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Do European fintech benefit from bank-affiliated VCs?

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A B S T R A C T

In the current study, we scrutinize the efficacy of bank-affiliated venture capital (BVC) in augmenting the performance of European FinTech firms, with a specific sample size of 105 firms. The investigation is anchored in a resource-based view (RBV) and examines the strategic comportment of banks vis-à-vis FinTech enterprises. Utilizing a dataset that encompasses pre-Brexit European FinTech firms from 2006 to 2019, we implement logistic regression models for our primary analysis. Propensity score matching is invoked to mitigate selection bias, and machine learning techniques are applied to address data imbalance. The empirical evidence demonstrates that FinTech firms backed by BVC exhibit superior profitability and asset performance compared to their non-BVC-backed counterparts. The robustness of these findings persists even after accounting for selection bias and data imbalance. The study posits that bank-affiliated venture capital serves as a pivotal criterion for FinTech entrepreneurs in investor selection, thereby enriching the scholarly discourse on the symbiotic relationship between traditional banking institutions and emergent financial technologies within a European context characterized by information asymmetry and resource-based complementarities.

1. Introduction

Venture capital (henceforth referred to as VC) is one of the most effective means of funding to finance high-tech entrepreneurial firms, which have hardly any access to other sources of funding (Lai et al., 2022). VC companies provide funds and are adept at identifying exceptionally promising digital technology ventures, affording them intensive monitoring, and bringing them value-added support (Salhman, 1990; Sapienza et al., 1994; Hellmann & Puri, 2000; Gompers & Lerner, 2001a; 2001b). However, little is known about how these screening and monitoring effects came to fruition for FinTech and to what extent VC companies may differ in terms of affiliation and measures of performance. In other words, there is a gap in the literature in understanding how and why, bank affiliation of VC affects or not the prior selection and subsequent performance of FinTech.

Although a good number of scholarly works examine independent, corporate, and governmental VC organizations, less attention is dedicated to bank-affiliated VC companies (henceforth referred to as BVCs). Hellmann et al. (2008) document that VC firms linked to banks seem to be more interested in finding complementarities with their activity portfolio than in higher investment returns. Gompers and Lerner (2001a) find that strategically focused and more specialized VC programs (e.g., finance-affiliated VC firms) appear to be stable and more able to provide further round financing without being forced to divest the venture. This complementarity search and strategic behavior of BVCs can notably lead them toward financing FinTech firms, affecting their performance following the VC

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funding (Zhang & Zhang, 2020). Furthermore, in numerous European nations, VC firms rely heavily on commercial banks as their primary financial benefactors. In the past decades, BVCs have played a highly important role in the European VC market (e.g., Bottazzi et al., 2008). Bertoni et al. (2015) indicate that the BVC investor type in Europe differs substantially in its investment patterns when compared to other VC types and that these BVC investment patterns are stable over time and similar across different European countries. In this regard, this research aimed to clarify the role of BVCs in European FinTech as determined by these two questions: (1) Do BVC-backed FinTech outperform non-BVC-backed FinTech? (2) If so, can the performance of BVC-backed FinTech be attributed to BVCs' ability to screen better performing FinTech *ex-ante*, or their capacity to monitor them to improve their profitability following the investment? Or can it be attributed to both effects?

The banking industry, one of the most traditional and conservative industries, is confronted with potentially disruptive financial technology (Dockery & Herbert, 1996; Frost, 2020). BVC investment allows banks to confront the threat of technology-driven firms and offer banks possibilities to benefit from financial technology developed by FinTech (Borah & Tellis, 2014). This article places emphasis on the role of banks through BVC investments in the continuing revolution and performance of FinTech given that a bank's investment motive strongly influences the venture's profitability (Lee et al., 2021). To the best of our knowledge, no study has been conducted to investigate the effects of BVC investment on FinTech performance. However, a stream of literature focuses on examining the behavior of BVC toward entrepreneurial firms (Andrieu, 2013; Croce et al., 2013; Cumming et al., 2022; Wang et al., 2002; Yoshikawa et al., 2004). This study attempts to fill the existing gap by comparing the pre-and post-investment performance of BVC-backed and non-BVC-backed FinTech using 201 European VC rounds that funded 105 FinTech from 2006 to 2019. The sample covers countries with similar FinTech landscapes and VC patterns (Frost, 2020).

The results indicate that BVC funding improves the performance of European FinTech more significantly compared with non-BVC funding. Moreover, it is found that BVCs screen FinTech according to higher economic performance. Nevertheless, the results based on sales returns don't provide valuable insights into the performance-enhancing capabilities of BVC funding for FinTech. To distinguish the *ex-ante* screening and *ex-post* monitoring effects of VC investment, the propensity score matching (PSM) methodology is used to alleviate the potential selection. The relevance of the findings is also tested with respect to the prevalence of VC companies from the UK in the sample, using the Synthetic Minority Oversampling Technique (SMOTE) algorithm to convert data into a balanced form.

This manuscript is structured as follows: Section 2 presents a comprehensive review of pertinent literature. Section 3 delineates the hypotheses, data collection procedures, and sample characteristics. Section 4 presents a univariate analysis of the data. Section 5 details and examines the outcomes. Section 7 employs robustness tests to evaluate the stability of the results, while Section 8 offers concluding remarks. Finally, Section 9 expounds upon the practical implications of the study.

2. Literature review

2.1. Venture capital investment in FinTech

Fintech refers to different financial technologies used to automate processes in the financial industry, from routine tasks to non-routine and cognitive processes (Goldstein et al., 2019; Heather et al., 2020). In the wake of the financial crisis, financial technology firms now offer more innovative solutions to problems encountered by traditional banks. This disruptive FinTech industry is growing at a rapid pace and accompanying the transformation of the business processes in several areas of finance, such as payment systems, trading, risk management, asset management, lending, accounting, mobile banking, equity crowdfunding, insurance, and investment banking (Heather et al., 2020). According to a KPMG report (KPMG Annual Report, 2019), the annual FinTech funding in 2018 was $112 billion, comprised of 2196 deals, which doubled compared to 2017. The emerging technologies that are being used across these FinTech segments include cloud computing, blockchain and distributed ledger technology, open-source computing and APIs, machine learning, and cybersecurity, among others (Chang et al., 2020). Like other types of startups, FinTech firms typically raise capital through various stages. The first stage is often seed funding, which may be provided by angel investors, family members, friends, accelerators, incubators, or VCs during the initial funding rounds (Fabozzi, 2016). Once the company has established itself and demonstrates the potential for growth, it may secure additional funding from VCs (Arjunwadkar, 2018). This can include early-stage equity investments such as Series A and Series B funding rounds. As the FinTech firm grows and requires additional funding, it may seek late-stage financing from VCs, such as Series C, D, E, and beyond, as well as from private equity investors (PE). Late-stage funding is typically used to expand operations, develop new products, or acquire other companies. This funding is usually provided by institutional investors or wealthy individuals who are willing to take on higher levels of risk in exchange for potentially higher returns (Klonowski & Hueske, 2020). By understanding the different stages of funding, FinTech firms can better prepare for and secure the necessary capital to support their growth and development.

Using data from the Venture Scanner database, Chemmanur et al. (2020) find that the majority of FinTech's funding takes the form of early-stage VC. Exceptionally, there was slightly more late-stage VC funding than early-stage VC funding in 2019, suggesting that the FinTech industry is presumably maturing. Haddad and Hornuf (2019) [1] find that VC investment opportunities for FinTech strongly differ by a geographic location given the large VC amounts raised for US and Asian FinTech, contrary to the VC funds available for European FinTech. They, therefore, observe that FinTech is primarily established in countries with available VC investors and that their returns are still weak, especially in some segments such as equity crowdfunding.

Kolokas et al. (2020) [2] examine how countries' VC and credit markets differently affect FinTech development on an international scale. They argue that VC investment in a country requires a growing FinTech industry in terms of value and volume to more positively influence FinTech growth and performance and that VC and credit markets are substitutes, especially in countries with more developed FinTech segments. As one of the leading players in the credit market, banks are well known to be making investments through payments, lending, and asset management, giving them the ability to benefit from the innovation developed by FinTech. But banks are also actively contributing to digital transformation by investing in financial innovations by means of BVC investment. Hill (2018) addresses the banks' participation in VC-backed FinTech. Based on significant bank investment in VC-backed FinTech, he deduces that banks have become active investors in FinTech, allowing them to capitalize on innovative financial solutions. According to a CB Insights report of 2017, most large banks have made at least some investments in the FinTech field, and the most active, during the last years, have been Goldman Sachs, Citi, Santander, Mizuho, and JPMorgan. A bank's strategy for a VC investment is to partner with a FinTech, using the bank's customer base in tandem with FinTech technology, a leaner structure, and a lighter regulatory and compliance constraint (Arner et al., 2016). Recent studies show that central European banks are set to remain contributors in VC funding for FinTech even amid the COVID-19 crisis. They argue that their motivations are to participate in promoting FinTech to generate higher performance, or with the intention of buying them at a subsequent time.

2.2. Venture capital investment and firm performance

The entrepreneurial finance literature highlights two ways through which VC investments positively affect the performance of entrepreneurial firms (Baum & Silverman, 2004). VC investors may act as a "scout" when they screen firms with great growth prospects. Colombo and Grilli (2010) show that the joint consideration of VC funds and human capital helps dissociate the selecting and monitoring functions performed by VC investors financing new Italian technology-based firms. Chemmanur et al. (2011) confirm that VCs in the US not only choose to invest in firms with higher efficiency but also help firms improve their efficiency after the investment is made. This study attempts to expand the findings of Chemmanur et al. (2011) by examining the contribution of VC, depending on its affiliation, to European FinTech pre- and post-investment.

The theoretical context arguing the screening effect of VC investment is the asymmetric information theory (Myers & Majluf, 1984). VCs are recognized as agents that are better able to address information asymmetry problems than other financial intermediaries, significantly when investing in private firms (Amit et al., 1998). Therefore, the screening ability of VCs could be a significant determinant of the superior performance of VC-backed firms (Shepherd & Zacharakis, 2007; Tyebjee & Bruno, 1984). Banks and FinTech companies are from the same industry and may therefore have lower information asymmetry, and this suggests that the screening effect of BVC investment on FinTech companies may be even more substantial than the screening effect on other types of private firms. This is because the reduced information asymmetry between banks and FinTech companies may make it easier for BVCs to assess the potential for success of these companies (Landskroner & Paroush, 1995). The reference to Fritsch and Schilder (2008) also adds credibility to this argument by providing a source supporting reduced information asymmetry in the banking industry.

Regarding the monitoring effect of VC investment and according to the agency cost theory (Jensen & Meckling, 1976), monitoring of VC-backed firms post-investment helps VC managers detect potential problems and reduce agency costs, thereby increasing firm performance (Admati & Pfleiderer, 1994; Lerner, 1995; Mitchell et al., 1997). But agency costs theory neglects to take into account that VCs perform a key coaching role far beyond monitoring (Colombo & Grilli, 2010). VC involvement allows the funded firm to increase the bundle of financial and managerial resources (Barney, 1991; Sapienza et al., 1994; Sørensen, 2007; Whitten et al., 2002). Hence, agency cost theory and a resource-based approach help establish that the monitoring effect is an essential driver of firm performance in the VC literature (Ireland et al., 2003; Meuleman et al., 2009; Shepherd et al., 2000).

