observed in the related literature on the US banking sector (Adams and Mehran 2012).

[2] A detailed discussion of the method used to identify the types of firms and motivations of banks is outlined in Appendix B. Empirical analyses of the types and motivations are provided in Sects. 5.3 and 5.4.

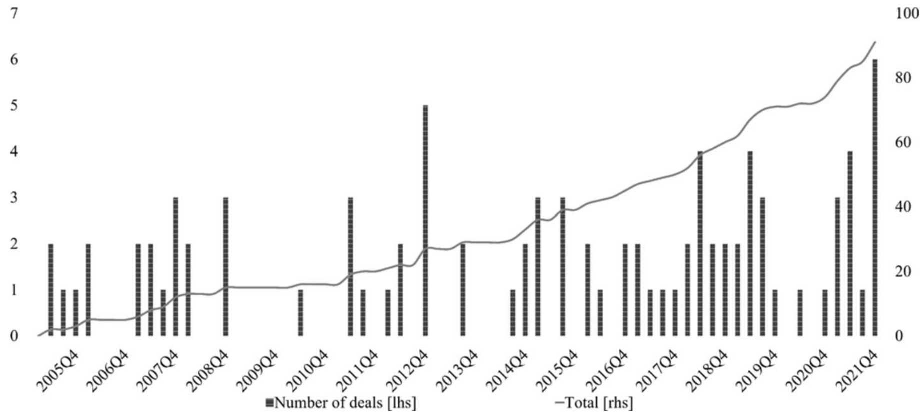

Fig. 2 Number of bank-fintech acquisitions (2005Q1-2021Q4). Source: Authors' calculations

3.2 Identifying banks' business models

The bank's 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 how financial ratios reflect bank strategy. We follow the literature by adopting an unsupervised cluster analysis called non-hierarchical K-means clustering that is based on variables from the banks' financial reports (see, e.g., Farne and Vouldis 2021; Vinas 2021; Martín-Oliver et al. 2017; Hryckiewicz and Kozłowski 2017; Ferstl and Seres 2012). Clustering algorithms, a subcategory of unsupervised machine learning, aim to infer a data structure by grouping observations with the highest homogeneity within clusters and the lowest similarity across clusters (Hoang and Wiegratz 2023). These algorithms have been used in a variety of contexts within the finance literature, including venture capitalists (Bubna et al. 2020), banks' business models (Ayadi et al. 2021), and mutual funds (Bubb and Catan 2022).

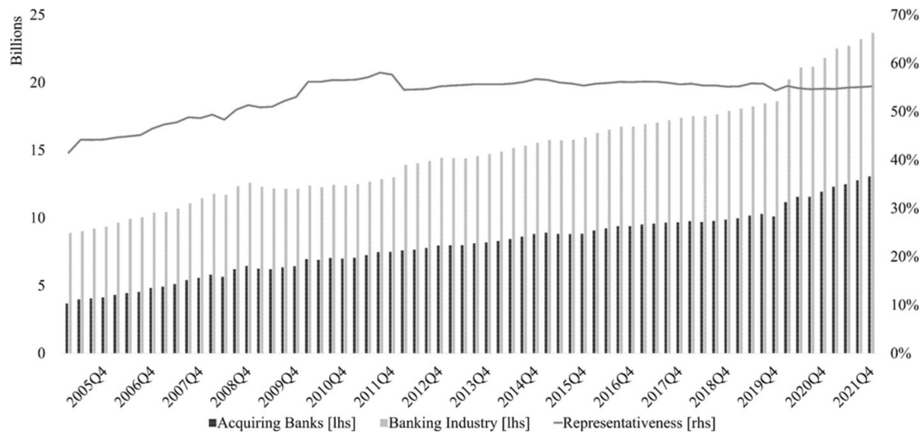

Fig. 3 Comparison between acquiring banks and the US banking industry in terms of total assets (2005Q1-2021Q4). Source: Authors' calculations

Table 1 A comparison of average values by banks' business models. This table shows a comparison of mean and standard deviation values of variables used in the clustering algorithm across the four business models: identified–diversified banks (BM1), wholesale banks (BM2), traditional banks (BM3), and investment banks (BM4) in the period under study (2005Q1-2021Q4). The number of banks is the total number that have adopted each business model. The ratio of consumer loans is a bank's lending to consumers divided by its total assets. The 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

	BM1		BM2		BM3		BM4	
	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		9,128	
Number of Banks	5,359		1,587		2,370		242	

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.[3] 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 identifies the share of bank's participation in the interbank market. Second, we use 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 of banks. Third, we use the share of total investments over total assets (Roengpitya et al. 2014; Hryckiewicz and Kozłowski 2017) as it identifies 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, 2017) to capture the strength of the bank's deposit base which enables it to avoid using other sources of funding (Milcheva et al 2019). And fifth, we use the non-interest income over adjusted operating income (Tran et al. 2021; Köhler 2015) which shows the share of other sources of income. Please see Appendix A for the full details of how we implement the non-hierarchical K-means clustering.

The results of the analysis are presented in Table 1 which identifies four distinct business models. After analyzing the characteristics of each model, we label them as follows: diversified banks (BM1), wholesale banks (BM2), traditional banks (BM3), and investment banks (BM4).

The first identified business model is diversified banks (BM1). Relative to other business models, banks in this group have the most balanced average values of the clustering variables. On the asset side, these banks have the second-highest percentage of consumer loans (3.64%) and bank loans (9.63%). While having an average value of 22.74% for the investment activities ratio, demonstrating a mix of assets. 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

3 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.

income of 16.17% is another sign of the diversified income structure of this group of banks. Diversified Banking has 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 banks (BM2). Banks under this business model have the highest percentage of loans to banks (Bank loans ratio) at 11%, indicating a wholesale orientation of loans through active participation in the interbank market. These banks have an average value of 2.87% for loans to consumers while having the lowest average total investment ratio (19.93%) and non-interest income ratio of 13.38%. Wholesale banks is the model of choice for about 1587 banks in our sample which accounts for 16.60% of the total.

