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FinTech and Bank Performance in Europe: A Text-mining Analysis

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Contents

RESUMEN

Este estudio tiene como objetivo explorar el impacto de la adopción de la tecnología financiera bancaria (Bank FinTech) en la industria bancaria. A través de un análisis de minería de textos del informe anual de 48 bancos comerciales europeos de 2015 a 2021, este artículo define el grado de Bank FinTech para cada banco y examina la relación entre el Bank FinTech y el desempeño bancario medido por el sistema CAMEL. Los resultados indican que el Bank FinTech está relacionado positivamente con la suficiencia de capital, la calidad de los activos, la eficiencia de la gestión, el poder de generar ganancias y la liquidez. En general, la adopción de Bank FinTech tiene un impacto positivo en el desempeño del banco. Este estudio es el primero en utilizar el análisis de minería de texto para definir el índice de Bank FinTech para los bancos comerciales europeos y examinar su relación utilizando el sistema CAMEL.

Palabras clave: Fintech, rendimiento bancario, minería de textos

Classificación JEL: G21, G23, G24

ABSTRACT

The purpose of this article is to investigate the influence of financial technology (FinTech) adoption by banks on the banking sector. Through text-mining analysis on the annual reports of 48 European commercial banks from 2015 to 2021, this article defines the bank FinTech degree for each bank and explores the link between bank FinTech and bank performance using the CAMEL rating system's indicator. The results suggest that bank FinTech is positively related to capital adequacy, asset quality, management efficiency, earnings power, and liquidity. In general, adopting bank FinTech can benefit banks. This paper is the first to use text-mining analysis to define the bank FinTech index for the European commercial banks and test their relationship applying the CAMEL system.

Keywords: Fintech, bank performance, text-mining

JEL Classification: G21, G23, G24

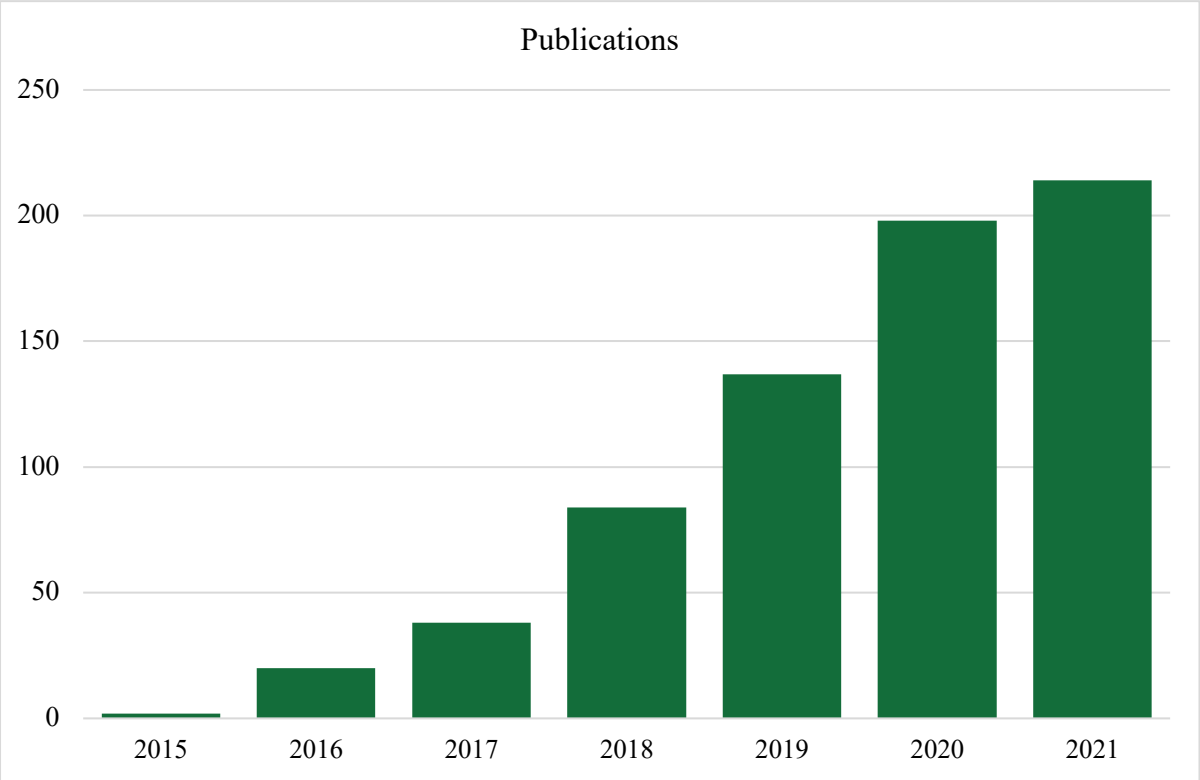
1. Introduction

Innovation and technology have an undeniable significance in the financial sector in the Fourth Industrial Revolution (Wang et al., 2021). The arrival of big data, blockchain, artificial intelligence, and other sophisticated technologies in financial organizations has had a major impact on financial markets throughout the world. Financial technology (FinTech) innovation has both benefitted and disrupted the financial industry. As incumbent financial entities, banks have been affected by FinTech in two ways: "outside FinTech" and "bank FinTech" (Cheng & Qu, 2020). Outside FinTech is mainly related to the appearance of FinTech firms, while bank FinTech indicates the innovative technology that has been applied by traditional banks. FinTech enterprises have emerged because of incorporating the novel technology into business models. They typically target specific value chain segments of financial institutions (Elsaid, 2021) and have performed well in niche market. Owing to the low-cost, boundless services and time-saving capabilities (Lee & Shin, 2018), FinTech companies could deliver better services that are more personalized based on big data analysis. Facing the threat of being replaced, banks would lose earning power and take riskier measures.

Following this contentious line of thought, there was a flood of empirical studies and theoretical publications on FinTech's impact on traditional financial institutions. As illustrated in Fig. 1, the topic of FinTech and banks has grown in prominence in recent years. The number of publications related has soared since 2015 when searching for the keywords *FinTech* and *bank* in the Web of Science Core Collection database. However, existing research on the Fintech's impact on bank performance is mixed and determining how to assess and quantify the development of FinTech and its influence is a critical component of any inquiry into this topic. Up to now, most papers focus on the theoretical analysis of this issue (Anagnostopoulos, 2018; Elsaid, 2021; Navaretti et al., 2018; Thakor, 2020). In terms of empirical research on the subject, several publications use the dataset collected by Cornelli et al. (2020), concentrating solely on credit FinTech, which is one type of outside FinTech, and ignoring the other forms (Le et al., 2021; Nguyen et al., 2021). Most of the empirical papers focus on the growth of outside FinTech's effect on banks, for example, Jagtiani & Lemieux (2018); Li et al. (2017) and Wang et al. (2020). By contrast, few studies focus on the analysis of bank FinTech due to the difficulty of collecting

data and analyzing the degree of bank FinTech. As for the analysis of bank performance, in many studies it is only measured in terms of efficiency (Lee et al., 2021 and Wang et al., 2021), profitability (Kim Lien et al., 2020; Phan et al., 2020), or share prices (Li et al., 2017).

Fig. 1. Number of articles on "FinTech" and "bank" published from 2015 to 2021.



Source(s): Web of Science Core Collection

As for the geographic context, the most researched country is China, followed by the United States. However, FinTech development in Europe is growing rapidly while it lacks empirical analysis (Baba et al., 2020). Table 1 includes the number of articles by region in the Web of Science Core collection. There is limited understanding of the influence of bank FinTech and comprehensive analysis of the bank's performance in Europe. This paper aims at filling this gap and providing empirical evidence on this topic.