The firm's resource-based view (RBV) is another theoretical framework that provides a valuable lens to understand the monitoring hypothesis of BVC investment in FinTech. According to RBV, a firm's competitive advantage, and superior performance depend on the availability and efficient deployment of strategic resources and capabilities (Barney, 1991). RBV emphasizes the complementarity of resources, which means that a particular resource's value is enhanced when combined with other complementary resources (Wernerfelt, 1984). In the context of BVC and FinTech, the complementary resources could include financial resources, managerial expertise, networks, and technology.

BVC investors can provide Fintech access to these complementary resources and help them achieve strategic objectives they would have otherwise been unable to accomplish. BVC investors bring financial resources, managerial expertise, networks, and industry-specific knowledge to the table. By providing FinTech with these resources, BVC investors can help them improve their performance and achieve superior outcomes. Furthermore, BVC investors may leverage their networks to provide FinTech access to potential partners, customers, and suppliers, which can help them achieve market penetration and scale. Therefore, the RBV framework highlights the importance of complementary resources and the need for BVC investors to provide them to FinTech. This complementarity can be particularly valuable for FinTech, which often faces significant resource constraints due to the rapid pace of innovation and the competitive nature of the industry. By providing complementary resources, BVC investors can help FinTech overcome these constraints and achieve superior performance.

2.3. The impact of VC affiliation

Venture capital firms are a critical source of funding for many entrepreneurial ventures, including those in the high-tech and fintech industries. These VC firms are typically classified based on their ownership and governance structures, including independent VC, corporate VC, and bank-affiliated VC. While the US VC industry is dominated by funds organized as limited partnerships, the banking-oriented capital markets in Europe have given rise to a significant number of BVC firms. Empirical research has shown that BVC investors are more likely to invest locally, where they can leverage their superior ability to gather information. Additionally, BVC firms tend to invest in older and larger companies, suggesting that their primary objective is to support a profitable relationship with their portfolio companies rather than maximizing financial returns. For FinTech entrepreneurs seeking VC funding, the bank affiliation of the investor can play a significant role in subsequent performance.

VC investors are identified and classified according to the ownership and governance of the management company. An investor characterized by an independent management company is classified as an independent VC. Investors whose parent companies are non-financial companies are classified as corporate VC, and those whose parent companies are banks as bank-affiliated VC. In the US, most of the industry consists of funds organized as limited partnerships and supported for a limited period (generally 10 years) by passive investors (Brophy & Haessler, 1994; Fiet & Fraser, 1994). In continental Europe, where capital markets are banking-oriented, VC firms affiliated with banks play an important role and often participate in VC and leveraged buyout activities (Bertoni et al., 2015).

The bank-based capital markets in Europe, as compared with the US, raise the question of the magnitude of BVC in financing high-tech entrepreneurial firms, particularly FinTech. The empirical study by Black and Gilson (1998) was one of the first to show that in continental Europe, commercial banks were the main contributors of VC firms, unlike the US, where pension funds were originally the main actors. Bertoni et al. (2015) examine the patterns of VC investment across different types of VC investors in Europe and compare them with the investment patterns observed in the US. They find that BVC investors in Europe are more likely to invest locally, where they can exploit their superior ability to gather information (Fritsch & Schilder, 2008). Their results demonstrate that BVC investors are more inclined to invest in older and larger companies, which conforms with the view that the primary objective of BVC investors is to support a bank relationship with funded companies or investees (Hellmann et al., 2008; Mayer et al., 2005).

3. Hypotheses, data, and sample

3.1. Hypotheses

Bank-affiliated venture capital (BVC) funds are a distinctive subset of venture capital investors that are affiliated with banking institutions. Prior research has suggested that these investors are primarily driven by finding complementarities with their parent firms' activities, rather than solely focusing on the success of the venture. Recent studies have also shown that banks with a well-defined digital strategy are more receptive to collaborating with or investing in fintech entrepreneurs. These factors suggest that BVCs are well-positioned to facilitate collaboration between banks and Fintech, especially as bank licenses become more restrictive. Additionally, low-quality financial patents and innovations are common, underscoring the potential for a bank-Fintech complementarity to produce high-quality innovation and performance. By combining their respective strengths, banks and Fintech firms could improve their ability to address information asymmetry issues and efficiently screen for high-performing ventures. These findings support the hypothesis that BVCs are better equipped to address information asymmetry problems than non-BVCs.

European BVC investors, in particular, have been found to have an advantage in terms of screening and selecting potential FinTech investments. They are able to act as "scouts" by gathering valuable information about promising investment opportunities. Specifically, BVCs are more effective at identifying and investing in firms with higher efficiency and lower risk due to their access to the resources and expertise of their parent banks. This advantage has been demonstrated by previous studies, such as Hellmann et al. (2008) and Andrieu and Groh (2012), who found that BVCs can help firms improve their efficiency after investment and reduce the risk of making inefficient investment decisions. As a result, BVCs may be better equipped than non-BVCs to address information asymmetry problems, which are especially pertinent in the FinTech industry where innovation and risk are inextricably linked. Based on the above literature review and theoretical arguments, we put forward the following hypothesis.

H1. European Bank-affiliated VCs are more likely to select high-performing FinTech than European non-bank-affiliated VCs due to the increased screening ability of banks' pre-investment.

Prior research has suggested that bank-affiliated venture capital (BVC) funds prioritize complementarity with their parent firms over the success of the venture, as evidenced by studies such as Hellmann et al. (2008). This suggests that BVCs may be more motivated by the potential synergies between the venture and their parent firms' existing activities, rather than the venture's individual performance. Additionally, recent research has indicated that banks with a defined digital strategy are more open to collaboration and investment with Fintech entrepreneurs, which could result in increased collaboration between Fintech and banks since bank licensing regulations become more stringent (Hornuf et al., 2021).

Moreover, low-quality financial patents and innovations have been observed in previous studies, indicating a potential opportunity for a bank-Fintech complementarity to generate higher-quality innovation and overall performance (Lerner et al., 2015). In sum, the aim of this section is to establish the potential benefits of bank-Fintech collaboration and to support the idea that such collaboration could result in improved innovation and performance in the Fintech industry. Drawing from agency cost theory and a resource-based approach, we propose the following hypothesis.

H1. BVC-backed European FinTech is more likely to outperform non-BVC-backed European FinTech due to more monitoring of BVCs post-investment.

3.2. Data and sample

A sample covering 6 European countries before Brexit (the UK, France, Spain, Italy, Germany, and Belgium) is constructed using multiple secondary data sources to test these two hypotheses. The main data sources used are Crunchbase (e.g., Alaassar et al., 2022; Hornuf et al., 2021), Orbis, and Diane. FinTech data and its funding rounds are collected from Crunchbase, whereas financial characteristics data is obtained from Diane (French FinTech) and Orbis (other European FinTech) databases [3].

Table 1
Pairwise correlations.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
(1) ROE Increase	1.00															
(2) ROA Increase	0.513***	1.00														
(3) ROS Increase	0.262***	0.533***	1.00													
(4) LP Increase	0.393***	0.562***	0.600***	1.00												
(5) VC Type	0.264***	0.221***	0.019	0.091	1.00											
(6) ROE $_{t = -1}$	−0.076	−0.068	−0.091	−0.070	0.094	1.00										
(7) ROA $_{t = -1}$	0.026	−0.313***	−0.124	−0.114	0.131	0.043	1.00									
(8) ROS $_{t = -1}$	0.070	0.074	−0.079	−0.068	0.075	0.008	0.049	1.00								
(9) Ln LP $_{t = -1}$	−0.152***	−0.191***	−0.364***	−0.129	0.096	0.243***	0.258***	0.042	1.00							
(10) Age	0.098	0.133	−0.083	0.127	0.191***	0.062	0.017	0.096	0.292***	1.00						
(11) Ln Size $_{t = -1}$	0.211***	0.223***	0.000	0.095	0.246***	−0.127	0.070	0.067	−0.036	0.431***	1.00					
(12) Banking segment Dummy	0.076	0.161***	0.135	0.136	0.133	−0.023	−0.097	0.036	−0.104	0.089	0.279***	1.00				
(13) Late-stage Dummy	0.139***	0.154***	−0.017	0.162***	0.107	−0.029	0.130	0.044	0.266***	0.359***	0.405***	0.027	1.00			
(14) Number of founders	−0.011	0.046	−0.003	−0.029	−0.145***	−0.074	0.056	0.027	−0.207***	−0.257***	0.057	0.047	−0.070	1.00		
(15) Leverage $_{t = -1}$	−0.042	0.075	−0.030	0.030	0.162***	0.000	−0.242***	0.028	0.020	0.407***	0.013	−0.038	−0.075	−0.163***	1.00	
(16) Ln VC size	0.197***	0.197***	0.091	0.134	0.267***	0.047	−0.028	0.001	0.022	0.160***	0.388***	0.161***	0.242***	−0.064	−0.020	1.00

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 1. Pairwise Correlations of Main Variables: This table elucidates the pairwise correlation coefficients between the main variables designated for inclusion in the subsequent regression analyses. Each cell in the matrix furnishes the Pearson correlation coefficient between the variables indicated by the respective row and column headers. Statistical significance levels are denoted by asterisks: *** indicates a significance level of 1%, ** represents 5%, and * signifies 10%. The diagonal line of the matrix, populated by 1.00, represents the correlation of each variable with itself, serving as a reference point for the correlation analysis. For instance, the correlation coefficient between ROE Increase (Row 1) and ROA Increase (Column 2) is 0.513 and is statistically significant at the 1% level, as denoted by the triple asterisks. To enhance interpretability: Variables labeled with $t = -1$ refer to the lagged values, capturing the historical data one period before the event of interest, The variable ‘VC Type’ is a binary indicator capturing whether the venture capital is bank-affiliated (BVC) or not, LP refers to liquidity position, and Ln signifies the natural logarithm transformation applied to normalize the distribution of certain variables., Control variables such as ‘Age,’ ‘Ln Size,’ and ‘Number of Founders’ serve as additional factors in the regression mode.

Funding rounds that were announced between January 1st, 2006, and December 31st, 2019 are selected. Data is collected on FinTech activity up to 2019 before Brexit, to ensure that data sources have sufficient time to consider a window of at least 12 months around the fiscal year to observe the effect of VC investment and counteract the effects resulting from the Brexit announcement. Extending the study to more than one country broadens the sample, especially since European countries present similar FinTech landscape and VC patterns in comparison to the US and Asia. The six European countries are mainly for data availability, especially financial data. The final sample consists of 201 VC rounds, which are funding 105 FinTech, comprising 73 bank-affiliated VC firms and 128 non-bank-affiliated VC firms.