The third identified business model is traditional banks (BM3). Banks with this type of 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 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. Traditional banks are the second largest cluster as they equal a total of 2370 banks, accounting for (24.80%) of all banks.

Investment banks (BM4) are the fourth identified business model. On the asset side, these banks are 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 with a consumer loans ratio of 2.16% and bank loans ratio of 2.07%. On the liabilities side, investment banks also have the lowest average CDA ratio (13.31%) indicating the reliance on volatile and risky financing resources. Investment banks contain the fewest banks (242), accounting for just 2.53% of the whole sample.

3.3 Initial examination of banks' FinTech acquisitions

In this subsection, we examine whether the banks' business model plays any significant role in FinTech acquisitions. To this end, Table 2 provides an overview of the types of target FinTech firms in our sample and how the various motives for acquiring these firms differ across the four business models. We classify the services provided by FinTech firms as: Payments and settlements (20 firms), data analytics (19 firms), lending (18 firms), 17 firms for financial software, and 17 firms for investment services. In addition, we identify the main motives for banks to acquire FinTech firms as introducing new products (36 acquisitions), enhancing capabilities (28 acquisitions), business scalability (22 acquisitions), and entering new markets (5 acquisitions). Please see Appendix B for the detailed method we use to identify the types of FinTech firms and the motives of banks for acquiring them.

Panel A in Table 2 shows the services provided by target FinTech firms across the different business models. Diversified banks are the most active in four out of five services: payment and settlements, data analytics, lending, and financial services software. Investment banks are the most active in acquiring investment services firms. Also, diversified banks completed 12 acquisitions of payment and settlements firms, followed by investment banks 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 banks completed four, while wholesale and traditional banks did not acquire any FinTech firms. It should be noted that the acquisition of data analytics firms allows banks to offer targeted

Table 2 An initial examination of banks' FinTech acquisitions. This table holds a summary of the types of FinTech firms identified within our sample and of the motives behind their acquisitions across different business models

	Diversified Banking	Wholesale Banking	Traditional Banking	Investment Banking	Total
Panel A: Types of FinTech Services					
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 banks' FinTech Acquisitions					
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

deals to clients such as debit card marketing. Regarding lending firms, diversified banks are first with 12 acquisitions, investment and wholesale banks each have three acquisitions, while traditional banks 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 banks completed 12 acquisitions, while traditional and investment banks each completed two, and wholesale banks completed one. These firms 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 banks are the most active with 10 acquisitions. Diversified banks come next with four followed by wholesale banks with two and traditional banks with one acquisition.

Panel B in Table 2 has a summary of the strategic motives behind banks acquiring FinTech firms across different business models. We can make the following observations: First, diversified and investment banks intensively use FinTech acquisitions to offer a wide range of financial services, with 20 and 12 acquisitions respectively. Wholesale banks only made four acquisitions for this purpose, while traditional banks do not use FinTech acquisitions to introduce new products. Second, in terms of enhancing internal technological capabilities, diversified and investment banks made the most acquisitions, with 19 and 6 acquisitions respectively. Traditional banks completed two acquisitions with the same motive, while wholesale banks only completed one acquisition. These acquisitions allow banks to improve their tech-enabled services, such as accepting online deposits and automating portfolio design and delivery. Third, diversified banks pursued growth strategies the most, with 14 acquisitions, followed by wholesale and investment banks with three acquisitions 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 banks completed a total of five FinTech acquisitions 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 industry, aiming to capitalize on the potential of that new market opportunity.

4 Methodology

In this section, we discuss the variables used in the analysis. It also outlines the econometric model of the baseline analysis.

4.1 Variables

Our main variable of interest is a binary variable called $FinTechAcquisition$ that equals one if a bank was involved in a FinTech acquisition in a given quarter, and zero otherwise. However, some banks in the sample conducted multiple acquisitions in the same quarter. To account for these duplicates, we have counted the acquisitions made during that quarter as one, disregarding other ones that occurred for the same bank during the same quarter. This count led to a reduction in the total number of banks with FinTech acquisitions from 91 to 84.

Furthermore, we follow the literature by adding 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 a bank's total assets. We follow Collevecchio et al. (2023) and add bank size to our baseline model as it differentiates larger banks from smaller banks. We argue that larger banks are more capable of conducting innovation acquisitions because of their greater ability to build an innovative environment through the availability of the necessary human, material, and financial resources, as empirically shown by Pi and Yang (2023). Moreover, several studies agree on the significant effect of size on a bank's decision to acquire other firms (Beccalli and Frantz 2013; Pasiouras et al. 2011; Focarelli et al. 2002). Consequently, we predict a positive relationship between bank size and the likelihood of acquiring FinTech firms.

We further add bank's equity ($Capitalization$) to our model and measure it as total equity over total assets. The theoretical background of the relationship between a bank's capital and its risk-taking has multiple views. For instance, according to the capital buffer theory, well-capitalized banks with levels above the regulatory 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 to preserve their capital position.

Next, we use the ratio of the return on equity (ROE) as a measure of banks' profitability. The relationship between bank profit and FinTech acquisitions can take different forms. For example, a positive relationship can exist 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 nonperforming loans ratio (NPL) to indicate the quality of the loan portfolio. Kwon et al. (2024) provide evidence that a bank's NPL can be considered a hindrance to a bank's capital which could limit its involvement in FinTech acquisitions. As such, we predict that NPLs will be negatively associated with the bank's FinTech acquisition activity.