Table 1. Number of articles by region in Web of Science Core Collection.

Country	Number of articles	Percentage
China	208	22.51%
USA	121	13.10%
UK	100	10.85%
Russia	46	4.98%
Indonesia	40	4.33%
Germany	37	4.00%
Italy	34	3.68%

Source(s): Web of Science Core Collection

"Everybody talks about financial innovation, but (almost) nobody empirically tests hypotheses about it" (Frame & White, 2004, p.116). The purpose of this study is to determine the measurement of bank FinTech and to investigate the influence of bank FinTech on bank performance with the CAMEL rating system and text-mining analysis. The research question of this study is: Can bank FinTech adoptions benefit European commercial banks' development?

This study first analyzed the development of FinTech in European banks and then collected data on bank FinTech. Following Cheng & Qu (2020) and Wang et al. (2020)'s suggestion for future research, this paper used text mining in the annual report of banks to measure the adoption and application of FinTech in banks, to expand the study on the scope of bank FinTech and collect novel data. Meanwhile, this article attempts to study comprehensive bank performance, including capital adequacy, asset quality, management efficiency, earning power, and liquidity risk, which are widely analyzed to measure performance, for instance, Masood et al. (2016), Quoc Trung (2021), Sahut & Mili (2011), etc. Using panel models, specially fixed-effect estimates, the empirical results show that bank FinTech is positively related to bank performance for all five indicators.

The present study contributes to the existing literature in the following aspects: Firstly, to date, there are just a few studies available focusing on the bank FinTech's relationship with commercial banks' performance, while most investigate the effect of outside FinTech and retail banks. Therefore, this paper can provide empirical evidence on this issue to help banks know how to efficiently apply bank FinTech. Secondly, apart from profitability and efficiency, which are the main aspects of bank performance, this paper also analyzed the effect of bank FinTech on capital sufficiency, credit risk, and liquidity risk. Finally, this study complements the analysis of European regions in the existing literature.

The remainder of this study is structured as follows. Section 2 presents the literature review and hypothesis. Section 3 describes the methodology, including the sample selected, the empirical model to be tested, and variables to be employed. Section 4 displays the descriptive and regression results and the discussions. In the end, conclusions, contributions, and future research lines are set out in section 5.

2. Literature review

2.1 Financial innovation and FinTech in Europe

Financial innovations include innovative goods, services, manufacturing techniques, and institutional structures to support the development of financial industry(Frame & White, 2004). FinTech is technologically enabled new business models, products, services, and processes (Financial Stability Board 2017), which implies that FinTech is the most significant component of financial innovation. It has the potential to transform the financial sector with sustainable innovation tendencies (Jucevicius, Juceviciene, and Zigiene, 2021). Since FinTech could disrupt and alter the financial system by making it more transparent, safe, and affordable (Kabulova and Stankevičienė, 2020). Since financial innovation has increased among banks in recent decades, there is a wide range of empirical research on its influence on bank performance and risk. The goal of this research is to contribute to this growing area of research by exploring the disruptive impact of FinTech adoption in banks on their performance.

Less attention has been paid to the EU region. However, the development in this area is neglectable. According to the data from the ECB statistical data warehouse, nearly a third of all non-cash payment transactions take place in Europe. The combined transaction amount of online alternative financial services reached 10.4 billion euros in 2017, up 20 times from 2012 (Baba et al., 2020). As for European

banks, most of them are pursuing FinTech solutions to improve efficiency and product experience. For instance, biometric fingerprint credit cards have been provided by NatWest/RBS, and Barclays provides finger vein scanner technology to its business customers for authentication.[1] Moreover, 71% of respondents hold that FinTech can help increase revenues and decrease the costs of commercial banking (European Banking Authority, 2019).

To further define the research trend and topic, this study applied a basic systematic literature review and used certain bibliometric indicators (Amirbagheri et al., 2019). The database used for searching papers related to the topic is Web of Science Core Collection database. The search was conducted in June 2022 utilizing the terms "FinTech" and "bank". The original search found 617 papers, which were eventually reduced to 600 when any documents that were not published in English were removed. These publications have a total of 4,098 citations, averaging 6.83 citations per paper. The h-index is 31, which means that out of 600 publications, 31 have 31 or more citations.

Fig. 2 shows the co-occurrence of keywords that occur four or more times, including 63 keywords out of 722 terms. The network visualization is created by VOS viewer program. Apart from FinTech and banking, which are the keywords that I used to search for the relevant articles, the most frequent keywords are *innovation, competition, performance, adoption, impact,* and *financial inclusion*. As a result, bank performance is an important issue in this area. *Competition* and *adoption* are two keywords that can show the two main influence: outside FinTech and bank FinTech adoption.

Fig. 3 depicts the keywords in order of their emergence throughout the year, which ranges from purple to yellow. *Commercial banks, bank performance,* and *profitability* are depicted as yellow bubbles on the left-top side, indicating that they have only recently arisen and are a relatively new issue to be explored. In Capgemini's report *Commercial banking: top trends in 2022*, it mentioned that: "First, it was retail banking. Now, advanced technology is shifting to – and disrupting – the commercial banks space" (Capgmini, 2022). Therefore, the new trend of research is for commercial banks, and this motivates this study to do the research within the European region.

[1] News from www.imf.org.

Fig. 2. Co-occurrence of author keywords (network).

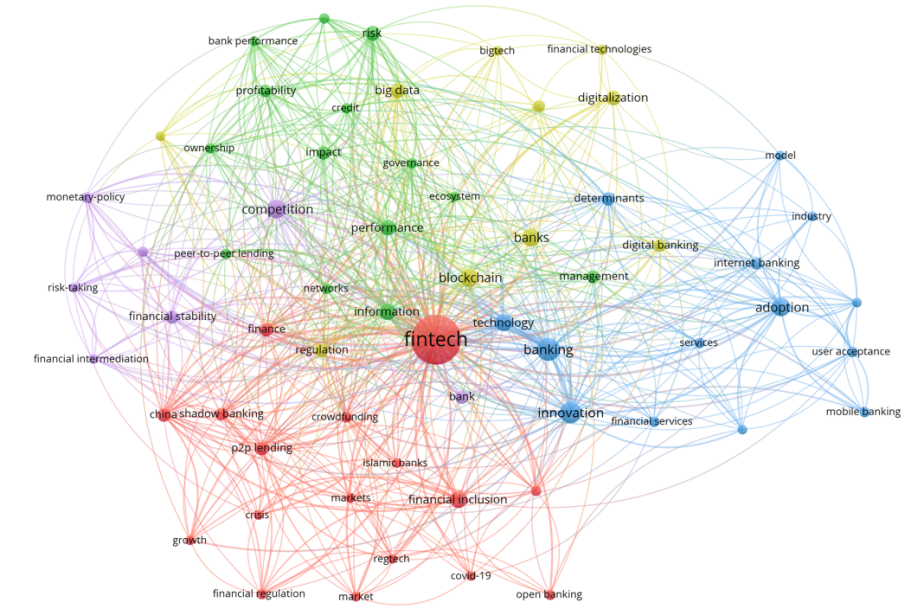
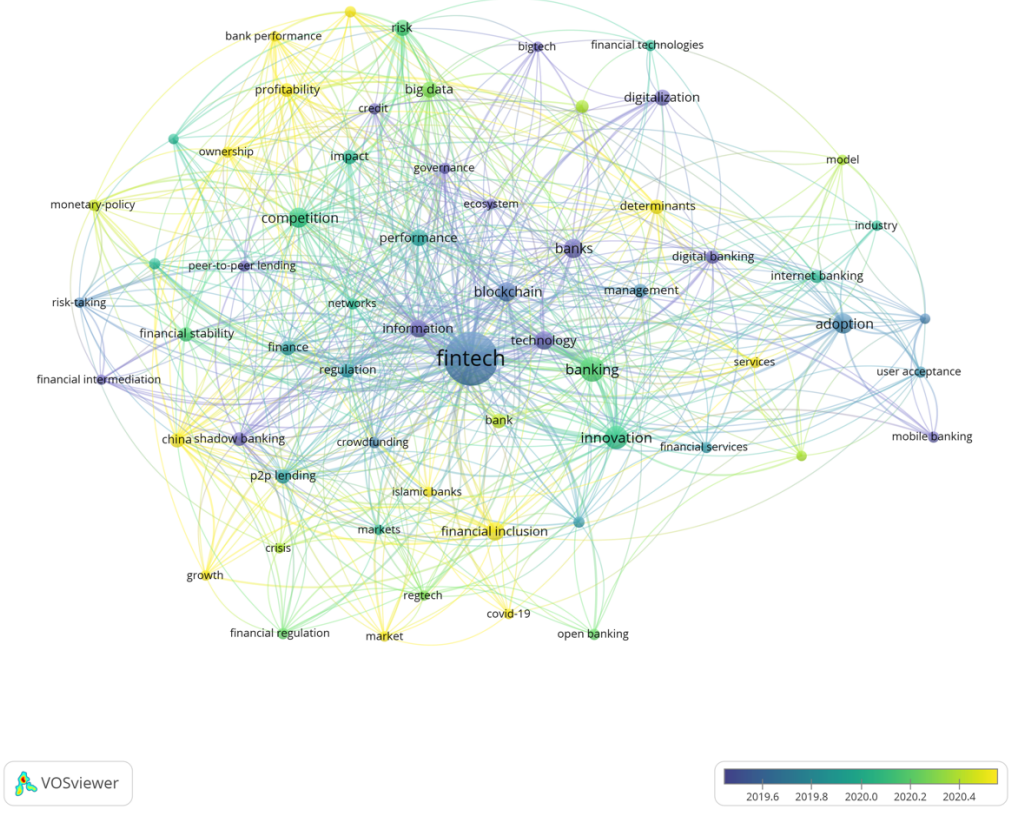