Table 1 presents the distribution of FinTech and their VC rounds according to their affiliation (BVC vs. non-BVC) by European country, funding stage, and FinTech segment. As shown in Panel A, FinTech and their corresponding VC rounds are more concentrated in the UK (46%) and France (24%), and at a lower level in Spain and Italy [4]. This is in line with Haddad and Hornuf (2019) study, which highlights that FinTech formations and investments occur more frequently in countries with well-developed capital markets and where supporting infrastructure and VC funding are readily available. The number of BVCs is lower in the sample for all countries, especially France, Spain, and Italy. Panel B reports the distribution of VC rounds and their types by funding stage. Only 15% of the VC investments reviewed concern the late stage, consistent with Chemmanur et al. (2020) [5] that the majority of FinTech funding concerns the early stages. 87.7% of BVC rounds take part after the seed stage, as opposed to 67% among non-BVC rounds. This confirms the observation that BVC funders prefer to invest in less risky stages (Hellmann et al., 2008). Building upon a previous study by Chemmanur et al. (2020), this study seeks to delve into the diverse characteristics and performance drivers of distinct segments within the FinTech industry. In particular, our investigation of the impact of venture capital (VC) investments on FinTech firms focuses on various segments identified by Venture Scanner's website. To expound upon our analysis, Panel C of our study report exhibits the absolute count and proportion of FinTech, and VC investment rounds disaggregated by the specific segment of a FinTech firm's primary activity. A noteworthy observation from our sample is that the majority of FinTech firms specialize in financial services related to payments and lending, which signifies the immense potential of these segments in the FinTech industry. To investigate the different dynamics among FinTech segments, Panel C presents the number and percent of FinTech and VC rounds by the segment of a FinTech's core activity. In the sample, more FinTech provides financial services related to payments and lending segments.

Building upon a previous study by Chemmanur et al. (2020), this study seeks to delve into the diverse characteristics and performance drivers of distinct segments within the FinTech industry. In particular, our investigation of the impact of venture capital (VC) investments on FinTech firms focuses on various segments identified by Venture Scanner's website. To expound upon our analysis, Panel C of our study report exhibits the absolute count and proportion of FinTech and VC investment rounds disaggregated by the specific segment of a FinTech firm's primary activity. A noteworthy observation from our sample is that the majority of FinTech firms specialize in financial services related to payments and lending, which signifies the immense potential of these segments in the FinTech industry.

4. Measurement and inference

4.1. Measurement of variables

4.1.1. Performance measurement using the logic regression model

The performance of FinTech, depending on the VC affiliation, is the major interest in this study. Hence, in the first series of our analysis, we use a logit model is performed to estimate the impact of VC affiliation on the change in performance after the VC funding. The dependent variable is a dummy variable that equals 1 if there is an improvement in the performance measure and 0 otherwise. Three logit regressions are conducted based on the three measures of performance used. The independent variable of interest (VC Type) is a dummy variable that equals 1 if a BVC backs the FinTech and 0 otherwise. A significant positive coefficient on this variable implies that BVC-backed FinTech generally has higher profitability than non-BVC-backed ones. The first proposed logistic model is written as:

$$P_i\ (Y = 1|X1, \ldots, X8) = \frac{e_1^{\beta\ VC\ type+\beta_2 Age+\beta_3 Size+\ldots+\beta_8\ VC\ size+cons}}{1 + e_1^{\beta\ VC\ type+\beta 2Age+\beta 3\ Size+\ldots+\beta 8\ VC\ size+cons}} \tag{1}$$

where the binary variable P_i is the probability of occurrence ($Y = 1$) of having an increase in performance measure; $X1, \ldots, X8$, are the eight explanatory variables; and "cons" is the constant. A latent variable y_i* is a continuous and non-observable variable representative of the performance change around VC investment, and this binary variable to be explained y_i (which can be P_i) is defined as:

$$\begin{cases} y_i = 1\ if\ y_i^* > 0 \\ 1 - \mathrm{y_i} = 0 \text{ if } \mathrm{y_i^*} \leq 0 \end{cases} \tag{2}$$

The control variables are age, size, banking segment dummy, late-stage dummy, number of founders, leverage, and VC size. These variables are used to assess venture performance following investment in the FinTech industry. Age is used as a control variable to proxy for the newness of the FinTech firm. The idea is that younger firms may have less developed infrastructure, fewer established relationships, and a more limited track record, which may affect their performance following investment. Therefore, controlling for age allows for a more accurate assessment of the impact of VC investment on FinTech performance. Size is another control variable used to account for differences in the scale of FinTech firms. Larger firms may have greater access to resources, established networks, and greater bargaining power, which may impact their performance following VC investment. Thus, controlling for size allows for a more accurate comparison of performance across firms. The banking segment dummy variable is used to distinguish between FinTech firms operating in the banking sector and those in other segments.

The expectation is that banking-segment FinTech firms may be more complementary to banks and their risk-averse behavior may result in a greater improvement in performance following VC investment. The late-stage dummy variable is used to account for differences in the stage of development of the FinTech firms at the time of VC investment. Late-stage firms may have a more established product or service, a customer base, and a proven business model, which may impact their performance following VC investment. Thus, controlling for the late-stage dummy variable allows for a more accurate assessment of the impact of VC investment on performance. The number of founders, leverage and VC size are additional control variables used to account for differences in the characteristics of the FinTech firms (Lahr & Mina, 2014; Murphy et al., 2016). These variables may impact the performance of the firms following VC investment, and thus controlling for them allows for a more accurate comparison of performance across firms. The foundation date taken from Crunchbase is used to calculate the age of FinTech as of the date of the VC announcement. The model controls for age as a proxy for newness. The performance improvement after the VC entry is expected to be more pronounced in banking-segment FinTech and during the late stages given banks' complementarity-based and risk-averse behavior.

4.1.2. Performance measurement using bayesian logistic regression model

In the second phase of this analysis, we investigate whether BVC-backed FinTech outperforms its non-BVC-backed counterparts. To achieve this objective, a Bayesian logistic regression model is employed to estimate the effect of VC affiliation on the change in performance following VC funding. Bayesian logistic regression models are used in the analysis of the effect of VC affiliation on the change in performance following VC funding as the reason that Bayesian logistic regression models can account for uncertainty in the estimates of the model parameters, which is particularly important when dealing with small sample sizes or sparse data. This can help ensure that the analysis results are reliable and accurate. Furthermore, it allows for the incorporation of prior knowledge or beliefs about the relationships between variables in the model. This can be particularly useful when modeling the effects of VC affiliation, as there may be strong theoretical or empirical evidence about the relationships between certain variables. In addition, it can handle both continuous and categorical predictors, which is essential when dealing with a mix of continuous and categorical variables that are often found in the analysis of the effects of VC affiliation and can provide a flexible framework for model selection and hypothesis testing, allowing researchers to compare different models and hypotheses and select the most appropriate one based on the data and prior knowledge. The dependent variables, "ROS", "ROA" and "ROE" are binary variables equaling 1 if there is an improvement in the measure of performance and 0 otherwise. These performances are based on equity, asset, and sales. The independent variable of interest, "VC type", is a dummy variable that equals 1 if a BVC backs the FinTech and 0 otherwise. The model controls for various relevant covariates, including age, size, banking segment dummy, late-stage dummy, number of founders, leverage, and VC size. By employing this model, the study seeks to determine whether BVC-backed FinTech exhibit a higher profitability level than non-BVC-backed FinTech, providing valuable insight into the value-added effects of BVCs on FinTech. The formula for Bayesian logistic regression would be:

$$logit(\pi i) = \beta 0 + \beta 1 VC\_typei + \beta 2 X2i + \beta 3 X3i + \ldots + \beta k Xki + \varepsilon i \tag{3}$$

where *logit(πi)* is the log-odds of FinTech *i* having an improvement in ROS, *VC_typei* is a binary variable indicating whether FinTech *i* is BVC-backed or not, *X2i* to *Xki* are other independent variables, and *β0, β1, β2, …,* βk are the corresponding regression coefficients. *εi* is the error term for FinTech *i.* The foundation date taken from Crunchbase is used to calculate the age of FinTech as of the date of the VC announcement. The model controls for age as a proxy for newness. The performance improvement after the VC entry is expected to be more pronounced in cases of banking-segment FinTech and during late stages given banks' complementarity-based and risk-averse behavior.

4.1.3. Better performance measurement using logit regression model

The second hypothesis examines the issue of whether the outperformance of BVC-backed FinTech already exists through the screening effect before companies receive funding. To perform this test, a logit model is run, wherein the dependent variable is a dummy variable that takes 1 for BVCs, and 0 otherwise. The second proposed logistic model is written as follows:

$$P_i(Y = 1|X1, \ldots, X8) = \frac{e^{\beta_1 Performance\ before\ VC + \beta_2 Age + \beta_3 Size + \ldots + \beta_8 VC\ size + cons}}{1 + e^{\beta_1\ Performance\ before\ VC + \beta_2\ Age + \beta 3 Size + \cdots + \beta_8\ VC\ size + cons}} \tag{2a}$$

where the binary variable P_i is the probability of occurrence ($Y = 1$) of having a bank-affiliated VC; *X1*, …, *X8*, are the eight explanatory variables; and "cons" is the constant. A latent variable y_i* is a continuous and non-observable variable representative of the VC affiliation, and this binary variable to be explained y_i (which can be P_i) is defined as:

$$\begin{cases} y_i = 1\ if\ y_i^* = BVC\ affiliation \\ 1 - y_i = 0\ if\ y_i^* = non - BVC\ affiliation \end{cases} \tag{3a}$$

The independent variables of interest include measures of performance pre-investment, namely ROS, ROA, and ROE in the year preceding the VC round announcement.

5. Univariate analysis

The data consists of a sample of FinTech firms and their corresponding VC rounds. To analyze which firm-level factors drive FinTech performance in terms of VC investment, descriptive statistics of variables identifying FinTech specifics are reported. These include variables related to the firm (i.e., size, age, segment, number of founders), its status (i.e., whether the FinTech is still active or not; whether it is private or listed).

Table 2, Panel A provides the summary statistics of FinTech characteristics. The average age of FinTech is four years, which reveals that the FinTech market in Europe remains young. Only 10% of the FinTech belong to the banking sector. Furthermore, the number of funding rounds exceeds on average five rounds per FinTech, which indicates the gradual funding adopted by VC funds based on the FinTech prospects of development over time. Almost all of the FinTech is still active (0.97) and non-listed (0.97). Regarding the exit alternatives, only 6% were acquired by banks, which may indicate that the main strategy of a VC investment by a bank is to partner with FinTech without necessarily intending to acquire it. Panel B of Table 2 provides an average amount raised in the relevant VC of €2.14 billion and a maximum funding amount of €23.8 billion.

In order to investigate to what extent prior FinTech performance differs according to the type of VC funding, and which VC type significantly enhances the post-VC performance of FinTech, the study defines performance measures, namely return on sales (ROS), return on assets (ROA), and return on equity (ROE). Table 3 reports the *t*-test results on the difference in measures of FinTech performance between BVCs and non-BVCs. The Wilcoxon test on the median is applied using the two-tailed Wilcoxon rank-sun test to ensure that outliers do not affect the results.

Panel A, Table 3 compares the average FinTech performance of the two groups of VCs during the year preceding the investment to control, at first glance, the *ex-ante* screening effect of VC investment. Further univariate analysis in Panel B consists of comparing post-investment FinTech performance between both subsamples to control for the *ex-post* monitoring effect of VC investment. First, in the year preceding the VC investment, BVC-backed FinTech has statistically better ROS and ROA than non-BVC-backed FinTech. For the other performance measure, the difference is not statistically significant. Second, in the year following the VC investment, BVC-backed FinTech has statistically higher performance measures than non-BVC-backed FinTech.