Moreover, we use the ratio of banks' non-interest expenses over total assets to measure their 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 that enables them to integrate cutting-edge technologies into their operations. In the related literature, Pasiouras et al. (2011) find that cost efficiency has a positive and statistically significant effect on a bank's decision to acquire targets. However, less efficient banks might consider FinTech firms as an appealing option for streamlining and automating internal operations. 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, 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 new technologies facilitated by the acquisition of FinTech firms. Furthermore, bank liquidity is included as the ratio of cash and short-term investment to total assets ($Liquidity$). As shown by Kwon et al. (2024), banks with greater liquidity are more capable of acquiring a FinTech firm. As a result, we predict a positive relationship between bank liquidity and the possibility of acquiring FinTech firms.

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 ratio of intangible assets to total assets ($Intangible$) to measure banks' internal FinTech development. Second, We follow Kwon et al. (2024) and Beccalli (2007) and use banks' IT expenditures. 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 banks' technological investment (Sedunov 2017). Data processing expenses are often used in the US banking literature to assess 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 one hand, banks that are developing their internal technological capabilities might consider acquiring FinTech firms as a growth opportunity, while 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 low IT expenditures may view FinTech acquisitions as a profitable option to avoid the costs and complications of setting up departments and using 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 represents the country's overall health and future prospects for profit and growth. Kwon et al. (2024) outline that banks located in a country with higher GDP growth are more likely to make FinTech acquisitions. Therefore, we predict that growth will be positively correlated with banks' FinTech acquisitions. The data are collected from the 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 (FRB). Table 3 provides the research variables' definitions.

Table 3 Definitions of variables. All bank-specific variables were collected from the call reports. The variable FinTechAcquisition was constructed by using the Zephyr and Refinitiv databases. Real GDP growth variable was collected from the US Bureau of Economic Analysis (BEA). Real interest rate was collected from the Federal Reserve Board (FRB)

Variable	Definition
FinTechAcquisition	A dummy variable that equals one if a bank participated in an acquisition with a FinTech firm in a given quarter, or zero 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
Nonperforming 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, gains and losses in foreign exchange market, 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
Real GDP Growth	The inflation adjusted percentage change in GDP
Real Interest Rate	The natural logarithm form of banks' nominal lending rate adjusted for inflation

Prior to conducting the main and additional regression analyses, we perform a preliminary analysis in Table 4 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 firm at least once during the sample period) and non-acquiring banks (banks that did not acquire any FinTech firms). The table displays the means and standard deviations (SD) of the variables used in the baseline regression analysis. These two metrics are supplemented by the mean difference (MD) that demonstrates the difference between both groups of banks in terms of absolute value (Abs) and statistical significance determined by the p-value.

Table 4 Summary statistics. 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 of 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 were winsorized at the 1% and 99% levels to avoid outliers from skewing the findings. Table 3 shows the definitions of all variables. MD in the last column refers to the mean difference between acquiring banks and non-acquiring banks in absolute (Abs) values

	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***
Bank-quarter Observations	406,675		1725		404,950		
Number of Banks	9,280		30		9,250		

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 4 shows that acquiring banks are statistically different from non-acquiring banks in terms of all variables: $Size$, ROE, NPL, $Efficiency$, $Liquidity$, $Intangible$, $Capitalization$, and $IT Expenditure$. First, in terms of $Size$, our results show that acquiring banks are larger than non-acquiring banks (15.90 vs 12.18) that indicate larger banks are more likely to acquire FinTech firms. This result is in line with the literature (Beccalli and Frantz 2013). Next, the result for ROE 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 a higher NPL than acquiring banks (1.27% vs 1.03%) that indicates banks who are more burdened with nonperforming loans are less likely to acquire FinTech firms. This is consistent with Kwon et al. (2024) findings. Similarly, non-acquiring banks are slightly less efficient with a higher non-interest expense to total assets 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 the intangible assets ratio ($Intangible$) is statistically different in acquiring banks (2.24%) than non-acquiring banks (0.45%) that indicates the banks who acquire FinTech firms 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 and abstain from acquisitions associated with uncertainties. Lastly, non-acquiring banks invest more in electronic data processing (EDP) equipment as can be seen in their IT expenditure ratio ($IT Expenditure$) of 4.62% compared with 3.25% ratio of acquiring banks.

The scores for the pairwise correlation matrix and variance inflation factor (VIF) among variables used in models estimating banks' FinTech acquisitions are presented in Table 5. The findings show that there is a low correlation between the independent variables. Also, the highest reported VIF score is 1.29, which is well below the threshold of 10 (Wooldridge 2012). This score indicates that combining the variables does not result in multicollinearity issues.

4.2 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.[4] The logit regression model has been extensively used in numerous settings involving bank M&As (Akhigbe et al. 2004; Correa 2009; Beccalli and Frantz 2013), banks' business models (Ayadi et al. 2021), and banks' 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 acquiring a FinTech firm:

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

where Z_{it} denotes the likelihood that a bank will acquire a FinTech firm. We use $FinTechAcquisition$ as the binary outcome variable that equals one if a bank acquires a FinTech firm in a given quarter and zero otherwise. β_0 is an intercept term. β_1 is the main coefficient of interest. BM refers to one of the four types of business models: $Diversified$, $Wholesale$, $Traditional$, and $Investment$. Depending on the regression specification, the business model indicator equals one if the bank follows the respective business model and zero otherwise.[5] $Size$ 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 to 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's total equity over total assets. $IT\_Expenditure$ is calculated as the ratio of data processing expenses scaled by non-interest expenses. $Macroeconomic$ comprises 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.

5 Results and discussion

In this section, we discuss the baseline results, robustness check, and an additional analysis.

[4] We provide two additional robustness checks in the online appendix. Specifically, we perform our main analysis using a probit model with annualized data. Both results are similar to the main results.

[5] Since each of the four dummy variables included in the variable BM corresponds to one of the identified business models, we follow the literature on the analysis of 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).