Fig. 3. Co-occurrence of author keywords (overlay).



2.2 Outside FinTech and bank performance

Lee & Shin (2018)summarized six FinTech business models: monetary alternative, lending, crowdfunding, wealth management, capital market, and insurance services. Monetary alternatives consist of cryptocurrency, such as bitcoin, and payment systems, for example, digital wallets, PayPal, Bizum, etc. (Knewtson & Rosenbaum, 2020). FinTech lending model are consisted of crowdfunding and non-intermediated peer-to-peer (P2P) lending. Obtaining financial support for a project or enterprise from a wide variety of people (Xiang et al., 2021), crowdfunding firms, such as GoFundMe and Crowdfunder, act as a bridge between the project owner and private investors interested in participating in the endeavor. On the contrary, P2P lending is a complementary form of bank loans that is targeted at customers who require urgent financial resources or who do not have sufficient credit records with banks. Since P2P lending platforms exclusively provide online services to match lenders and borrowers (Xiang et al., 2021), they do not need to invest in a deposit-taking branch network or ATMs. Besides, they are less regulated compared to traditional financial institutions, they have lower operating costs and provide cheaper service than banks (Thakor, 2020). Compared with traditional banking, these alternatives can provide services faster and cheaper. As for the fourth type of FinTech companies, robo-advisors are widely used in the wealth management sector through big data analysis and machine learning to provide investment portfolios for customers automatically (Abraham et al., 2019). The advantages of robo-advisors can be characterized as ease of use, fewer fixed costs, reduced behavioral biases, and significant tax savings (Abraham et al., 2019). Such kinds of companies include Wealthfront and Betterment. Foreign currency transfers and trading in FinTech are two of the most common business models in the capital market. The expenses are lower, and the process is more convenient, as with other services provided by FinTech firms, with examples of Robothood, eToro, etc. (Lee & Shin, 2018). The insurance model of FinTech is also called “InsurTech”. By using the cloud computing and information storage, they can provide fast and suitable insurance plans for customers. InsurTech companies include Ladder and CoverFox.

The impact of outside FinTech on bank performance can be supported by consumer theory and disruptive innovation theory (Elsaid, 2021). According to consumer theory, consumers would select the most cost-effective bundles of items. In this way, if new services meet the same client expectations as

existing services, they might be used to replace the former ones (Keller and Aaker, 1990). From the other side, disruptive innovation theory suggests that FinTech as an innovative business model has the capability of utilizing advanced technology to supply goods and services with lower price and higher quality, thus resulting in the market competition (Christensen, 2013).

Up till now, most of empirical academics focus on the impact of outside FinTech, and among them, only the lending and monetary FinTech firms are investigated. In 2021, many studies have found that the growth of the FinTech industry may help banks become more efficient by employing different measurements of efficiency, such as Data Envelopment Analysis (Le et al., 2021; Wang et al., 2021) and Stochastic Frontier analysis (Lee et al., 2021). By using global, Indonesian, and Chinese data, Nguyen et al. (2021), Phan et al. (2020) and Zhao et al. (2022) find that FinTech development and bank profitability have a similar unfavorable association. According to Li et al. (2017), investing in FinTech star-ups can boost the share price of retail banks.

2.3 Bank FinTech and bank performance: hypothesis development

Bank FinTech can be referred to the financial innovation that banks develop in their own products or services without cooperating with non-bank FinTech firms or start-ups (European Banking Authority, 2019). It is worth noting that in the banking industry, there are three stages of financial innovation (Cheng & Qu, 2020). Before 2010, the most representative product of innovative banking was online banking. From 2011 to 2015, mobile banking become an extension of online banking. And from 2015, the emerging technologies including big data, distributed technology, etc. (Wang et al., 2021) become popular. This last period witnesses the arising of innovative FinTech firms. Despite the emergence of FinTech innovation throughout the world and growing interest in FinTech, little is known about how it will disrupt the existing banking sector and their financial business models (Chen et al., 2019).

The “innovation-growth” view and “innovation-fragility” hypotheses have opposing viewpoints on the influence of financial innovation. Lee et al. (2021) conclude that “innovation-growth” view suggests a beneficial effect of FinTech firms on bank performance, since financial innovation can broaden the range of banking services, boost banks’ risk-sharing capabilities, and improve resource allocation efficiency. At the same time, FinTech has profited by minimizing transaction costs and mitigating the

information asymmetry problem created by distance limits (Grennan & Michaely, 2021). On the contrary, according to "innovation-fragility" hypothesis, financial innovation can increase banks' risk tolerance, resulting in over-crediting of overall financial markets and the incidence of financial crises (Lee et al., 2021). This hypothesis posits that FinTech is negatively related to bank performance. Traditional banks are usually unable to meet lending demand due to rigorous regulation (Zhao et al., 2022), thus both shadow banks and FinTech lenders have flourished and reduced traditional financial institutions' market share (Buchak et al., 2018). The empirical findings on the impact of FinTech on banks are mixed. Table 2 summarizes the different findings of this relationship.