Fig. 1 shows that there are differences in the selection patterns of BVC and non-BVC investments for European FinTech. According to Fig. 1.1, the hazard rates for BVC investments are significantly lower for younger companies and clearly increase along with the firm's age. This indicates that BVC invests more in mature FinTech, which is consistent with the recent evidence on captive VCs in Europe (Bertoni et al., 2015; Cumming et al., 2017; Wang et al., 2002). Fig.1.2 indicates that the hazard estimates of non-BVCs are

Table 2
Sample composition of European FinTech and their funding rounds.

	FinTech		VC rounds		Non-BVC rounds		BVC rounds	
	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Panel A. European countries								
UK	42	40%	93	46%	49	24%	44	22%
France	29	28%	48	24%	31	16%	17	8%
Belgium	1	1%	2	1%	0	0%	2	1%
Spain	18	17%	33	16%	29	14%	4	2%
Italy	10	9%	19	10%	15	8%	4	2%
Germany	5	5%	6	3%	4	2%	2	1%
Total	105	100%	201	100%	128	64%	73	36%
Panel B. Funding stage								
Seed	–	–	51	25%	42	21%	9	4%
Early	–	–	119	59%	70	35%	49	24%
Late	–	–	31	16%	16	8%	15	8%
Total	–	–	201	100%	128	64%	73	36%
Panel C. FinTech segments								
Financial management solutions	12	11%	25	12%	15	7%	10	5%
Investing	8	8%	16	8%	10	5%	6	3%
Payments	22	21%	33	16%	18	9%	15	7%
Mortgages and Lending	16	15%	39	19%	23	11%	16	8%
InsurTech	9	9%	16	8	14	7%	2	1%
Banking	10	10%	22	11%	10	5%	12	6%
Accounting Management	9	8%	14	7%	13	7%	1	0%
Asset Management	10	9%	19	10%	10	5%	9	4%
RegTech	1	1%	1	1%	1	1%	0	0%
Crowdfunding	6	6%	12	6%	10	5%	2	2%
Cryptocurrency and blockchain	2	2%	4	2%	4	2%	0	0%
Total	105	100%	201	100%	128	64%	73	36%

Table 2. This table delineates the distribution of FinTech firms in terms of geographical concentration (Panel A), funding stage (Panel B), and market segment (Panel C). The data is derived from a sample of 105 European FinTech firms and encompasses funding rounds between 2006 and 2019. Percentages for each subsample are calculated relative to the entire sample size. Seed rounds, as defined, range between $10,000–$2 million, Early-stage rounds between $1 million–$30 million, and Late-stage rounds typically exceed $10 million. The industry segments are classified based on the comprehensive descriptions provided by Crunchbase). All percentages are rounded to the nearest whole number, and all monetary values are in USD.

Table 3
Summary statistics of FinTech and VC rounds.

	Obs.	*Mean*	*Median*	*Std. Dev.*	*Min*	*Max*	*25% Quantile*	*75% Quantile*
***Panel A**. FinTech*								
Age	105	4.009	3	3.824	0	26	2	5
Number of employees$_{t-1}$	105	85.971	14	361.701	1	2637	4	36
Number of employees$_{t+1}$	105	115.619	20	370.398	1	2921	7	70
Total assets$_{t-1}$ (m€)	105	1,93	1.14	7,47	0.0047	45,3	0.25	4.78
Total assets$_{t+1}$ (m€)	105	3,74	2.548	13,7	0.0185	80,4	0.89	10.42
Banking segment Dummy	105	0.095	0	0.295	0	1	0	0
Number of founders	105	2.380	2	1.251	1	7	2	3
Active status	103	0.971	1	0.169	0	1	1	1
Private status	105	0.971	1	0.167	0	1	1	1
Acquired by a bank Dummy	105	0.057	0	0.233	0	1	0	0
Panel B. VC rounds								
VC type	201	0.363	0	0.482	0	1	0	1
VC size (m€)	201	2,14	4.420	4,49	0.023	23,8	0.95	17.87

Table 3. This table provides descriptive statistics for a sample of 105 European FinTech companies and their 201 associated VC rounds, covering data from 2006 to 2019. Panel A enumerates key attributes of FinTech firms, such as their age, workforce size, total assets, and status, among others. Panel B elucidates characteristics of venture capital (VC) rounds, including the type and size of the VC involved. All variables have been winsorized at the 1% and 99% levels to mitigate the influence of outliers. The sample's mean, median, standard deviation, minimum, and maximum values for each variable are presented. Monetary figures are denoted in millions of euros (m€). The data is sourced from publicly available databases, and the statistics are calculated based on these records. Variables in Panel A and B are defined as of the year preceding (t-1) and the year following (t+1) the respective funding round, thus capturing a temporal snapshot. Note that 'Banking segment Dummy' indicates whether the FinTech firm is in the banking segment, with '1′ representing presence and '0′ absence. Similarly, 'Active status' and 'Private status' are binary indicators, with '1′ signifying 'Active' or 'Private,' respectively, and '0′ otherwise. 'Acquired by a bank Dummy' indicates acquisition by a bank, with '1′ signifying acquisition and '0′ otherwise.

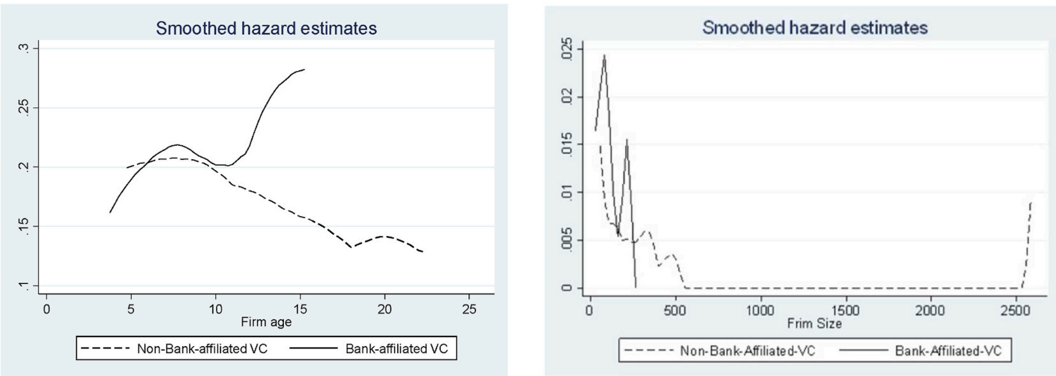

Fig. 1. Baseline hazard rate of receiving BVC and non-BVC investments.

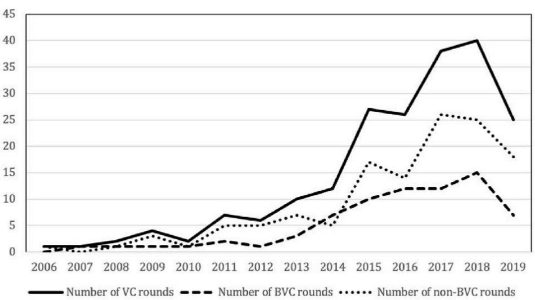

Fig. a. BVC and non-BVC rounds

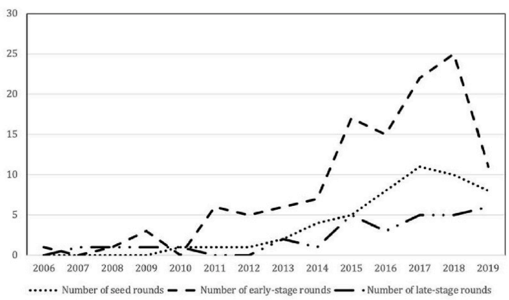

Fig. b. Seed, Early-stage and Late-stage rounds

Fig. 2. Distribution of VC rounds for European FinTechs by calendar year.

higher for larger companies, which is inconsistent with Fritsch and Schilder (2008) (see Fig. 2).

6. Findings on the contributions of BVC to FinTech

6.1. Do BVC-backed FinTech outperform non-BVC-backed FinTech?

Table 4 presents the results of the logit regressions. In Models 2–3, the positive and significant coefficient of VC type implies that BVC investment is associated with an increase in financial and economic profitability following the investment. This finding appears intuitive and may exactly reflect the objective of investors in boosting the profitability of the equity stake and assets in order to capture higher returns from their investment. Based on this finding, it is confirmed that BVCs have more of a value-added effect on FinTech than non-BVCs. However, there is no evidence that BVC-backed FinTech enjoys a more improved return on sales compared to non-BVC-backed FinTech. Overall, this result confirms the findings on the monitoring effect of VC firms for entrepreneurial and technology-based firms (Chemmanur et al., 2011; Gompers & Lerner, 2001a; Guo & Jiang, 2013; Hellmann & Puri, 2000), and expands it to emphasize a more pronounced value-added effect generated by BVC for FinTech.

Table 4 demonstrates the posterior distribution summaries of parameter estimates of the Bayesian logistic regression model. Based on the Bayesian logistic regression model results for panel A, the odds of the outcome variable (ROS binary) are significantly associated with some of the predictor variables. Specifically, the odds of the outcome are positively associated with being in the banking sector, with an estimated odds ratio of 4.09 (95% credible interval: 0.94 to 13.38), compared to being outside the banking sector, while holding all other variables constant. This suggests that companies in the banking sector are more likely to experience the outcome of interest. The odds of the outcome are also positively associated with VC Type Dummy, a dummy variable indicating whether a company is funded by venture capital, with an estimated odds ratio of 1.19 (95% credible interval: 0.59 to 2.22), holding all other variables constant. However, the credible interval includes 1.0, which indicates that the evidence for this effect needs to be stronger and more conclusive. In addition, the odds of the outcome are negatively associated with Age and ln_size, with estimated odds ratios of 0.93 (95% credible interval: 0.86 to 1.01) and 0.97 (95% credible interval: 0.81 to 1.16), respectively, holding all other variables constant. This suggests that older companies and larger companies are less likely to experience the outcome of interest. This means that there is some evidence to support the claim that older companies and larger companies are less likely to experience the outcome of interest, although this evidence is not yet conclusive. The credible interval, which includes the value of 1.0, indicates that more research is needed to confirm this effect. The paragraph also mentions that Age and ln_size have negative associations with the odds of the outcome, which means that as a company gets older or larger, it becomes less likely to experience the outcome. These findings suggest that the predictors included in the model are important in explaining the variability in the outcome variable. Overall, these findings suggest that the predictors included in the model are important factors in explaining the variability in the outcome variable.

The presented findings support the hypothesis that companies in the banking sector are more likely to experience the outcome of interest compared to those outside the banking sector. This is indicated by the estimated odds ratio of 4.09, which suggests a strong positive association between being in the banking sector and the outcome variable. The finding that the odds of the outcome are positively associated with VC Type Dummy, although less conclusive due to the credible interval including 1.0, also provides some support for the hypothesis, as it suggests that VC funding may increase the likelihood of the outcome of interest.