Table 5 The scores of the pairwise correlation matrix and variance inflation factor (VIF). This table shows the pairwise correlation matrix and VIF scores for the independent variables used in the regression analysis. Table 3 shows the definitions of all variables

	Size	ROE	NPL	Efficiency	Liquidity	Intangible	Capitalization	IT Expenditure	GDP Growth	Interest Rate	VIF
Size (ln)	1										1.27
ROE (%)	0.11	1									1.27
NPL (%)	0.02	−0.39	1								1.29
Efficiency (%)	−0.08	0.05	0.07	1							1.06
Liquidity (%)	−0.30	−0.11	0.01	0.06	1						1.17
Intangible (%)	0.29	−0.01	−0.03	0.04	−0.09	1					1.15
Capitalization (%)	−0.12	−0.08	−0.06	0.16	0.18	0.16	1				1.15
IT_Expenditure (%)	−0.11	−0.02	0.02	0.06	0.01	−0.03	−0.01	1			1.02
GDP_Growth (%)	0.01	0.06	−0.04	−0.02	0.01	−0.01	−0.01	−0.03	1		1.06
Interest_Rate (%)	−0.11	0.13	−0.21	0.02	−0.06	0.04	0.02	−0.03	0.12	1	1.12

5.1 Impact of banks' business models on FinTech acquisitions

Table 6 presents the results of the logistic regression.[6] We find a significant and positive relationship between the diversified business model and the likelihood of acquiring FinTech firms as shown in column (1). This relationship indicates that banks with a diversified business model (i.e., more variety of asset compositions and revenue sources) are more likely to be active in acquiring FinTech firms. Given the characteristics of diversified banks, our results supplement the findings of Demsetz and Strahan (1997) who demonstrate that banks with greater leverage, supported by larger assets, better financing, and diverse incomes, may take on more lending risks than other banks. In addition, Wu et al. (2020) indicate that greater diversification can indirectly increase banks' 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 and negative relationship between the wholesale business model and FinTech acquisitions as shown in column (2). The results indicate that banks with a greater level of activity in the interbank market are less likely to acquire FinTech firms. Wholesale banks have a lower appetite for risk-taking, hence they have less interest in acquiring FinTech firms than the banks with other business models. This appetite may 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 the traditional business model, the results in column (3) show a negative and statistically significant relationship at the 5% level, indicating that this business model, relative to the others, is not more likely to acquire FinTech firms. One probable explanation is that strategic acquisitions of FinTech firms may not be in line with a 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 acquisitions in the form of collaboration with FinTech firms. 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 the acquisitions of FinTech firms. It indicates that banks with an investment business model are more inclined to engage in FinTech acquisitions compared to other business models. However, with a total of 24 FinTech acquisitions, investment banks may be more selective in their acquisitions due to their acumen over other business models. Furthermore, Hryckiewicz and Kozłowski (2017) highlight the increased systemic risk associated with the investment business models. This risk may potentially influence investment banks' risk-taking decisions.

Next, we analyze the role of bank-specific characteristics in FinTech acquisitions. In all four models, we find that the coefficient for bank size, as measured by the natural logarithm form of its total assets, is positively and statistically significant at the 1% level. This coefficient 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 acquisitions. Furthermore, in

[6] The sample size decreases to 9,280 banks and 406,675 bank-quarter observations in the regression estimation due to missing data on regression variables.

Table 6 Impact of banks' business models on FinTech acquisitions. This table shows the logit regression results for the dependent variable $FinTechAcquisition$ which is a binary variable that equals one if a bank acquires a FinTech firm in a given quarter and zero otherwise. The results are presented for four business models, each of which relates to one of the four types of banks identified: diversified banks (BM1); wholesale banks (BM2); traditional banks (BM3); and investment banks (BM4) in the period under study (2005Q1-2021Q4). Table 3 shows the definitions of all variables. Time fixed effects were added to account for unobserved time-varying factors. All variables were winsorized at the 1% and 99% levels to avoid outliers from skewing the study's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality. The scores for the variance inflation factor (VIF) are reported as mean values of the independent variables and are used to check for multicollinearity

	(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	9,280	9,280	9,280	9,280
Wald Chi2	220.4	231.5	230.5	253.2
VIF	1.15	1.16	1.16	1.17

* p<0.1, ** p<0.05, *** p<0.01

models (1), (2), and (3), we show that more liquid banks are more likely to acquire FinTech firms, with a positive and significant coefficient value (at the 1% level). Consistent with the findings of Kwon et al. (2024), this coefficient indicates that more liquidity encourages the bank to take more risk and may lead to the acquisitions of FinTech firms.

Moreover, we find 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, the results show a statistically significant and 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 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 the type of business model has a significant influence on banks' decisions to acquire FinTech firms. We show that the diversified and investment business models are more likely than other business models to acquire those firms. Conversely, wholesale and traditional business models have cautious attitudes 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.

5.2 Propensity score matching

To check the robustness of our main results, we use propensity score matching (PSM) (Rosenbaum and Rubin 1983). This method is particularly useful in our context as it balances the sample size that overcomes 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 PSM 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 the banks' capitalization ratio (Kwon et al. 2024) and size (Del Gaudio et al. 2024) as the literature has shown them to be significant factors for banks' 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 capitalization ratio and size between acquiring and non-acquiring banks before and after matching are shown in Table 7. Before matching, the mean difference in absolute terms between the two groups for bank capitalization is 0.515 with a p-value of 0.346. Size has 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 is used.