2.3.1 Capital adequacy

Capital adequacy evaluates a bank's ability to meet debts on time (Masood et al., 2016) and measures the robustness of banks (Wang et al., 2021). "Innovation-growth" theory argue that financial innovation can improve the risk sharing capability of banks (Nachman et al., 1995). While the classic concept of "innovation fragility" assumes that financial innovation would increase aggressive risk-taking, leading to a decrease in capital adequacy (Beck et al., 2016). In terms of empirical results, according to Zhao et al. (2022), FinTech growth in China can help banks increase their capital ratio. FinTech innovations has the potential to improve the banking industry's overall stability thus reduce the motivation of banks to take risks (Wang et al., 2020). Therefore, bank FinTech adoption can play the role of improving the capital protection of banks. With the help of FinTech, banks will take fewer risks and maintain a more stable development. Based on these considerations, this paper argues that bank FinTech can have a positive effect on the banks' capital ratio.

H1. *Bank FinTech positively affects the capital adequacy of banks.*

2.3.2 Asset quality

Bank credit risk is primarily produced by banks' shared exposure to macroeconomic risk factors, and it is often quantified as the percentage of non-performing loans to gross loans (Festić et al., 2011; Schinasi, 2005). According to "innovation-growth" view and technology spillover effects, employing innovative technology helps banks improve their efficiency in risk processing and, as a result, lower their credit

risk. For example, by utilizing the in-house built analytics library NOLA 2.0, powered by Google Cloud, HSBC increased the calculation speed of evaluating counterparty credit risk and derivative valuation adjustments by 10x. The cloud computing technology helped HSBC gain a competitive advantage in risk management and risk analytics.[2] In the empirical area, Wang et al. (2020) and Zhao et al. (2022) find that the growth of FinTech exacerbates banks' risk taking in general. By contrast, Cheng and Qu (2020) posits that FinTech can benefit banks by reducing credit risk, demonstrating that the positive impacts of FinTech outweigh the negative ones for China's commercial banks. On the one hand, financial innovation can diversify the types of banking products and services and improve the quality of banking services. On the other hand, with FinTech applications such as blockchain, big data, etc., banks can improve the efficiency of risk management and intercept risky transactions, thus reducing the credit risk faced by traditional banks (Berger, 2003). Therefore, owing to the benefits of financial technology, this paper argues that bank FinTech can have a positive influence on reducing credit risk and resulting in the improvement of asset quality.

***H2**. Bank FinTech positively affects the asset quality of banks.*

2.3.3 Management efficiency

Based on the traditional "innovation-growth" view, by employing novel technology, traditional banks would reduce their operation costs and improve their allocation efficiency. FinTech lenders, for example, process requests 20 percent quicker than traditional banks (Fuster et al., 2019; Wang et al., 2021), and they can do the decision of provision of loans automatically without personal interaction (Bazot, 2018). Besides, online banking and digital payments save the costs of facilities like ATMs, while they process payments and settlement more quickly and safely with the application of cloud computing, blockchain, etc. (Baker & Wurgler, 2015). Empirical proof of this can be found, for instance, in Lee et al. (2021), who confirm that the FinTech industry's growth can boost banks' cost efficiency while also improving the technologies they use. Similarly, Wang et al. (2021) and Le et al. (2021) demonstrate empirically that the advent of FinTech has increased the bank efficiency in the context of China and worldwide,

[2] News is from https://ffnews.com.

suggesting that financial technology can reduce information asymmetry. Considering the novel way of providing services and the benefit of bank FinTech on the efficiency management, this paper suggests a positive relationship between FinTech adoption and bank efficiency.

***H3**. Bank FinTech positively affects the efficiency of banks.*

2.3.4 Earnings power

In order to preserve their market share, banks seek improvement through the benefit of FinTech. Emerging technology can benefit banks by lowering operational costs and service speed (Wang et al., 2021) according to "innovation-growth" view. However, the principal competitive advantage of banks comparing with FinTech firms are the trust from customers. Applying innovative technology and facing unknown results may lead customers lose their confidence in banks, thus resulting in the diminished bank profitability.

Empirical evidence suggests that bank profitability can be harmed as a result of the growth of FinTech enterprises (Nguyen et al., 2021; Phan et al., 2020; Zhao et al., 2022). FinTech firms will take some market shares from banks, reducing banks' earning power. However, DeYoung (2005) find that the profits of online-only banks grow quickly owing to the learning effect and economies of scale. Furthermore, banks will profit from the digitalization of banking activities in a variety of ways, including improved customer relationships and the capacity to create new value chains and business models (Elsaid, 2021). The technology spillover concept argues that financial innovation can help commercial banks promote the upgradation of services and the transformation of businesses, which will lead to an increment in profit and productivity. Therefore, this study argues that bank FinTech can positively affect profitability of European commercial banks.

***H4**: Bank FinTech positively affects the profitability of banks.*

Table 2. Prior studies related to FinTech's impact on bank performance. ("+" indicates the positive impact and "-" for negative impact)

Author(s)/Year	Country	Sample period	Sample size	Bank performance	Impact
Chen and Qu (2020)	China	2008-2017	60 banks	credit risk	-
Lee et al. (2021)	China	2003-2017	500 firm-year observations	efficiency	+
Le et al. (2021)	Global	2013-2017	203 banking systems	efficiency	-
Li et al. (2017)	USA	2010-2016	47 banks	share price	+
Nguyen et al. (2021)	Global	2013-2018	73 countries	profitability	+
				bank risk	-
Phan et al. (2020)	Indonesia	1998-2017	41 banks	profitability	-
Want et al. (2020)	China	2011-2018	1698 firm-year observations	bank risk	+
Wang et al. (2021)	China	2009-2018	113 banks	efficiency	+
Zhao et al. (2021)	China	2003-2018	120 banks	capital adequacy	+
				asset quality	-
				efficiency	+
				profitability	-
				liquidity risk	-

2.3.5 Liquidity management

Liquidity refers to a bank's capacity to convert its financial assets into cash quickly or to meet all of its financial commitments before the due date (Masood et al., 2016). Liquidity management is very important for commercial banks, since illiquidity is a dangerous sign of immediate distress that would destroy the trust from the public to banks (Adebayo et al., 2011). And for commercial banks, the loan and advances to total deposit ratio can show their management of liquidity and attractiveness to customers. With the employment of FinTech, banks can process customer needs more quickly and analyze customer preference better using cloud computing (Thakor, 2020). Therefore, the amount of deposit should rise, and the liquidity ratio would decrease. As for empirical findings, Cheng & Qu, (2020) and Zhao et al. (2022) demonstrate that financial innovation can decrease the liquidity ratio of banks. This study suggests a positive relationship between bank FinTech and liquidity management.

***H5**: Bank FinTech positively affects the liquidity management of banks.*

3. Methodology

This section has three objectives. First, it describes the sample selection and data processing. Then, the measurements and variables to be used in this study are presented. Finally, the empirical model for testing the hypotheses is introduced.

3.1 Sample and data collection

The data for this study was initially gathered from the top 60 European public commercial banks that have already applied FinTech to their business models in the years 2015 to 2021. After eliminating the samples with missing data, the final samples are 48 banks over a 7-year-period from 2015 to 2021, covering 22 European countries and resulting in 336 bank-year observations. Then 336 financial reports are collected for the purpose of obtaining the FinTech data in the text-mining analysis.

As for data collection, the indicators for banks are gathered from the Eikon database provided by Refinitiv. The ranking of banks is based on the total assets in the financial report. It is common to use either market capitalization or total assets to rank banks, and this paper chooses to use total assets as

the measurement of bank size because many academic papers have used them as the criteria (Dietrich & Wanzenried, 2011; Menicucci & Paolucci, 2016; Petria et al., 2015). The FinTech data comes from the banks' annual reports, which are gathered through the Eikon database and each bank's official website. Moreover, this study chose the period starting from 2015, considering the development of FinTech in Europe has been accelerated then (European Banking Authority, 2019), so that more data could be gathered within this time period. Furthermore, the data acquired from the annual reports of public banks can circumvent the language difficulty because public banks produce their financial reports in English every year. Table 3 shows the number of samples in each country.