6.2. Diagnostic accuracy of logistic regression models in predicting FinTech firms' performance increases

The table presents a comprehensive evaluation of three distinct logistic regression models that predict the likelihood of financial

Table 4
T-test for the difference in FinTech performance around VC round announcements.

	Non-BVC (N = 128)	BVC (N = 73)	Difference (Non-BVC - BVC)	t-Statistics	z-Statistics (Wilcoxon rank-sum test)
Panel A. Before VC round announcement					
$ROS_{t=-1}$	−188.038	−5.897	−182.141	−1.05	−2.864***
$ROA_{t=-1}$	−0.561	−0.328	−0.233	−1.86*	−1.982**
$ROE_{t=-1}$	−0.52	20.447	−20.967	−1.35	−0.408
Panel B. After VC round announcement					
$ROS_{t=+1}$	−5.584	−0.501	−5.083	−2.45**	−4.339***
$ROA_{t=+1}$	−0.531	−0.25	−0.282	−3.45***	−4.254***
$ROE_{t=+1}$	−0.681	−0.743	0.061	0.1	−2.766***

Table 4. This table portrays the mean performance metrics of FinTech firms before and after receiving venture capital (VC) investment, focusing on two subsamples: those affiliated with bank-affiliated venture capital (BVC) and those that are not (Non-BVC). The data encapsulates 128 Non-BVC and 73 BVC rounds, covering the period from 2006 to 2019. Panel A delineates performance metrics before VC round announcements, whereas Panel B captures the same after the announcement. Performance is measured using Return on Sales (ROS), Return on Assets (ROA), and Return on Equity (ROE). Column (5) provides t-statistics calculated to test the significance of the mean difference between the two groups, while column (6) presents z-statistics derived from the two-tailed Wilcoxon rank-sum test. Asterisks (***, **, *) indicate levels of statistical significance at 1%, 5%, and 10%, respectively. All statistical tests are two-tailed, and p-values are adjusted for multiple comparisons where appropriate. The term 'N' refers to the sample size for each subsample.

performance improvements within FinTech firms, as measured by increases in Return on Sales (ROS), Return on Assets (ROA), and Return on Equity (ROE). The performance of each model is assessed using several key diagnostic metrics. Sensitivity, or the true positive rate, reflects the model's ability to correctly predict actual increases in financial performance. Specificity measures the true negative rate, indicating the model's accuracy in identifying cases where there is no increase. Positive and Negative Predictive Values provide insights into the model's precision in predicting true increases and non-increases, respectively. Lastly, the overall percentage of cases that are correctly classified by each model serves as a general accuracy indicator.

From the provided data, the ROS increase model demonstrates high sensitivity, indicating a robust capability in detecting true performance improvements. However, its low specificity suggests a limitation in correctly identifying instances without an increase. The ROA and ROE models display a more balanced sensitivity and specificity, suggesting an equitable distribution of predictive accuracy for both positive and negative instances. The Positive Predictive Value across all models suggests a moderate likelihood that a predicted performance increase is accurate, while the Negative Predictive Value denotes the models' ability to correctly identify the absence of an increase. The Correctly Classified percentage encapsulates the overall effectiveness of the models, providing a snapshot of their overall predictive accuracy in the context of FinTech firm performance.

6.3. Multicollinearity assessment of regression variables in FinTech performance analysis

The table delineates the collinearity diagnostics of a regression analysis, essential for assessing the degree of multicollinearity among the variables within a model. Multicollinearity can often distort the parameter estimates and weaken the statistical power of the analysis. In this table, each variable under consideration, such as VC Type, Age, Firm Size, and others, is assessed with the Variance Inflation Factor (VIF), its square root, Tolerance, and R-squared values. VIF values exceeding 10 would typically indicate high multicollinearity, but all variables here show VIF values well below this threshold, suggesting that multicollinearity is not a concern for this model. Tolerance and R-squared are inverse indicators of multicollinearity; where Tolerance close to 0 or R-squared close to 1 would indicate a potential problem, the values provided here are within acceptable limits.

For instance, the variable 'Age' has a VIF of 1.69 and an R-squared of 0.410, indicating that while there is some correlation with other variables, it is not to a degree that would cause alarm. Similarly, 'Ln Size $t = -1'$ has a VIF of 1.70, which is slightly higher and corresponds to a similar R-squared value, suggesting a moderate but not excessive overlap in what this variable explains compared to others in the model. The 'Banking segment Dummy' and 'Number of founders' have the lowest VIF values, indicating that these variables are the least collinear with the others. Overall, the diagnostics presented in the table suggest that the regression model is stable and that the variables included provide distinct and valuable information to the analysis.

6.4. Do BVCs select better-performing FinTech?

When BVC is attracted to performing FinTech (Hypothesis 2), then the coefficient on the performance measure is expected to be positive and significant, which would indicate that existing FinTech performance is a predictor of future BVC funding. Control variables are included in the analysis to test for the impact of Fintech's and VC's specificities Table 5 presents the results. The coefficient on pre-investment ROA is positive and significant, which is consistent with asset performance being a predictor of whether FinTech will get financing from a BVC or not. However, the coefficients of ROS and ROE are not significant. Moreover, there is evidence that having higher leverage prior to investment is driving BVCs to fund FinTech, which is counterintuitive to the risk-averse investment behavior of banks. It is also observed that FinTech implemented by more founders seems less likely to attract investment from BVCs. The higher number of founders may be significant for the VC investor since this can complicate the future monitoring of the firm (Hellmann & Puri, 2002; Lerner, 1995). In model 2, the amount of investment is observed to be positively and significantly correlated with the VC type. This result implies that BVCs tend to have more strategic financing behavior in terms of funding size. The support of BVC to FinTech through a high funding amount provides a relevant signal regarding the value-added effect sought by BVCs in their investment strategy (Arner et al., 2016).

The inclusion of control variables in the analysis aimed to assess the specificities of both the FinTech and VC industries, as well as to identify predictors of future BVC funding. While the coefficient on pre-investment ROA yielded a positive and significant result,

Table 5
Classification performance of logit models for financial performance increases in FinTech firms.

	(1) Logistic model for ROS Increase	(2) Logistic model for ROA Increase	(3) Logistic model for ROE Increase
Sensitivity	97.64%	65.00%	59.79%
Specificity	9.46%	67.33%	69.23%
Positive predictive value	64.92%	66.33%	64.44%
Negative predictive value	70.00%	66.02%	64.86%
Correctly classified	65.17%	66.17%	64.68%

Table 5. The table provides a summary of the classification effectiveness of logistic regression models used to predict increases in various financial performance metrics—Return on Sales (ROS), Return on Assets (ROA), and Return on Equity (ROE)—for FinTech firms. Each model's predictive accuracy is evaluated based on several statistical measures: Sensitivity (true positive rate), Specificity (true negative rate), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and the overall percentage of cases Correctly Classified. These measures provide a comprehensive overview of the models' performance, revealing their strengths in correctly identifying performance increases and their limitations, as reflected by the varying percentages across the different outcomes and predictive values.

indicating that asset performance is a potential predictor of FinTech funding, the coefficients of ROS and ROE did not demonstrate significant effects. It is noteworthy that higher leverage prior to investment was observed to drive BVCs to fund FinTech, which appears to run counter to conventional risk-averse investment behavior exhibited by banks. Additionally, a higher number of founders implementing the FinTech solution was found to reduce its attractiveness to BVCs, possibly because it complicates future monitoring of the firm. Model 2 revealed a positive and significant correlation between the amount of investment and VC type, suggesting that BVCs adopt a strategic financing approach regarding funding size. Therefore, the significant coefficient on the variable of interest, i.e., the performance measure, suggests that existing FinTech performance is a strong predictor of future BVC funding, whereas the lack of significance of the control variables could imply that they do not substantially influence BVCs' investment decisions in the FinTech industry Tables 6 and 7.

In sum, the estimates suggest that economically well-performing FinTech may be more attractive to BVCs. Entrepreneurs may minimize the uncertainty of being rejected by BVCs by approaching them only when their FinTech are already achieving strong economic performance. This evidence on the enhanced screening effect of BVCs in selecting performing FinTech is also new and extends that of VC companies, which tend to choose higher performing entrepreneurial firms (Chemmanur et al., 2011; Guo & Jiang, 2013; Sahlman, 1988, 1990; Shepherd & Zacharakis, 2007).

The results of the study suggest that BVCs are more likely to fund FinTech startups that demonstrate strong economic performance prior to investment. This finding supports Hypothesis 2, which suggests that BVCs are attracted to performing FinTech. The positive and significant coefficient on the pre-investment ROA indicates that asset performance is a predictor of whether FinTech will receive funding from a BVC or not. However, the coefficients of ROS and ROE are not significant, suggesting that they are not strong predictors of BVC funding. In addition, the study finds that higher leverage prior to investment drives BVC funding, which is counterintuitive to the risk-averse investment behavior of banks.

The positive and significant correlation between the amount of investment and the VC type suggests that BVCs tend to have more strategic financing behavior in terms of funding size. Overall, the study concludes that economically well-performing FinTech may be more attractive to BVCs, and entrepreneurs may increase their chances of receiving BVC funding by approaching them only when their FinTech has achieved strong economic performance. These findings extend previous research on VC companies' screening of higher performing entrepreneurial firms and suggest an enhanced screening effect of BVCs in selecting performing FinTech.

The findings of the study suggest that BVCs are more likely to invest in FinTech solutions implemented by fewer founders, potentially due to the complexity associated with monitoring a higher number of founders. Moreover, the positive and significant correlation between investment amount and VC type indicates that BVCs adopt a strategic financing approach concerning funding size. In summary, the study concludes that economically successful FinTech solutions are more attractive to BVCs, and entrepreneurs may increase their chances of securing BVC funding by seeking investments only after their FinTech has achieved robust economic performance. These results contribute to the existing literature on VC companies' screening of high-performing entrepreneurial firms and suggest that BVCs may exercise a more robust screening process when selecting FinTech companies that demonstrate strong economic performance.

7. Robustness tests

7.1. Propensity score matching for selection bias: is the outperformance of BVC-backed FinTech driven by the screening effect?

BVCs may select higher-quality FinTech to invest in, leading to a more robust performance post-investment. Following Rosenbaum and Rubin (1983a) and Chemmanur et al. (2011), this section examines whether the outperformance of BVC-backed FinTech truly comes from the monitoring efforts and not from the initial screening efforts of the BVC. The selection bias is controlled using the Propensity Score Matching methodology, in which FinTech are matched with different dimensions related to location, segment, and pre-VC performance. The propensity score is defined by Rosenbaum and Rubin (1983a) to be the probability of treatment assignment,

Table 6
Collinearity diagnostics for venture capital financing models.