Similar to our main results, Table 8 shows that the diversified business model has a positive and significant coefficient, while the wholesale business model shows a negative coefficient of the same magnitude. However, the traditional and investment business models lose their

Table 7 Balancing of covariates. This table shows the results of using propensity score matching (PSM) to match two samples: banks that 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 banks' total assets). MD is the mean difference between acquiring banks and non-acquiring banks in absolute (Abs) values and its statistical significance (p-value)

	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
Number of Banks	30	9280			30	45		

Table 8 Impact of banks' business models on FinTech acquisitions by using a PSM sample. 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 one if a bank acquires a FinTech firm in a given quarter, and zero otherwise. Both the $Size$ and $Capitalization$ variables are not included in the estimation as they are used as matching variables. The results are presented for each of the four business models identified: diversified banks (BM1); wholesale banks (BM2); traditional banks (BM3); and investment banks (BM4) in the period under study (2005Q1-2021Q4). Table 3 shows the definitions of all variables. Time fixed effects are included to account for unobserved time-varying factors. All variables were winsorized at the 1% and 99% levels to avoid outliers from skewing the study's findings

	(1)	(2)	(3)	(4)
Diversified Banking	1.851***			
	(0.565)			
Wholesale Banking		−2.087***		
		(0.625)		
Traditional Banking			0.188	
			(0.754)	
Investment Banking				0.064
				(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

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

significance. Regarding bank-specific variables, we find that the coefficients for liquidity are positive and statistically significant. Consequently, the results indicate that sample selection bias has no effect on the results of the main analysis.

5.3 Further analysis: What type of FinTech firms do banks acquire?

We discussed in Sect. 3.3 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 firms operating in the US 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 firms have positive effects 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 have negative effects.

We use Eq. 1 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 firm acquired by banks. As explained earlier, we identify five types of FinTech firms in our sample: payment & settlements, data analytics, lending, investment services, and financial services software.[7] Tables 9, 10 and 11 present the regression results in five panels each representing one type of FinTech firm.

The findings of the regression analysis for the payment and settlement FinTech firms (PayTech) are shown in Panel A of Table 9. Innovation in the rapid payment sector 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 these firms and the focus on innovation-driven initiatives by investment banks. Although the results do not indicate any significant differences among other 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 acquirers make 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 size has significant and positive coefficients, indicating that larger banks are more likely to acquire PayTech firms, the capitalization ratio is negatively associated with the likelihood of acquiring PayTech firms.

Panel B of the same table shows the findings pertaining to FinTech firms in data analytics. The results demonstrate that diversified banks show a greater propensity to acquire data analytics firms than the 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, reward, and benefit 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 banks since they did not engage in any data analytics acquisitions during the research period. Consistent with previous observations, we ascertain that larger banks are more inclined to engage in transactions involving FinTech firms in data analytics. Similarly, banks with higher liquidity, lower efficiency, and advanced technology (as measured

[7] Please see Appendix B for further information on the methodology used to classify banks' FinTech acquisitions in our sample. In addition, Table 14 presents the types of FinTech firms and their main characteristics.

Table 9 Payment and data analytics as target FinTech firms. 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 equals one if the bank acquired a FinTech firm of the corresponding type, and zero otherwise. The analysis period is from 2005Q1 to 2021Q4. Table 3 shows the definitions of all variables. Time fixed effects are included to account for unobserved time-varying factors. All variables were winsorized at the 1% and 99% levels to avoid outliers from skewing the study's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality

	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)

Table 9 continued

	Panel A: Payment Firms				Panel B: Data Analytics Firms			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
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	9,273	9,273	9,273	9,273	7,304	6,556	5,293	7,304

* p<0.1, ** p<0.05, *** p<0.01

by both banks' intangibles and IT expenditure) show an increased likelihood of acquiring data analytics firms.

Panel C of Table 10 displays the outcomes related to lending FinTech firms. Diversified banks have a 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 acquiring lending technologies, such as digital lending platforms and financing/leasing services, as a means to stay relevant in the dynamic lending industry. Conversely, wholesale banks have 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 do not engage in any acquisitions of lending firms. This seemingly counter-intuitive observation may be explained by their preference for collaborating with FinTech firms instead of outright acquisitions, as it is perceived as a less risky strategy that allows 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 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 to acquiring FinTech lending firms.

The findings in Panel D of the same table indicate that investment business models have a greater propensity to acquire FinTech firms offering investment services, in contrast to the other business models. Acquiring firms specializing in investment advisory services, wealth management, and trading platforms appear 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, indicating 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.[8] Also, the results show that more liquid banks are more likely to acquire FinTech firms in investment services.

Finally, in Panel E of Table 11, we present the regression results for FinTech firms specializing in financial services software. Diversified banks have a positive and significant relationship, possibly owing to the diverse nature of their clientele. With 12 acquisitionss, 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 one acquisition for financial software showing limited interest in this type of FinTech firm, as indicated by the negative and significant coefficient. Upon checking the details of this acquisition we find that it is specifically related to money transfer technology. Furthermore, the negative coefficient observed for traditional banks may reflect their risk-averse acquisition strategy, as they prefer collaborating with venture FinTech firms as a less risky alternative. For investment banks, the negative coefficient indicates a lack of interest in acquiring financial technology software firms; instead, they may

[8] 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.

Table 10 Lending and investment services as target FinTech firms. This table shows the logistic regression results for the two dependent dummy variables: *Lending*, and *InvestmentServices*. They are shown in two panels: C and D. Each dummy variable equals one if the bank acquired a FinTech firm of the corresponding type, and zero otherwise. The analysis period is from 2005Q1 to 2021Q4. Table 3 shows the definitions of all variables. Time fixed effects are included to account for unobserved time-varying factors. All variables were winsorized at the 1% and 99% levels to avoid outliers from skewing the study's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality

	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)

Table 10 continued

	Panel C: Lending Firms				Panel D: Investment Services Firms			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
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	2,890	2,890	2,890	2,890
Number of banks	7,537	7,537	5,496	7,537	133	133	133	133

* p<0.1, ** p<0.05, *** p<0.01

be more 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.