Table 3. Sample description by region.

Country	Number of banks	Percentage
United Kingdom	6	31.82%
Spain	5	22.73%
Italy	4	22.73%
Sweden	4	18.18%
Austria	3	13.64%
France	3	13.64%
Germany	3	13.64%
Denmark	2	13.64%
Greece	2	13.64%
Netherlands	2	9.09%
Norway	2	9.09%
Turkey	2	9.09%
Belgium	1	9.09%
Czech Republic	1	4.55%
Finland	1	4.55%
Hungary	1	4.55%
Ireland	1	4.55%
Liechtenstein	1	4.55%
North Macedonia	1	4.55%
Poland	1	4.55%
Russia	1	4.55%
Switzerland	1	4.55%

3.2 Variables and measurements

3.2.1 Bank performance

Based on the CAMEL rating system suggested by the U.S.-based Uniform Financial Institution Rating System, the measurement of bank performance can be divided into five aspects: capital ratio, asset quality, management efficiency, earnings power, and liquidity management (Zhao et al., 2022). This measurement is employed by numerous studies (Alqahtani et al., 2016; Sahut & Mili, 2011). Each of these five variables is treated as dependent variables in the five empirical models.

Capital adequacy can measure the stability and robustness of banks (Wang et al., 2021). Higher capital adequacy means a more stable system. The variable used is the capital ratio (CAR), which is calculated as the total capital to total asset ratio.

Asset quality is used to evaluate the credit risk of banks. This paper used the non-performing loans to total loans ratio (NPL) to measure this performance. The greater the ratio, the more credit risk there is, and the poorer the asset quality is.

Management efficiency shows if the bank does the business efficiently or not. Bank efficiency is measured by the ratio of non-interest expense to the value of revenue net of interest expense before loan loss provision (EFF) in this paper. The higher ratio indicates the lower efficiency.

Earning power is mainly evaluated by the banks' profitability. This paper utilizes the ratio of income before discontinued operations and extraordinary items divided by total assets (ROA) to measure the profitability of banks.

In this study, liquidity management is computed as the total loan to total deposit ratio (LIQ) in this study. The lower ratio indicates a lower level of leverage risk and better liquidity management.

3.2.2 Bank FinTech

This paper uses the annual report of banks to collect the information and measure the bank FinTech. Bank FinTech can show the application status of FinTech in banks and is treated as an independent variable. Generally, the first part of annual report of commercial banks includes the strategic report,

where the proposition, strategy, and business model are presented in detail. Therefore, we could know their business strategy about FinTech based on what they have mentioned in the annual report. For example, a higher frequency of FinTech related vocabulary that appeared in the annual report indicates the higher degree of bank FinTech that they have adopted or applied. This study is the first to use text-mining analysis of each bank's financial report to define the bank FinTech index. Text-mining technique use data mining technology to retrieve relevant data based on a large quantity of unorganized and diverse texts using intelligent algorithms, including text classification, word frequency statistics, text grouping, etc. (Cheng & Qu, 2020).

Specifically, this paper applied the word list of FinTech adapted from Cheng & Qu (2020) and Wang et al. (2020) and calculated the word frequency through Python 3.9 to output the result for banks in each year. In total, 70 words related to FinTech are checked in Python. The most frequent twenty words are listed in Table 4. With the frequency of words related to FinTech, I used the maximum value as the denominator to compute the bank FinTech degree as a percentage value.

Table 4. Bank FinTech word list for text-mining in Python.

Digital bank	Online bank	Internet bank	E-bank	E-money
Electronic trading	Crowdfunding	E-investment	Microcredit	Digital investment
E-invoice	Alternative finance	E-insurance	Blockchain	E-credit
Cryptocurrency	Digital currency	Robo-advisor	Online broker	Peer-to-peer lending

3.2.3 Control variables

Referring to the previous study of Cheng & Qu (2020), Nguyen et al. (2021), Phan et al. (2020), Wang et al. (2021) and Zhao et al. (2022), this paper use bank size (SIZE) and loan loss reserves (LLR) as bank-specific control variables considering that they have potential impact on bank performance. The

data are collected from Eikon database. As for macroeconomic control variables, this paper includes gross domestic product growth rate (GDP) and consumer price index (CPI) as suggested by the study of Annor et al. (2020), Bhattarai (2020), Menicucci & Paolucci (2016), Petria et al. (2015), and Quoc Trung (2021), who found evidence that these macroeconomic factors can affect bank performance. The summary of variables is shown in Table 5.

3.3 Empirical model and technique

The literature that examines the influence of outside FinTech on bank performance (Nguyen et al., 2021; Phan et al., 2020; Zhao et al., 2022) inspired the empirical model used in this study. The empirical research models are as follows:

To examine if bank FinTech has an influence on capital adequacy:

$$CAP_{i,t} = \beta_0^1 + \beta_1^1 FINTECH_{i,t} + \beta_2^1 SIZE_{i,t} + \beta_3^1 LLR_{i,t} + \beta_4^1 GDP_t + \beta_5^1 CPI_t + \varepsilon_{i,t}^1$$

To determine if there is a link between bank FinTech and asset quality:

$$NPL_{i,t} = \beta_0^2 + \beta_1^2 FINTECH_{i,t} + \beta_2^2 SIZE_{i,t} + \beta_3^2 LLR_{i,t} + \beta_4^2 GDP_t + \beta_5^2 CPI_t + \varepsilon_{i,t}^2$$

To assess the association between the explanatory variable and bank efficiency:

$$EFF_{i,t} = \beta_0^3 + \beta_1^3 FINTECH_{i,t} + \beta_2^3 SIZE_{i,t} + \beta_3^3 LLR_{i,t} + \beta_4^3 GDP_t + \beta_5^3 CPI_t + \varepsilon_{i,t}^3$$

To investigate the impact of FinTech degree on profitability:

$$ROA_{i,t} = \beta_0^4 + \beta_1^4 FINTECH_{i,t} + \beta_2^4 SIZE_{i,t} + \beta_3^4 LLR_{i,t} + \beta_4^4 GDP_t + \beta_5^4 CPI_t + \varepsilon_{i,t}^4$$

To evaluate how bank FinTech affect liquidity risk of banks:

$$LIQ_{i,t} = \beta_0^5 + \beta_1^5 FINTECH_{i,t} + \beta_2^5 SIZE_{i,t} + \beta_3^5 LLR_{i,t} + \beta_4^5 GDP_t + \beta_5^5 CPI_t + \varepsilon_{i,t}^5$$

Where dependent variables include capital ratio (CAR), non-performing loans ratio (NPL), efficiency ratio (EFF), return-on-asset (ROA), and loan-to-deposit ratio (LIQ). The most important explanatory variable is FINTECH, which stands for Bank FinTech application of banks and is measured through text-mining and word frequency in the financial reports. The macroeconomic control variables contain GDP growth rate (GDP) and consumer price index (CPI). Moreover, the bank-specific control variables are logarithm of bank total asset (SIZE) and loan loss reserves (LLR). According to the results of Breusch-pagan test and Hausman test, the fixed effect model is the most appropriate for the dataset to test the relationship.

Table 5. Variables description.