Variable	VIF	Sqrt VIF	Tolerance	R-squared
VC Type	1.20	1.10	0.833	0.166
Age	1.69	1.30	0.590	0.410
Ln Size $_{t=-1}$	1.70	1.30	0.587	0.412
Banking segment Dummy	1.11	1.05	0.901	0.098
Late-stage Dummy	1.36	1.16	0.737	0.262
Number of founders	1.13	1.06	0.887	0.112
Leverage $_{t=-1}$	1.35	1.16	0.742	0.257
Ln VC size	1.24	1.12	0.804	0.195

Table 6. The table provides collinearity diagnostics for a multivariate analysis examining the effects of various predictors on FinTech performance. The Variance Inflation Factor (VIF) and its square root are reported for each variable to assess the degree of multicollinearity. Additionally, the Tolerance and R-squared values offer further insight into the uniqueness of the information provided by each predictor. These diagnostics are crucial in evaluating whether the variables in the model are too highly correlated with each other, which can undermine the reliability of the coefficient estimates. The table suggests that the variables present acceptable levels of multicollinearity, with VIF values not indicating severe collinearity issues that would warrant concerns for the regression analysis validity.

Table 7
Enhancement of FinTech performance following VC funding rounds according to the VC type.

	ROS Increase		ROA Increase		ROE Increase	
	Model 1		Model 2		Model 3	
Constant	−0.185	(-1.025)	−2.27**	(-1.116)	−1.977**	(-0.891)
VC Type	−0.044	(-0.337)	0.677**	(-0.333)	0.983***	(-0.333)
Age	−0.065	(-0.05)	0.001	(-0.054)	0.011	(-0.055)
Ln Size $_{t=-1}$	−0.070	(-0.276)	0.224	(-0.278)	0.291	(-0.285)
Banking segment Dummy	1.121*	(-0.607)	0.777	(-0.53)	−0.008	(-0.484)
Late-stage Dummy	0.079	(-0.522)	0.596	(-0.543)	0.257	(-0.490)
Number of founders	−0.051	(-0.125)	0.153	(-0.123)	0.028	(-0.129)
Leverage $_{t=-1}$	0.016	(-0.048)	0.051	(-0.058)	−0.05	(-0.046)
Ln VC size	0.173	(-0.151)	0.178	(-0.165)	0.166	(-0.124)
Year Effect	Yes		Yes		Yes	
Industry Effect	Yes		Yes		Yes	
Pseudo R-squared	0.029		0.083		0.08	
P-value for Chi^2	0.588		0.008		0.008	

Table 7. This table presents logit regression estimates that evaluate the impact of venture capital (VC) type on performance increases—measured through Return on Sales (ROS), Return on Assets (ROA), and Return on Equity (ROE)—in FinTech firms. The sample includes 201 observations and spans from 2006 to 2019. The dependent variable in each model is a binary indicator, assigned the value '1′ if there is a performance increase and '0′ otherwise. The key independent variable, 'VC Type,' is also binary, set to '1′ if the FinTech firm is backed by bank-affiliated venture capital (BVC) and '0′ otherwise. Control variables, detailed in the Appendix, include the age of the firm, its size (Ln Size t = −1), the number of founders, and a dummy variable for the banking segment, among others. Standard errors, robust to heteroskedasticity via the Huber-White method, are reported in parentheses below each estimate. Statistical significance levels are indicated with asterisks (***, **, *), representing 1%, 5%, and 10% levels, respectively. The 'Pseudo R-squared values and 'P-value for Chi 2' are reported to provide further context on the model fit and overall significance. All p-values are two-tailed, and where applicable, adjustments for multiple comparisons have been made.

(i.e., VC affiliation to bank) conditional on observed baseline covariates:

$$e_i = Pr(Z_i = 1 | X_i) \tag{5}$$

Table 9 provides a comprehensive overview of the results obtained from the statistical analysis conducted to evaluate the impact of BVC and non-BVC investments on the performance of FinTech companies in Europe. The analysis employed the Propensity Score Matching (PSM) approach, which allowed for matching BVC and non-BVC investments based on a range of relevant variables, such as firm size, age, and geographic location. The findings of the analysis reveal that BVC-backed FinTech companies exhibit superior performance compared to non-BVC-backed FinTech companies. Specifically, the results demonstrate that BVC-backed firms achieve higher levels of profitability in terms of both assets and equity. This evidence suggests that BVCs play a crucial role in driving the growth and success of FinTech companies in Europe, providing much-needed financial and strategic support. These results have significant implications for policymakers, investors, and other stakeholders in the European FinTech ecosystem. The evidence indicates that BVCs are a key factor in the development and expansion of the FinTech sector and that their contribution to the growth and profitability of FinTech firms cannot be overstated.

7.2. Imbalanced data between the UK and other European countries: Synthetic Minority Oversampling Technique (SMOTE)

Despite the sample's representativeness in light of the 2021 PwC report, the dataset remains imbalanced, which may skew the analysis results. To address this concern regarding the prevalence of VCs initiated by FinTech from the UK (46%), this section conducts logit estimations on VCs rounds by oversampling the minority groups (i.e., France, Spain, Belgium, Italy, Germany) by duplicating their examples, although these examples don't add any new information to the model. This method is referred to as the SMOTE technique, a type of data augmentation for minority groups (Chawla, Bowyer, Hall, & Kegelmeyer, 2002; Shrivastava, Jeyanthi, & Singh, 2020). Table 8 presents the SMOTE estimation results for monitoring and screening effects analyses. Thus, after controlling for imbalanced data in the sample, it is found that BVC financing leads to higher levels of asset and equity profitability (Panel A), which is robust to the earlier results in Table 4, and therefore consistent with the monitoring effect of BVCs. However, the results, shown in Panel B, are inconsistent with the screening effect, which means that the imbalanced data may bias the estimates of BVC screening in Table 10.

7.3. Endogenous switching two-stage model

In the unfolding landscape of FinTech, the symbiotic relationship between venture capital (VC) investment and firm performance cannot be understated. This intricate relationship reaches another level of complexity when considering the presence of endogeneity, a mutual influence, and interdependence between a firm's financial standing and its subsequent performance. Far from being a mere statistical nuance, endogeneity embodies the real-world feedback loops that can exist in business ecosystems. A FinTech firm's performance may attract specific types of VC, just as certain types of VC investment—particularly those affiliated with Bank Venture Capital (BVC)—may steer the performance of the firm in new directions.

Table 8
Posterior distribution summaries of parameter estimates of bayesian logistic regression model.

Panel A (ROS increase)					
	Odds ratio of parameter posterior estimate	Standard deviation of posterior distribution	Monte-Carlo standard error (MCSE)	Median of posterior distribution	95% cred. Interval
Constant	952	212	0.779	407	0.258
VC Type	119	0.415	0.019	112	0.592
Age	0.933	0.037	0.001	0.932	0.860
Ln Size $_{t\ =\ -1}$	0.970	0.085	0.004	0.966	0.813
Banking segment Dummy	408	383	0.206	316	0.937
Observation:194					
Acceptance rate: 0.195					
Panel B (ROA increase)					
	Odds ratio of parameter posterior estimate	***Standard deviation of posterior distribution***	***Monte-Carlo standard error (MCSE)***	***Median of posterior distribution***	***95% cred. Interval***
Constant	2.721	9.131	0.292	0.522	0.015
VC Type	7.393	5.041	0.249	6.149	2.103
Age	1.315	0.131	0.006	1.299	1.100
Ln Size $_{t\ =\ -1}$	1.011	0.121	0.004	1.009	0.796
Banking segment Dummy	2.128	2.063	0.108	1.617	0.344
Observation:127					
Acceptance rate: 0.188					
Panel C (ROE increase)					
	Odds ratio of parameter posterior estimate	***Standard deviation of posterior distribution***	***Monte-Carlo standard error (MCSE)***	***Median of posterior distribution***	***95% cred. Interval***
Constant	2.029	5.717	0.186	0.536	0.024
VC Type	4.069	1.891	0.085	3.700	1.562
Age	1.080	0.061	0.004	1.079	0.969
Ln Size $_{t\ =\ -1}$	1.017	0.102	0.004	1.017	0.828
Banking segment Dummy	0.666	0.414	0.019	0.548	0.183
Observation:127					
Acceptance rate: 0.166					

Table 8. This table provides Posterior Distribution Summaries of Parameter Estimates derived from Bayesian Logistic Regression Models for FinTech firms, encompassing 194 observations for ROS increase (Panel A), 127 for ROA increase (Panel B), and 127 for ROE increase (Panel C). The models span data from 2006 to 2019. The dependent variable in each panel is binary, assigned a '1′ if there is an increase in the respective performance measure (ROS, ROA, or ROE) and '0′ otherwise. The primary independent variable, 'VC Type,' is also binary, set to '1′ if the FinTech firm is supported by bank-affiliated venture capital (BVC) and '0′ otherwise. The table reports five key metrics for each variable: the Odds Ratio of the Parameter Posterior Estimate, the Standard Deviation of the Posterior Distribution, the Monte-Carlo Standard Error (MCSE), the Median of the Posterior Distribution, and the 95% Credibility Interval. Control variables, detailed in the Appendix, include the age of the firm and its logarithmically transformed size (Ln Size t = −1), among others. Standard errors are robust to heteroskedasticity per White (1980) and are clustered at the firm level. Statistical significance is denoted by asterisks (***, **, *), representing the 1%, 5%, and 10% levels, respectively. The acceptance rate for each model is also reported to indicate the model's convergence performance.

Our study aims to untangle these complexities by employing a robust analytical framework: the Endogenous Switching Two-Stage Least Squares (ES2SLS) model. This model is bifurcated into two pivotal components: the 'selection' equation and the 'outcome' equations, each serving a distinct purpose but collectively offering a more holistic understanding of the FinTech-VC dynamics.

The selection equation serves as the initial filter, determining the nature of VC affiliation a FinTech firm has. This is captured mathematically by a criterion function, I_i:

$$I_i = \begin{cases} 1, if \gamma Z_i + u_i > 0 \\ 0, if \gamma Z_i + u_i \leq 0 \end{cases} \tag{6}$$

Once this affiliation type is identified, we proceed to the outcome equations, which delve into the actual impact on FinTech performance metrics:

For firms fortunate enough to be affiliated with a Bank Venture Capital (Regime 1):

$$\text{Regime 1 (BVC affiliation)} : y1i = \beta 1X1i + \varepsilon 1i \quad \text{if } Ii = 1 \tag{7}$$

$$\text{Regime 2 (non-BVC affiliation)} : y2i = \beta 2X2i + \varepsilon 2i \quad \text{if } Ii = 0 \tag{8}$$

Here, the variables *yji*, *X1i*, and *X2i* are not mere placeholders; they encapsulate real-world complexities. They signify performance metrics and influencing factors, such as market conditions and internal efficiencies that could vary based on the VC affiliation. By understanding these variables and their nuanced interactions, we can better appreciate how different VC investments will likely impact FinTech firms. These equations, albeit mathematical, encapsulate an array of real-world variables—market conditions, internal efficiencies, and many others—that could swing based on the type of VC affiliation. In essence, the ES2SLS model serves as a lens, bringing

Table 9
Selection by Bank-affiliated VC according to prior FinTech performance.