5.4 Further analysis: Why do banks acquire FinTech firms?

We provide a further empirical analysis of the motives of banks to acquire FinTech firms. Little research has been conducted to investigate the motivations of alliance between both these 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 to 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 FinTechs gain easier market entry, increased revenue, and broader innovative products. In this analysis, we aim to empirically examine the influence of business models on the banks' motivation to acquire FinTech firms. To this end, we use Eq. 1 to examine the likelihood of banks acquiring FinTech firms based on their motives behind the acquisitions. In particular, we estimate five models each with a dependent dummy variable representing one of the four motives behind banks acquiring FinTech firms.[9]

The regression results are presented in Tables 12 and 13. Panel A of Table 12 presents some notable observations regarding the effects of 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 use 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 in the creation of innovative products. Although not statistically significant, diversified banks show a positive coefficient. Diversified banks made 20 acquitions, potentially owing to the capacity of investment and diversified business models to tolerate 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 acquisitions aimed at introducing new products, indicating limited interest in FinTech firms for this purpose. Traditional banks; meanwhile, they did not use FinTech acquisitions to introduce new products. Additionally, the findings indicate that larger banks with greater liquidity are more likely to acquire FinTech firms to launch new products.

Moreover, panel B in Table 12 shows positive coefficients for both diversified and investment banks, albeit statistically insignificant. These coefficients highlight the relevance of FinTech acquisitions in fostering in-house capabilities for diversified and investment banks. Conversely, wholesale and traditional banks display negative coefficients, indicating their lower likelihood 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.

[9] Please see Appendix B for further information on the methodology used to classify banks' FinTech acquisitions in our sample. In addition, Table 15 presents the motives of banks to acquire FinTech firms.

Table 11 Financial Services Software as target FinTech firms. This table shows the logistic regression results for the dependent dummy variable $FinancialServicesSoftware$ which equals one if the bank acquired a FinTech firm that provides financial services software, and zero otherwise. The analysis period is from 2005Q1 to 2021Q4. Table 3 shows the definitions of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables were winsorized at the 1% and 99% levels to avoid outliers from skewing the study's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality

	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				−0.008
				(1.035)
Size (ln)	1.391***	1.329***	1.263***	1.265***
	(0.211)	(0.199)	(0.199)	(0.199)
ROE (%)	−0.003	−0.005	−0.013	−0.013
	(0.063)	(0.063)	(0.057)	(0.056)
NPL (%)	−0.443	−0.323	−0.364	−0.347
	(0.362)	(0.330)	(0.324)	(0.318)
Efficiency (%)	−0.449	−0.430	−0.376	−0.358
	(0.334)	(0.324)	(0.307)	(0.305)
Liquidity (%)	0.047**	0.026	0.030*	0.030
	(0.020)	(0.018)	(0.018)	(0.022)
Intangible (%)	−0.009	0.029	0.055	0.065
	(0.147)	(0.136)	(0.138)	(0.137)
Capitalization (%)	−0.002	−0.001	−0.027	−0.025
	(0.078)	(0.074)	(0.076)	(0.076)
IT_Expenditure (%)	−0.006	0.011	−0.001	−0.001
	(0.076)	(0.074)	(0.070)	(0.070)
GDP_Growth (%)	−0.119	−0.116	−0.113	−0.112
	(0.149)	(0.148)	(0.147)	(0.147)
Interest_Rate (ln)	−8.209	−8.045	−8.019	−7.954
	(5.617)	(5.577)	(5.546)	(5.524)
N	300,961	300,961	300,961	300,961
Number of banks	9,196	9,196	9,196	9,196

* p<0.1, ** p<0.05, *** p<0.01

Table 12 Introducing new products and enhancing capabilities as strategic motives for banks' FinTech acquisitions. This table shows the logistic regression results for the two dependent dummy variables: $NewProducts$ and $EnhancingCapabilities$. They are shown in two panels: A and B. Each dummy variable equals one if the bank's strategic aim behind the FinTech acquisition is the corresponding motivation, and zero otherwise. The analysis period is from 2005Q1 to 2021Q4. Table 3 shows the definitions of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables were winsorized at the 1% and 99% levels to avoid outliers from skewing the study's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality

	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)

Table 12 continued

	Panel A: Introducing New Products				Panel B: Enhancing Capabilities			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
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	9,278	9,278	6,939	9,278	9,272	9,272	9,272	9,272

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

The results for business scalability motivation are presented in Panel C in Table 13. It should be noted that the targeted market of each business model influences both the growth strategy and its execution. Similar to Panel B in Table 12, no business model has statistically significant indications. However, diversified banks have a positive coefficient. This coefficient means that banks with this business model are attracted to expansion strategies that involve the risky acquisition of FinTech firms. This inclination may be supported by their capacity to undertake additional risks, as evidenced by diversified banks completing 14 acquisitions for growth purposes in the period under study. On the contrary, the wholesale, traditional and investment business models are less likely to make FinTech acquisitions as a means of expanding their businesses. This likelihood does not necessarily indicate 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 that are 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 that deter banks from acquiring financial technology firms for expansion purposes.

Finally, Panel D in Table 13 presents the regression results of banks' 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 business models, investment banks display 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 banks mean that FinTech acquisitions serve 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 banks did not engage in FinTech acquisitions to enter new markets. Consistent with our previous findings, larger banks are more likely to acquire FinTech firms as a means of expanding into new markets.

6 Conclusion

In this paper, we present the first attempt to empirically examine the role of the banks' business models in their decisions related to FinTech acquisitions. We employ a unique sample of US banks' FinTech acquisitions over a period of 17 years between 2005Q1 and 2021Q4.

We present four main findings. First, our analysis shows 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 sample falls under the category of diversified business models that are characterized by a mixed asset structure with features from both traditional and investment banking. Additionally, we demonstrate that US banks with a wholesale business model actively participate in the interbank market, as evidenced by their higher average loan ratio compared to other business models. The second most prevalent business model among US banks in our sample is the traditional banks, comprising those 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.