Variable	Type	Description	Measurement
Panel 1. Bank performance			
CAP	Dependent	Capital adequacy	Total capital / total risk weighted asset
NPL	Dependent	Asset quality	Total non-performing loans / total loans
EFF	Dependent	Management efficiency	Interest expense / revenue net of interest expense before loan loss provision
ROA	Dependent	Earning power	Income before discontinued operations & extraordinary items / total assets
LIQ	Dependent	Liquid ratio	Net loans / total deposits
Panel 2. Bank FinTech			
FINTECH	Independent	Degree of Bank FinTech	Word frequency / the maximum value (681)
Panel 3. Bank Control variable			
SIZE	Control	Firm size	Logarithm of total assets
LLR	Control	Loan loss reserves	Loan loss reserves / total loans
Panel 4. Macro Control variable			
GDP	Control	Economic growth	GDP growth rate
CPI	Control	Change in prices paid by consumers	Consumer price index

Note: The formulas for Panel 1 - Bank performance variables are cited from Eikon database.

4. Results and discussion

The statistics and regression findings from my research are discussed in this section. It first summarizes the descriptive statistics for bank performance ratios, as well as the bank FinTech statistics obtained by text-mining analysis. Then the results of estimation models for testing the hypothesis and the discussion of the results are presented.

4.1 Descriptive analysis

Table 6 shows the dataset's descriptive statistics. Regarding the dependent variables, the mean of CAP, NPL, EFF, ROA, and LIQ have values of 18.86%, 26.64%, 57.1%, 0.64%, and 1.05, respectively. Based on the criteria used by Masood et al. (2016), with a CAP higher than 11%, the performance can be considered a healthy ratio. So, capital adequacy has a relatively good performance. As for non-performing loans, the average is much higher than the criteria of 9.5%, indicating the asset quality of this sample set is quite low. And as the efficiency ratio, it is also higher than the 46% standard, which means that, in general, they are not very efficient. As for ROA, when greater than 1.5%, it can be viewed as a healthy ratio. And the liquid ratio is also higher than the 0.8 criteria. One of the factors that may influence the bank performance can be outliers. So, when processing the data, I did the winsorizing in order to avoid such an influence.

For the independent variable FINTECH, the original minimum value is 8, while the maximum is 681. Its average is 176.2. It has increased since 2015, reached its peak in 2020 and decreased slightly in 2021. The high value in the year 2020 is mainly due to the influence of the pandemic (Cepel et al., 2020; Miklaszewska et al., 2021). The whole bank FinTech degree shows an increasing trend. The detailed numbers are presented in Fig.4. Converting the original values to percentage terms, the range of FinTech adoption degree is from 1.17% to 100%, while the average is 25.88%. On average, this bank FinTech degree is not very high.

Table 6. Descriptive statistics of variables.

Variable	Observation	Mean	Std. Dev	Minimum	Maximum
CAP (%)	336	18.86	3.95	10.6	41.68
NPL (%)	336	26.64	48.69	0.0302	89.24
EFF (%)	336	57.10	21.69	-2.81	202.9
ROA (%)	336	0.64	0.75	-4.01	3.18
LIQ	336	1.05	0.43	0.13	3.32
FINTECH (%)	336	25.88	18.87	1.17	100
SIZE	336	12.93	1.75	8.434	17.53
LLR (%)	336	2.94	3.97	0.1	21.36
GDP (%)	336	1.48	3.82	-10.84	25.32
CPI (%)	336	1.79	2.70	-1.264	16.6

Source(s): Eikon database

Fig. 4. Trend of Bank FinTech according to text-mining analysis.

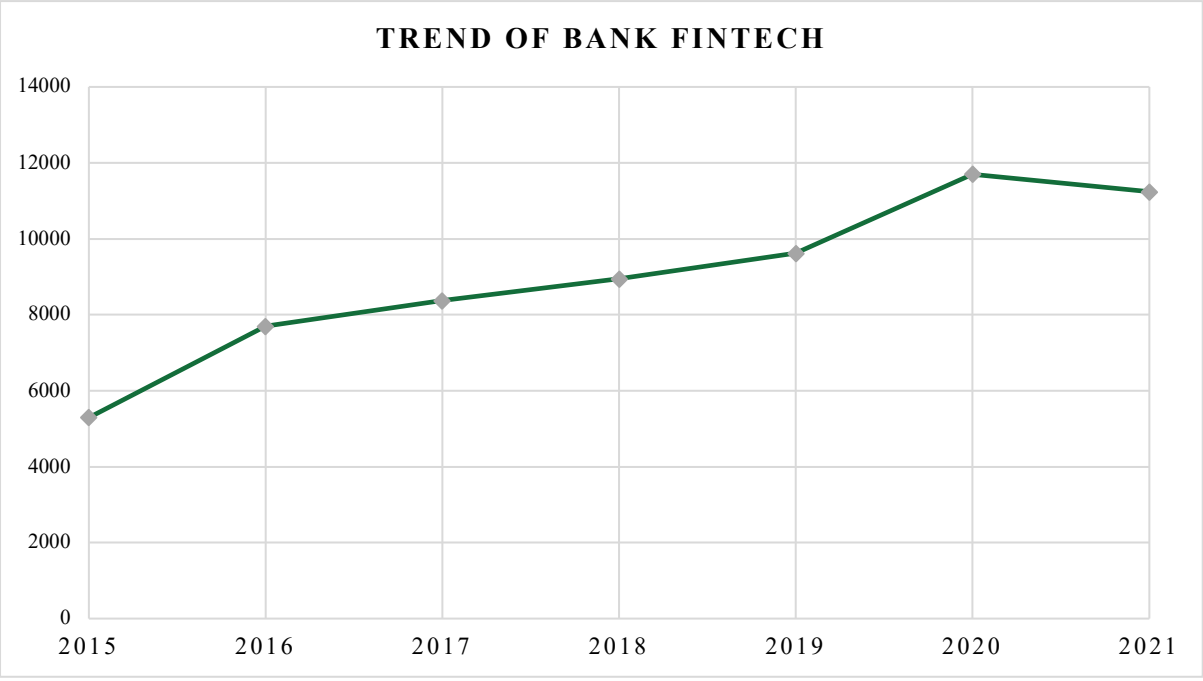


Table 7. Correlation matrix of the variables.

	CAP	NPL	EFF	ROA	LIQ	FINTECH	SIZE	LLR	GDP	CPI
CAP	1									
NPL	-0.0110	1								
EFF	-0.0430	-0.0380	1							
ROA	-0.0750	0.0420	-0.635***	1						
LIQ	0.135**	0.0510	-0.150***	0.0620	1					
FINTECH	-0.0470	-0.0630	-0.095*	0	-0.239***	1				
SIZE	0.0680	-0.0540	-0.0350	0.0810	0.133**	0.256***	1			
LLR	-0.354***	0.896***	-0.0230	-0.0830	-0.236***	-0.0700	-0.119**	1		
GDP	-0.092*	-0.0100	-0.0630	0.187***	0.0680	-0.114**	-0.00100	-0.0500	1	
CPI	-0.0690	-0.0110	-0.329***	0.402***	-0.00100	0.324***	0.153***	-0.0260	0.188***	1

In Table 7, the pair-wise correlation coefficients of all the variables are presented with the significance level. According to the correlation, the FINTECH variable is positively correlated with CAP and ROA, while it is negatively related to NPL, EFF and LIQ. The explanatory factors have no significant association. Furthermore, I did the variance inflation factors (VIFs) test to examine the multicollinearity issue. And to obtain the accurate relationship, the empirical models are estimated through econometrics techniques.

4.2 Regression results

Before doing the regression, I tested if there existed a multicollinearity problem of the variables. The results of the VIFs test are all lower than 5, as shown in Table 8, suggesting that there is no serious multicollinearity problem.

Table 8. Results of examining multicollinearity using VIFs.