	Types of Venture Capital					
	Model 1		Model 2		Model 3	
ROS $_{t = -1}$	0.004	(-0.006)				
ROA $_{t = -1}$			0.700***	(-0.24)		
ROE $_{t = -1}$					0.015	(-0.058)
Age	−0.025	(-0.063)	−0.031	(-0.065)	−0.026	(-0.065)
Ln Size $_{t = -1}$	0.393	(-0.327)	0.391	(-0.342)	0.526	(-0.355)
Banking segment Dummy	0.437	(-0.555)	0.72	(-0.565)	0.456	(-0.547)
Late-stage Dummy	−0.172	(-0.513)	−0.266	(-0.534)	−0.137	(-0.526)
Number of founders	−0.303**	(-0.138)	−0.317**	(-0.141)	−0.292**	(-0.141)
Leverage $_{t = -1}$	0.114**	(-0.048)	0.203***	(-0.048)	0.121**	(-0.049)
Ln VC size	0.631**	(-0.251)	0.702***	(-0.258)	0.601**	(-0.250)
Constant	−4.553***	(-1615)	−4.828***	(-1607)	−4.642***	(-1548)
Year Effect	Yes		Yes		Yes	
Industry Effect	Yes		Yes		Yes	
N. Obs.	201		201		201	
Pseudo R-squared	0.136		0.159		0.132	
P-value for Chi^2	0		0		0	

Table 9. This table offers logit regression estimates to examine the types of venture capital firms—specifically, bank-affiliated vs. non-bank-affiliated (BVC vs. non-BVC)—that opt to invest in FinTech companies based on their prior performance metrics: Return on Sales (ROS), Return on Assets (ROA), and Return on Equity (ROE). The dataset comprises 201 observations and spans the period from 2006 to 2019. In each model, the dependent variable is a binary indicator that is set to ‘1′ if the venture capital is bank-affiliated and ‘0′ otherwise. The primary variable of interest is the FinTech firm’s performance in the year preceding the investment. Three models are presented to isolate the effects of ROS (Model 1), ROA (Model 2), and ROE (Model 3). Control variables include the age of the FinTech firm, its logarithmically transformed size (Ln Size t = −1), a banking segment dummy, late-stage dummy, the number of founders, and leverage at t = −1. These variables are further detailed in the Appendix. Standard errors, robust to heteroskedasticity via the Huber-White method, are reported in parentheses adjacent to each estimate. Statistical significance is indicated with asterisks (***, **, *), denoting the 1%, 5%, and 10% levels, respectively. The table also reports Pseudo R-squared values and *P*-values for the Chi-squared tests to provide an indication of model fit and significance. Year and industry effects are controlled for in all models.

Table 10
Enhancement of FinTech performance following BVC and non-BVC investments (matched by PSM).

	ROS increase		ROA increase		ROE increase	
	Model 1		Model 2		Model 3	
VC Type	−0.044	(-0.337)	0.677**	(-0.332)	0.983***	(-0.333)
Age	−0.065	(-0.051)	0.001	(-0.051)	0.011	(-0.051)
Ln Size $_{t = -1}$	−0.07	(-0.276)	0.224	(-0.277)	0.291	(-0.28)
Banking segment Dummy	1.121*	(-0.602)	0.777	(-0.539)	−0.008	(-0.503)
Late-stage Dummy	0.079	(-0.487)	0.596	(-0.507)	0.257	(-0.489)
Number of founders	−0.051	(-0.129)	0.153	(-0.128)	0.028	(-0.128)
Leverage $_{t = -1}$	0.016	(-0.049)	0.051	(-0.056)	−0.05	(-0.051)
Ln VC size	0.173	(-0.147)	0.178	(-0.151)	0.166	(-0.154)
Constant	−0.185	(-0.968)	−2.279**	(-0.999)	−1.977**	(-1.009)
Year Effect	Yes		Yes		Yes	
Industry Effect	Yes		Yes		Yes	
N. Obs.	201		201		201	
Pseudo R-squared	0.0294		0.0828		0.0802	
P-value for Chi^2	0.4565		0.0033		0.0043	

Table 10. This table presents logit regression estimates examining the impact of venture capital type—specifically, bank-affiliated (BVC) versus non-bank-affiliated—on performance increases in FinTech firms. The sample consists of 201 observations and employs Propensity Score Matching (PSM) to control for confounding factors. The primary matching criteria are the country of origin, the business segment, and the performance measures prior to venture capital investment. Each model focuses on a different performance metric: Return on Sales (ROS) in Model 1, Return on Assets (ROA) in Model 2, and Return on Equity (ROE) in Model 3. The dependent variable in each model is a binary indicator, set to ‘1′ if there is an increase in the respective performance metric around the time of the VC announcement and ‘0′ otherwise. The key independent variable, ‘VC Type,’ is also binary, taking the value ‘1′ if the FinTech firm is backed by a BVC and ‘0′ otherwise. Control variables, which are elaborated in the Appendix, include the age of the firm, its logarithmically transformed size (Ln Size t = −1), a dummy variable for the banking segment, and others. Standard errors, reported in parentheses next to each estimate, are robust to heteroskedasticity. Statistical significance is indicated by asterisks (***, **, *), representing the 1%, 5%, and 10% levels, respectively. The models also account for year and industry effects, and key statistics like the Pseudo R-squared values and *P*-values for the Chi-squared tests are reported to offer an understanding of the model’s explanatory power and overall significance.

into focus the intricate dynamics between FinTech performance and VC investment. It offers us the academic rigor to unpack these complexities while also providing the human touch to understand why they matter.

Intriguingly, the notion of endogeneity finds its relevance here. Understanding and controlling for this endogeneity is pivotal for achieving a precise interpretation of the FinTech-VC relationship. The ES2SLS model is designed to tackle this issue, offering statistical rigor and real-world applicability. By accounting for endogeneity, the model ensures the integrity of our analytical results and makes them more interpretable and actionable for stakeholders in the FinTech ecosystem Tables 11A–11B.

7.4. Enhancement of FinTech performance following VC funding rounds according to the VC type (GMM)

Our research has furthered the investigation of endogeneity in the context of FinTech performance following VC funding rounds by implementing a Generalized Method of Moments (GMM) model. This advanced econometric technique allows us to use the size of the venture capital (VC) firm and firm leverage as instruments, which serve to correct any potential biases arising from endogenous explanatory variables. The GMM model's robustness is evidenced through the postestimation tests, which include checks for endogeneity and Hansen's J tests for overidentifying restrictions. The results, as displayed in Table 4, confirm the exogeneity of the model's regressors and affirm the validity of the selected instruments, given the non-significant Hansen's J statistic Chi^2 test.

Table 12 presents a detailed assessment of the performance impact of VC funding on FinTech companies, stratified by the type of VC. It employs a binary dependent variable that signifies whether there was an improvement in performance metrics such as Return on Sales (ROS), Return on Assets (ROA), and Return on Equity (ROE). The key independent variable of interest is the VC type, which is differentiated by whether the FinTech is supported by a Business Venture Capital (BVC) or not. Alongside this, a set of control variables, which are exhaustively listed in Appendix, are incorporated to control for other factors that may influence performance. The results indicate statistically significant improvements in certain performance measures, with the level of significance denoted by asterisks, offering an empirical insight into the specific contributions of VC types to FinTech performance Table 13.

8. Conclusion

This study offers a comprehensive examination of the role Bank Venture Capital (BVC) investments play in shaping the performance landscape of FinTech firms within the pre-Brexit European context. Utilizing an extensive dataset comprising 201 venture capital rounds involving 105 FinTech companies across six European nations, the investigation addresses two pivotal research questions. First, does BVC affiliation enhance the financial performance of FinTech firms, and if so, how? Second, do BVCs exhibit superior acumen in mitigating issues related to information asymmetry in their investment choices?

Anchored in agency cost theory and resource-based views (Riikkinen & Pihlajamaa, 2022; Hornuf et al., 2021; Navaretti, Calzolari, Mansilla-Fernandez, & Pozzolo, 2018; Murinde, Rizopoulos, & Zachariadis, 2022), our findings reveal that BVCs not only contribute financial resources but also add intangible value to FinTech companies post-investment. This additional layer of value manifests as an observable outperformance of BVC-affiliated FinTech firms when compared to their non-BVC counterparts. Such outperformance is not a mere statistical artifact; it signifies the practical advantages FinTech firms can reap through strategic BVC partnerships. On the other

Table 11a
Synthetic minority oversampling technique (SMOTE).

Panel A. Performance enhancement following BVC funding (SMOTE)

	ROS increase		ROA increase		ROE increase	
	Model 1		Model 2		Model 3	
VC Type	0.026	(-0.068)	0.212***	(-0.069)	0.308***	(-0.071)
Age	−0.012	(-0.008)	−0.003	(-0.008)	0.001	(-0.008)
Ln Size $_{t = -1}$	0.016	(-0.061)	0.07	(-0.062)	0.02	(-0.063)
Banking segment Dummy	0.239**	(-0.099)	0.134	(-0.101)	−0.151	(-0.104)
Late-stage Dummy	−0.075	(-0.101)	−0.051	(-0.103)	0.156	(-0.105)
Number of founders	−0.023	(-0.032)	0.046	(-0.032)	0.046	(-0.033)
Leverage $_{t = -1}$	−0.01	(-0.01)	−0.008	(-0.01)	−0.003	(-0.01)
Ln VC size	0.066	(-0.040)	0.084**	(-0.041)	−0.001	(-0.042)
Constant	0.323	(-0.268)	−0.256	(-0.273)	0.301	(-0.279)
Year Effect	Yes		Yes		Yes	
Industry Effect	Yes		Yes		Yes	
N. Obs.	201		201		201	
Adjusted R-squared	0.055		0.123		0.094	
F-Statistic	2.474**		4.536***		3.602***	

Table 11. Panel A: This table delineates the linear regression estimates scrutinizing venture capital type's influence— bank-affiliated (BVC) or non-bank-affiliated—on subsequent performance enhancements in FinTech firms. The sample consists of 201 observations. The models are designed to capture the effect on three separate performance metrics: Return on Sales (ROS) in Column (1), Return on Assets (ROA) in Column (2), and Return on Equity (ROE) in Column (3). The dependent variables in each model are the respective performance metrics. The focal independent variable is 'VC Type,' coded as a binary variable that assumes the value '1′ if the FinTech entity is supported by a BVC and '0′ otherwise. Control variables, whose definitions are elaborated in the Appendix, encompass the age of the firm, its logarithmically transformed size (Ln Size t = −1), a dummy for the banking segment, the stage of the firm (Late-stage Dummy), the number of founders, and the leverage at t = −1. Standard errors are parenthetically enclosed next to each coefficient, and these are calculated to be robust to heteroskedasticity. Statistical significance is annotated using asterisks (***, **, *) to denote the 1%, 5%, and 10% levels, respectively. The table also reports each model's Adjusted R-squared values and F-Statistics to indicate the goodness of fit and the overall model significance.

Table 11b
Synthetic minority oversampling technique (SMOTE).