Table 13 Business scalability and entering new markets as strategic motives for banks' FinTech acquisitions. This table shows the logistic regression results for the two dependent dummy variables: $BusinessScalability$ and $NewMarkets$. They are shown in two panels: C and D. Each dummy variable equals one if the bank's strategic aim behind the FinTech acquisition is the corresponding motivation, and zero otherwise. The analysis period is from 2005Q1 to 2021Q4. Table 3 shows the definitions of all variables. Time fixed effects were included to account for unobserved time-varying factors. All variables were winsorized at the 1% and 99% levels to avoid outliers from skewing the study's findings. All variables were lagged by one period to mitigate potential concerns about endogeneity and reverse causality

	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)

Table 13 continued

	Panel C: Business Scalability				Panel D: Entering New Markets			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
IT_Expenditure (%)	−0.08	−0.073	−0.072	−0.072	−0.086	−0.072	−0.083	0.015
	(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	9,279	9,279	9,279	9,279	5,837	5,366	4,169	5,837

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Second, we find that business models explain FinTech acquisitions. Diversified banks are more inclined to acquire FinTech firms. The results are consistent with the reasoning that diversified banks derive benefits from their diverse assets, funds, and income structures, providing them with the flexibility to embrace greater risks in the form of FinTech acquisitions. Moreover, external acquisitions may be advantageous relative to developing internal capabilities. Furthermore, our empirical analysis finds that banks with a wholesale business model are less likely to engage in FinTech acquisitions. We posit that wholesale banks have 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. Also, our findings indicate that banks with traditional business models are less likely to acquire FinTech firms. This is likely reflects a greater risk aversion to unfamiliar tech-driven models relative to the traditional safe narrow banking focus. Conversely, the investment business model has a selective approach to 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.

Third, 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, our empirical evidence highlights the propensity of diversified banks to engage in acquisitions of FinTech firms specializing in data analytics, lending, and financial software services that set them apart from other business models. This distinction underscores their strategic approach towards income and investment diversification. On the other hand, wholesale banks show 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 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 that make them particularly suited to provide such niche services. Investment banks are also more likely to acquire PayTech firms that may be attributed to the strategic alignment between the disruptive nature of those firms and investment banks' focus on innovation-driven initiatives.

Our fourth main result reflects 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 provides compelling evidence of investment banks' tendency to employ FinTech acquisitions strategically to both introduce new products and to facilitate 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 identifies that diversified banks show no statistically significant inclination towards a specific aim. Conversely, our findings demonstrate that banks adopting a wholesale business model have a reduced likelihood of acquiring FinTech firms to enhance in-house FinTech capabilities. This hesitation likely stems 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.

Appendix A The non-hierarchical K-means clustering technique

We use non-hierarchical K-means clustering to identify the banks' business models. It is a widely used method to produce 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 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 method, 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 mean value 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 continues to 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).

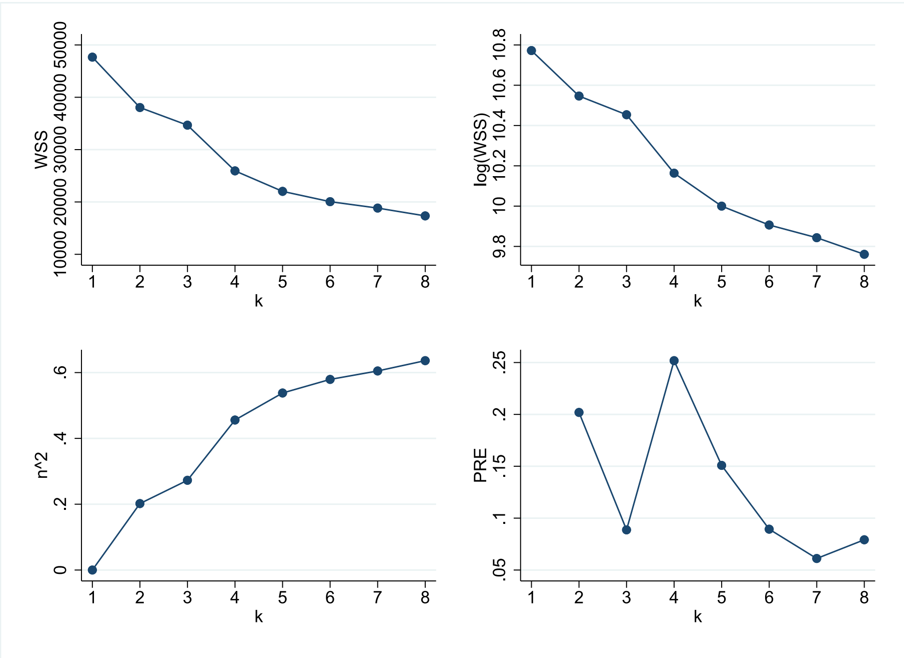

Fig. 4 Determining the appropriate number of clusters

The most challenging part of the k-means clustering 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 4 shows that $k = 4$ is the optimal number of clusters for our investigation. As the number of clusters increases, 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 the 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.

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 $n_k^2 = 1 - \frac{WSS(k)}{TSS}$. The 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 Fig. 4, at n_4^2 a reduction of WSS by 42% and PRE_4 indicates a reduction in WSS of 25% compared with PRE_3. Both results give further support to $k = 4$.