Variable	**VIF**	**1/VIF**
FINTECH	1.190	0.838
CPI	1.190	0.840
GDP	1.080	0.927
SIZE	1.050	0.950
LLR	1.020	0.979
Mean VIF	1.110	

In order to choose the suitable model, I first did four regressions: Pool Ordinary Least Square estimates (POLS), between estimate (BE), fixed effects estimate (FE), and random effects estimate (RE) for five empirical models separately. Then the Breusch Pagan test is performed, and the result indicates that POLS is not preferred since there is individual heterogeneity. The Hausman test is used to assess if the FE or RE model should be utilized. The FE model is to test the link between possible explanatory factors and the dependent ones within an entity, considering the specific characteristics of each observation. The random effects model, on the other hand, posits that variation between entities is random and

unrelated to the predictors in the model (Salike & Ao, 2018). According to our test results, for all the five models, RE is inconsistent while FE is efficient and consistent, which leads this paper to use FE estimates.

Table 9 shows in detail the results for the four regressions for *Model 1* of CAP as an example. The regressions for the other four models lead to the same model selection and the detailed results are presented in the *Appendix*.

Table 9. Regression results of four different models.

	POLS	**BE**	**FE**	**RE**
VARIABLES	CAP	CAP	CAP	CAP
FINTECH	-2.382**	-5.209	2.257**	2.057**
	(1.162)	(3.275)	(0.954)	(0.933)
SIZE	0.129	0.200	2.097**	0.236
	(0.121)	(0.269)	(0.843)	(0.258)
LLR	-0.337***	-0.393***	0.0169	-0.112*
	(0.0529)	(0.125)	(0.0742)	(0.0642)
GDP	-0.0779	0.0889	-0.0476	-0.0622*
	(0.0564)	(0.332)	(0.0317)	(0.0320)
CPI	-0.0500	-0.0950	0.122	0.120
	(0.0775)	(0.201)	(0.0879)	(0.0790)
Constant	19.10***	18.89***	-9.435	15.47***
	(1.613)	(3.544)	(11.05)	(3.392)
Observations	336	336	336	336
R-squared	0.153	0.366	0.496	-

*Note: For the years 2015 to 2021, the regressions are run on a balanced data panel of 48 commercial banks and 336 bank-year observations. The estimate results for four regression models — pooled OLS, Fixed effect, Between effect, and Random effect – are compared in this table. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The numbers in parenthesis are standard errors.*

4.2.1 Capital adequacy

According to the fixed effect regression result of *Model 1* in Table 10, at the 5% threshold of significance, bank FinTech has a positive relationship with capital ratio, with the coefficient equal to 2.257. The outcome is also in line with the empirical discovery made by Beck et al. (2016) and Zhao et al. (2022), suggesting that the higher degree of bank FinTech can improve the capital protection of banks and that FinTech will assist banks to have enough capital on reserve to endure the losses, thus lowering the possibility of insolvency risk. This finding backs up the "innovation-growth" theory and supports H1, which indicates that FINTECH is positively related to the capital adequacy of European commercial banks.

As for control variables, bank size is positively related to capital adequacy and the coefficient is 2.097, which is in accordance with Annor et al. (2020) and Bhattarai (2020)'s findings, who examine the determinant factors of capital adequacy of commercial banks and discover a positive link with bank size.

4.2.2 Asset quality

As we can see from the statistical result of *Model 2*, bank FinTech has a detrimental influence on non-performing loan ratios. A lower NPL indicates a higher asset quality and lower credit risk for the bank. The findings are consistent with those of Cheng & Qu (2020), who discovered a negative link between bank FinTech and bank credit risk. This is consistent with the "innovation-growth" view, suggesting that the higher degree of application of bank FinTech can result in a lower ratio of non-performing loans thus reducing the credit risk of banks by diversifying the products and services. Therefore, H2 is supported.

Regarding the bank-specific control variables, credit risk is inversely proportional to size, and the coefficient is 4.218. This is consistent with the study of Morina (2020) who has examined the factors that influence credit risk in commercial banks. Moreover, the loan-loss-reserves have a positive effect on NPL, which is in accordance with the finding of Waemustafa & Sukri (2015).

Table 10. Regression results of the effect of Bank FinTech on bank performance.

	Model 1	Model 2	Model 3	Model 4	Model 5
VARIABLES	**CAP**	**NPL**	**EFF**	**ROA**	**LIQ**
FINTECH	2.257**	-6.376***	-7.015*	0.452**	-0.205***
	(0.954)	(1.837)	(3.603)	(0.223)	(0.0752)
SIZE	2.097**	4.218***	-3.342	-0.0792	-0.136**
	(0.843)	(1.622)	(3.466)	(0.197)	(0.0664)
LLR	0.0169	2.055***	-0.300	0.154***	0.00326
	(0.0742)	(0.143)	(0.454)	(0.0173)	(0.00585)
GDP	-0.0476	-0.0376	-0.428***	0.0322***	0.00344
	(0.0317)	(0.0610)	(0.118)	(0.00739)	(0.00250)
CPI	0.122	0.0588	0.347	-0.0109	-0.00779
	(0.0879)	(0.169)	(0.358)	(0.0205)	(0.00693)
Constant	-9.435	-53.91**	103.9**	1.063	2.933***
	(11.05)	(21.27)	(46.15)	(2.579)	(0.870)
Observations	336	336	336	336	336
Adjusted-R^2	0.496	0.491	0.421	0.313	0.278

*Note: The regressions are run on a balanced data panel of 48 banks and 336 bank-year observations for the year from 2015 to 2021. This table show five fixed-effect regression model testing the impact of Bank FinTech on the 5 aspects of bank performance – capital adequacy (C), asset quality (A), management efficiency (M), earning power (E) and Liquidity ratio (L). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The numbers in parenthesis are standard errors.*

4.2.3 Management efficiency

In the *Model 3*, FINTECH has a substantial negative influence on the efficiency ratio at a 10 per cent significance level. This means that with a higher bank FinTech adoption degree, the ratio of non-interest expense divided by the value of revenue net of interest expense before loan loss provision will be lower, and the banks will be more efficient. This result supports the "innovation-growth" view, so that the adoption of bank FinTech can help banks reduce costs while increasing income diversification. It is also consistent with the findings of Lee et al. (2021) and Wang et al. (2021), who investigated the impact of financial innovation and technology on Chinese bank efficiency and found a positive association between them. This result supports H3.

In terms of control variables, the rate of GDP growth has a negative impact on the efficiency ratio, meaning a positive effect on bank efficiency. The outcome is in accordance with the finding of Le et al. (2021) and Zhao et al. (2022).

4.2.4 Earnings power

Based on the regression results of *Model 4*, FinTech is positively related to bank profitability at a 5 per cent significance level. The coefficient is 0.452 with the standard error equal to 0.223. This result supports the "innovation-growth" theory and contradicts the "innovation-fragility" hypothesis. In fact, the prevalence of cooperation with FinTech firms and the application of bank FinTech is the trend since technology innovation can reduce operation costs and increase the growing and earning power. Previous literature found that financial innovation is positively associated with bank growth, for example Beck et al. (2016) and Lee et al. (2020). While the majority of research has discovered a negative correlation between the growth of FinTech start-ups and bank profitability, this paper obtained the result that applying bank FinTech can help banks maintain their market share and improve profitability. This result also supports the H4.

As for the controls, the loan-loss reserves and GDP growth rate are positively related to ROA, which is in accordance with Menicucci & Paolucci (2016) and Petria et al. (2015).