Appendix B Classifying banks' 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 is not straightforward. Therefore, we rely on a robust textual analysis to classify banks' 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) to answer the following questions:

Table 14 Identifying the types of FinTech firms. This table shows the characteristics of five types of FinTech firms: payment, data analytics, lending, financial services software, and investment services

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 comprises FinTech firms that provide data analytics services such as loyalty programs, marketing tools, online promotions, rewards and benefits programs, deals, and coupons and cashback applications
Lending	This category contains the FinTech firms that provide financing solutions. Services include digital lending, financing & leasing services, and point-of-sale (POS) financing
Financial Services Software	This category comprises the FinTech firms that provide innovative financial software. It includes services such as financial security and safety applications, money transfers, credit cards, and online banking services
Investment Services	This category comprises the investment FinTech firms that provide services in the domain of investment such as wealth management, online hedge fund platforms, financial models, and investment advising

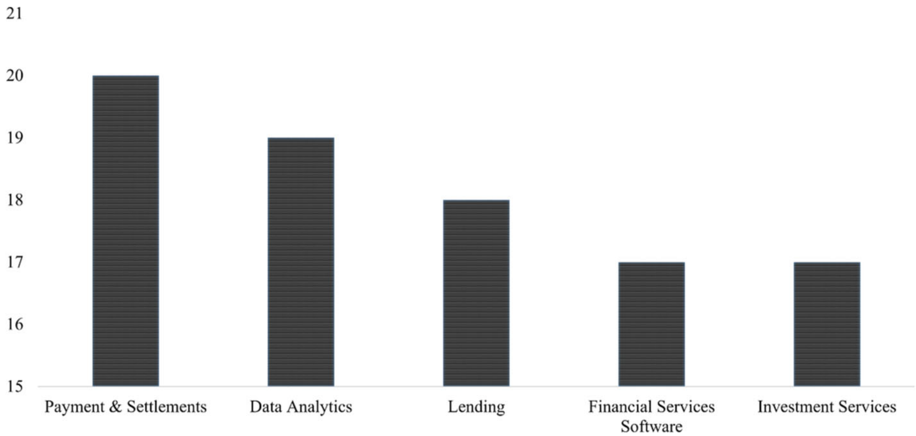

Fig. 5 Types of FinTech Firms (2005Q1-2021Q4)

- What are the types of FinTech firms that banks acquire?
- What are the motivations behind banks' acquisitions of FinTech firms?

To answer the first question, we review the business description provided by the Zephyr and Refinitiv databases for target firms in all 91 banks' FinTech acquisitions included in the study in order to determine the type of services provided by each 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 FinTech acquisitions, we use the same method 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 nine 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 these studies and using our QCA methodology, we

Table 15 Identifying the Motivations Driving Banks' Acquisitions of FinTech Firms. This table shows the characteristics of four bank motivations: introducing new products, enhancing capabilities, pursuing business scalability, and entering new markets

Motivation	Characteristics
Introducing New Products	Acquiring FinTech firms allows banks to create and offer new innovative financial solutions
Enhancing Capabilities	Some banks see FinTech acquisitions 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, such as expanding 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

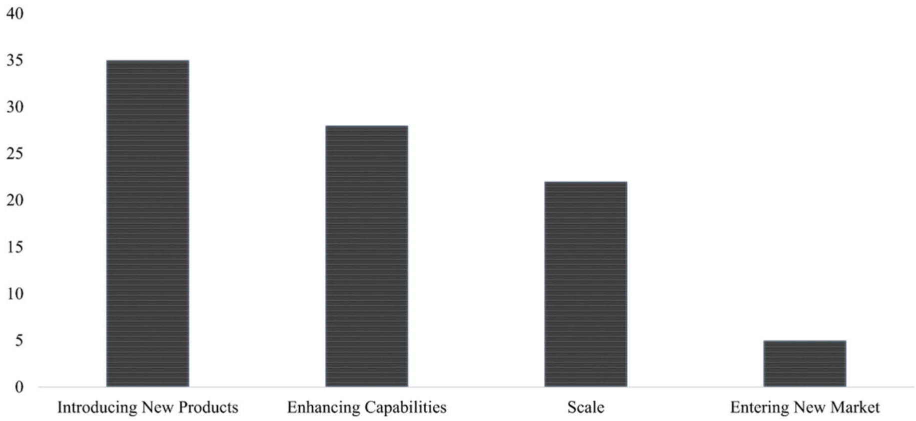

Fig. 6 Motivations Driving Banks' Acquisitions of FinTech Firms (2005Q1-2021Q4)

distinguish between five types of FinTech firms and identify their main characteristics as shown in Table 14.

The results of implementing the QCA to identify the types of FinTech firms are summarized in Fig. 5. In our sample of banks' FinTech acquisitions, the firms acquired can be classified into five types: payment and settlements (20 acquisitions), data analytics (19 acquisitions), lending (18 acquisitions), financial services software (17 acquisitions), and investment services firms (17 acquisitions). It should be noted that although there are further categories of FinTech firms 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.

Next, in order to identify the motivations driving banks' acquisitions of FinTech firms, we employ a similar QCA. We thoroughly analyze each announcement of a FinTech acquisition by gathering information from regulatory authorities, official websites, and media sources. By using this QCA, we identify four distinct motives and are outlined in Table 15, along with their key characteristics. A comprehensive overview of the findings obtained through the implementation of the QCA, specifically pertaining to the identification of motivations behind FinTech acquisitions, is presented in Fig. 6. The acquisitions under consideration are classified into the following four categories: introducing new products (36 acquisitions), enhancing capabilities (28 acquisitions), pursuing business scalability (22 acquisitions), and entering new markets (5 acquisitions).

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Data Availability The data used in this study comes mainly from three sources: Federal Financial Institutions Examination Council (FFIEC), Zephyr and Refinitiv. Banks' financial data is publicly accessible through the FFIEC. However, banks' FinTech acquisitions data is restricted to paid subscriptions to the Zephyr and Refinitiv databases. Once subscription is acquired in these databases, the interested researcher can easily follow our analysis as we provide detailed steps about it.

Declarations

Conflict of interest The authors declare that there is no Conflict of interest.

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