4.2.5 Liquidity management

In *Model 5*, bank FinTech is negatively related to the liquidity ratio at a 1 per cent significance level. The coefficient is -0.205. A lower LIQ indicates a lower ratio of loan-to-deposit and better liquidity management. This finding backs up the "innovation-growth" theory, implying that using bank FinTech can help banks provide services faster and more efficiently than traditional ways and improve their management of liquidity. For example, by applying cloud computing, traditional banks can store and manage client data more efficiently than conventional techniques. This result is consistent with the findings of Cheng & Qu (2020) and Zhao et al. (2022) and it supports H5. Regarding the control variables, bank size is negatively associated with liquidity ratio.

According to the results of all models, the adoption of bank FinTech has a positive impact on bank performance. The hypotheses and the "innovation-growth" view are both supported. Table 11 summarizes the regression results and impact of FinTech on bank performance.

Table 11. Summary of the results of FinTech's impact and of the hypothesis.

Variable	Regression result sign	Performance	FinTech's impact
CAR	+	Capital adequacy	positive
NPL	-	Asset quality	positive
CTI	-	Management efficiency	positive
ROA	+	Earning power	positive
LIQ	-	Liquidity management	positive

5. Conclusions

The purpose of this research is to analyze the impact of FinTech adoption and applications on banks' performance through the CAMEL rating system, text-mining analysis, and fixed effect model. This paper started by discussing the motivation, then reviewed the theories and articles to find the state of art of this topic, designed the empirical study, presented the results of the regression model, and finally discussed the contribution and future research lines. The results suggest that adopting financial technology in commercial banks is meaningful and can improve the banks' performance in different ways. This study also finds that for European commercial banks, financial innovation has a positive influence, such that the innovation-growth view is supported.

5.1 Contributions and implications

The topic of bank FinTech adoption's impact on banks is quite new. This study adds to the current body of knowledge in three ways. To begin, this research uses the CAMEL grading method to measure bank performance, providing a more in-depth examination of the subject. Second, the most difficult part of this kind of research is gathering data. In contrast to existing literature that only focuses on the impact of the development of FinTech firms, this research collected bank FinTech data through text-mining analysis to provide a more comprehensive picture of this issue. Finally, this study uses data from European banks to fill in the empirical literature gap in the region, and it is useful for the European banking industry in preparing for future opportunities and challenges.

In terms of implications, the findings of this study have revealed the benefits of adopting FinTech in the banking system. As "innovation-growth" view is also supported by the results, it is recommended for banks to concentrate more on the development of financial innovation and FinTech to improve their performance.

5.2 Limitations and suggestions for future research

One of the limitations of this study is that it does not differentiate between various types of FinTech applications. To extend the research, future studies can analyze different categories of FinTech and test if their relationship with banks is heteroskedastic. The majority of research focuses on FinTech credit,

although payment is very closely linked to banks (Elsaid, 2021). As a result, future research could expand the analysis by including the dimensions of FinTech and determining whether their influence on banks is similar.

Another limitation resides in the lack of additional information about banks. This study only chooses to investigate the annual reports of European banks. Apart from the annual report, social media and news about banks can also be used in the text-mining analysis so that the result can be more accurate based on different sources.

Thirdly, this research collected data from 48 banks covering 22 countries. Future research can enlarge the sample size and explore the impact using cluster analysis based on different countries.

Finally, several more components may be included to round out the interaction between FinTech and banks. For example, Nguyen et al. (2021) use banking regulation as a moderator, whereas Zhao et al. (2022) use patent numbers and patent quality as mediators. Moreover, the impact of the COVID-19 pandemic on this relationship can also be evaluated in future studies.

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Appendix A

Table A1. Four regression models for NPL.

	POLS	**BE**	**FE**	**RE**
VARIABLES	NPL	NPL	NPL	NPL
BF	-1.165	2.286	-6.376***	-3.656**
	(1.365)	(3.101)	(1.837)	(1.600)
SIZE	-0.911***	-1.013***	4.218***	-0.815***
	(0.142)	(0.254)	(1.622)	(0.252)
LLR	2.175***	2.228***	2.055***	2.096***
	(0.0622)	(0.119)	(0.143)	(0.0920)
GDP	-0.0840	-0.502	-0.0376	-0.0564
	(0.0663)	(0.314)	(0.0610)	(0.0599)
CPI	-0.141	-0.230	0.0588	0.0253
	(0.0910)	(0.190)	(0.169)	(0.123)
Constant	12.22***	13.35***	-53.91**	11.55***
	(1.894)	(3.355)	(21.27)	(3.321)
Observations	336	336	336	336
R-squared	0.836	0.916	0.491	
Number of NUM		48	48	48

Standard errors in parentheses

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

Table A2. Four regression models for EFF.

	POLS	**BE**	**FE**	**RE**
VARIABLES	EFF	EFF	EFF	EFF
BF	3.767	3.419	-7.015*	-5.775*
	(4.262)	(11.13)	(3.603)	(3.466)
SIZE	-0.902**	-0.482	-3.342	-0.970
	(0.407)	(0.914)	(3.466)	(0.847)
LLR	-0.281	-0.289	-0.300	-0.230
	(0.184)	(0.390)	(0.454)	(0.283)
GDP	-0.195	0.00648	-0.428***	-0.393***
	(0.199)	(0.889)	(0.118)	(0.118)
CPI	-1.800***	-3.286***	0.347	-0.0656
	(0.456)	(1.009)	(0.358)	(0.336)
Constant	72.07***	68.82***	103.9**	72.68***
	(5.255)	(11.67)	(46.15)	(11.22)
Observations	336	336	336	336
R-squared	0.146	0.274	0.417	
Number of NUM		48	48	48

Standard errors in parentheses

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

Table A3. Four regression models for ROA.

	POLS	**BE**	**FE**	**RE**
VARIABLES	ROA	ROA	ROA	ROA
BF	-0.380	-0.916	0.452**	0.306
	(0.242)	(0.579)	(0.223)	(0.230)
SIZE	0.0447*	0.0462	-0.0792	0.0471
	(0.0252)	(0.0475)	(0.197)	(0.0505)
LLR	-0.0125	-0.0444*	0.154***	0.0854***
	(0.0110)	(0.0221)	(0.0173)	(0.0150)
GDP	0.0232**	0.0565	0.0322***	0.0294***
	(0.0117)	(0.0587)	(0.00739)	(0.00807)
CPI	0.114***	0.149***	-0.0109	0.0216
	(0.0161)	(0.0354)	(0.0205)	(0.0189)
Constant	-0.0796	0.0202	1.063	-0.436
	(0.335)	(0.626)	(2.579)	(0.665)
Observations	336	336	336	336
R-squared	0.212	0.445	0.313	
Number of NUM		48	48	48

Standard errors in parentheses

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

Table A4. Four regression models for LIQ.

	POLS	**BE**	**FE**	**RE**
VARIABLES	LIQ	LIQ	LIQ	LIQ
BF	-0.779***	-1.033**	-0.205***	-0.251***
	(0.138)	(0.441)	(0.0752)	(0.0744)
SIZE	0.0361**	0.0514	-0.136**	0.00386
	(0.0144)	(0.0362)	(0.0664)	(0.0316)
LLR	-0.0270***	-0.0267	0.00326	0.00329
	(0.00628)	(0.0169)	(0.00585)	(0.00547)
GDP	-0.000226	0.0115	0.00344	0.00400
	(0.00670)	(0.0447)	(0.00250)	(0.00250)
CPI	0.0102	0.0165	-0.00779	-0.0112*
	(0.00920)	(0.0270)	(0.00693)	(0.00653)
Constant	0.880***	0.715	2.933***	1.097***
	(0.191)	(0.477)	(0.870)	(0.416)
Observations	336	336	336	336
R-squared	0.168	0.191	0.278	
Number of NUM		48	48	48

Standard errors in parentheses

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