Panel B. Selection by BVC according to prior performance (SMOTE)						
	Types of Venture Capital					
	Model 1		Model 2		Model 3	
ROS t = −1	−0.000	(0.000)				
ROA t = −1			−0.103**	(0.040)		
ROE t = −1					0.000	(0.000)
Age	−0.017*	(0.008)	−0.016*	(0.008)	−0.018**	(0.008)
Ln Size t = −1	0.094	(0.064)	0.057	(0.065)	0.102	(0.063)
Banking segment Dummy	0.082	(0.104)	0.086	(0.102)	0.080	(0.104)
Late-stage Dummy	0.144	(0.105)	0.156	(0.104)	0.148	(0.105)
Number of founders	−0.080**	(0.033)	−0.085**	(0.032)	−0.081**	(0.033)
Leverage t = −1	0.034***	(0.010)	0.035***	(0.010)	0.035***	(0.010)
Ln VC size	0.079*	(0.043)	0.099**	(0.043)	0.078*	(0.042)
Constant	0.032	(0.285)	−0.089	(0.284)	0.043	(0.281)
Year Effect	Yes		Yes		Yes	
Industry Effect	Yes		Yes		Yes	
N. Obs.	201		201		201	
Adjusted R-squared	0.111		0.1369		0.116	
F-Statistic	4.130***		4.967***		4.294***	

Table 11. Panel B. This table presents the results of SMOTE (Synthetic Minority Over-sampling Technique) estimates examining the preferences of Venture Capitals (VCs) for investing in FinTech firms based on their antecedent performance metrics—Return on Sales (ROS), Return on Assets (ROA), and Return on Equity (ROE). The dataset encompasses 201 observations. Model 1 focuses on the relationship between ROS at t = −1 and the likelihood of receiving VC investment. Model 2 centers on ROA at t = −1, and Model 3 investigates the role of ROE at t = −1. The dependent variable in each model is binary, set to '1′ if there is an increase in the respective performance metric or if the VC is bank-affiliated, depending on the panel, and '0′ otherwise. Control variables, which are more extensively defined in the Appendix, include the age of the firm, its size (log-transformed as Ln Size t = −1), a dummy variable for the banking segment, the stage of the firm (Late-stage Dummy), the number of founders, and the firm's leverage at t = −1. Standard errors are reported in parentheses and are robust to heteroskedasticity. The table also includes year and industry effects indicators to control for temporal and sectoral variations. Adjusted R-squared values and F-statistics are reported to provide insights into the model's explanatory power and overall statistical significance. Statistical significance is denoted by asterisks, where ***, **, and * represent the 1%, 5%, and 10% levels, respectively.

hand, our investigation also delves into BVCs' ability to address information asymmetry, guided by the framework of asymmetric information theory. The data indicates that BVCs possess an enhanced capability for discerning high-performing FinTech firms, making their investment choices particularly insightful. Importantly, these findings suggest that BVCs are well-positioned to navigate the complexities of the FinTech sector, where information gaps can be particularly problematic (Riikkinen & Pihlajamaa, 2022; Hornuf et al., 2021).

The validity of these findings is further substantiated through advanced statistical methodologies. Specifically, we employ propensity score matching to control for selection bias and the Synthetic Minority Oversampling Technique (SMOTE) to balance data, thereby enhancing the robustness of our conclusions. In doing so, the study not only aligns with existing literature but also offers a novel lens through which to view the specific impact of BVC affiliation on FinTech performance.

9. Limitations and future studies

Acknowledging the study's limitations is crucial for a nuanced and balanced interpretation of its findings. Firstly, the research is constrained by its geographic and temporal focus on a pre-Brexit European setting. This limitation begs the question of how generalizable these findings are to other contexts, including post-Brexit Europe or other global markets. Secondly, the study's reliance on traditional financial metrics like profitability and economic performance offers a somewhat limited lens through which to view FinTech success. This focus may inadvertently overlook other critical success factors, such as customer engagement, technological innovation, or market influence, thereby affecting the comprehensive interpretation of what success means in the FinTech landscape.

Additionally, the study does not address the potential impact of regulatory changes on BVC investments in FinTech companies. Regulatory shifts can have significant repercussions for investment decisions and venture capital behavior, potentially altering the dynamics highlighted in this study. Therefore, the absence of this regulatory perspective could be considered a noteworthy limitation. Looking ahead, future research presents several compelling avenues. A post-Brexit investigation would provide invaluable insights into how political and economic shifts influence the BVC-FinTech investment landscape. Furthermore, the study could be extended by incorporating a broader array of performance metrics, including but not limited to exit performance and customer engagement metrics. Such an expansion would offer a richer, multi-dimensional understanding of FinTech firm success. Lastly, integrating a regulatory perspective into the analysis of BVC investments in FinTech firms could offer a more holistic view, accounting for the influence of legislative changes on investment behaviours and outcomes.

Table 12
Endogenous switching regressions for BVC- and non-BVC-backed FinTech.

Panel A. First-stage						
Types of Venture Capital						
	Model 1		*Model 2*		*Model 3*	
IPO_FinTech	0.000	(-0.002)	−0.142	(-0.255)	−0.112	(-0.275)
M&A_FinTech	0.000	(0.000)	−0.017	(-0.035)	−0.024	(-0.039)
Age	−0.028***	(-0.002)	−0.001	(-0.030)	0.000	(-0.030)
Ln Size t = −1	0.078	(-0.062)	0.341	(-0.188)	0.335	(-0.190)
Banking segment Dummy	0.380	(-0.311)	0.313	(-0.302)	0.310	(-0.301)
Late-stage Dummy	0.470	(-0.402)	0.067	(-0.313)	0.010	(-0.319)
Number of founders	−0.091	(-0.028)	−0.282	(-0.089)	−0.273	(-0.089)
Leverage t = −1	0.067	(-0.034)	0.068	(-0.047)	0.062	(-0.042)
Ln VC size	0.211***	(-0.016)	0.476	(-0.153)	0.511	(-0.161)
Constant	−1.437***	(-0.153)	−3.291	(-0.937)	−3.506	(-0.986)

Panel B. Second-stage												
	Model 1				*Model 2*				*Model 3*			
	Non-BVC		*BVC*		*Non-BVC*		*BVC*		*Non-BVC*		*BVC*	
Age	−0.015***	(-0.002)	−0.028	(-0.002)	0.011	(-0.014)	−0.020	(-0.021)	0.015	(-0.015)	−0.027	(-0.021)
Ln Size t = −1	0.043	(-0.037)	−0.043	(-0.114)	0.024	(-0.079)	−0.008	(-0.127)	0.064	(-0.085)	0.077	(-0.123)
Banking segment Dummy	0.211	(-0.177)	0.351	(-0.195)	0.304	(-0.161)	0.173	(-0.186)	0.006	(-0.173)	0.144	(-0.187)
Late-stage Dummy	0.261	(-0.230)	−0.283	(-0.189)	0.232	(-0.154)	−0.041	(-0.152)	−0.002	(-0.165)	0.138	(-0.151)
Number of founders	−0.05	(-0.018)	−0.070	(-0.075)	0.044	(-0.033)	0.031	(-0.092)	0.009	(-0.165)	0.021	(-0.090)
Leverage t = −1	0.037	(-0.021)	0.007	(-0.020)	0.136	(-0.034)	0.012	(-0.017)	−0.035	(-0.036)	0.01	(-0.018)
Ln VC size	0.117***	(-0.010)	0.022	(-0.102)	0.043	(-0.036)	0.079	(-0.115)	0.064	(-0.037)	0.009	(-0.115)
Constant	0.202	(-0.064)	0.810	(-0.973)	−0.121	(-0.213)	0.032	(-0.957)	−0.081	(-0.038)	0.390	(-0.946)
Rho	1.000***	(0.000)	0.113	(-0.978)	0.325	(-0.309)	0.192	(-0.582)	0.325	(-0.229)	0.312	(-0.558)
Sigma	0.554	(-0.037)	0.449	(-0.048)	0.447	(-0.035)	0.474	(-0.052)	0.480	(-0.306)	0.474	(-0.068)

Panel C. Treatment effect									
	Model 1				*Model 2*			*Model 3*	
	Choose to adopt	Choose not to adopt	Treatment effect	Choose to adopt	Choose not to adopt	Treatment effect	Choose to adopt	Choose not to adopt	Treatment effect
Adopted	0.644	1.469	−0.825**	0.643*	0.841	−0.197*	0.657	0.634	0.023**
Not adopted	0.563	0.495	0.067**	0.494	0.414	0.080**	0.443	0.382	0.060**
Heterogeneity effect	0.080**	0.974**	−0.893**	0.149**	0.427*	−0.278*	0.214**	0.251**	−0.037**

Table 12.
Panel A: First-stage Estimates.
Panel A presents the first-stage regression results, focusing on the determinants that influence whether a FinTech firm receives funding from a bank-affiliated venture capital (BVC). Two key unobservable variables are included: IPO_FinTech and M&A_FinTech, representing the number of IPOs and M&A deals involving FinTech firms in the firm's country one year prior to the VC investment, respectively. The model incorporates control variables like age, firm size, and sector-specific indicators. Interestingly, **Age** appears to have a negative and statistically significant influence on BVC affiliation at the 1% level, indicated by **-0.028*****.
Panel B: Second-stage Estimates.
Panel B delves into the performance impact of receiving funding, differentiating between BVC and non-BVC rounds. It considers performance variables alongside other control variables such as firm age and size. For instance, in Model 1, **Age** has a negative and statistically significant effect on Non-BVC funded firms at the 1% level (**-0.015*****), while the effect is not statistically significant for BVC-funded firms (**-0.028**). This suggests that younger firms may benefit more from non-BVC funding regarding performance metrics.
Panel C: Treatment Effect.
Panel C quantifies the treatment effects of adopting or not adopting BVC funding. It presents the treatment effect across three models, capturing the outcomes for firms that choose to adopt and those that do not. For example, in Model 1, the treatment effect of adopting BVC funding is **-0.825****, statistically significant at the 5% level. This indicates that firms that opt for BVC funding may experience a significant decrease in the outcome variable compared to those that do not, controlling for other factors.
By triangulating the findings across these three panels, the analysis offers a nuanced understanding of both the determinants and the consequences of BVC funding in the FinTech sector. Importantly, these results are based on robust statistical methods, providing a level of confidence in the study's conclusions. Statistical significance is denoted as follows: *** for the 1% level, ** for the 5% level, and * for the 10% level. For further details on variable definitions and control variables, please refer to the Appendix.

Table 13
Enhancement of FinTech performance following VC funding rounds according to the VC type (GMM).

	ROS Increase	ROA Increase	ROE Increase
	(1)	(2)	(3)
VC Type	0.409	0.735*	0.478
	(1.09)	(1.86)	(1.49)
Age	−0.014	0.001	−0.003
	(-1.36)	(0.06)	(-0.36)
Ln Size $_{t = -1}$	−0.070	−0.027	0.047
	(-0.81)	(-0.28)	(0.58)
Banking segment Dummy	0.184*	0.115	−0.009
	(1.76)	(0.88)	(-0.08)
Late-stage Dummy	0.008	0.084	0.077
	(0.07)	(0.65)	(0.74)
Number of founders	0.051	0.099**	0.053
	(1.23)	(2.22)	(1.38)
Constant	0.493***	−0.009	0.122
	(3.05)	(-0.06)	(0.87)
N. Obs.	201	201	201
Wald Chi^2	7.76	21.19	13.55
C Chi^2 (p-value)	1.237 (0.266)	2.179 (0.139)	0.314 (0.574)
Hansen's J Chi^2 (p-value)	0.140 (0.707)	0.051 (0.820)	1.686 (0.194)

Table 13. This table reports GMM estimates of the performance increase following the VC investment according to the VC type. The dependent variable, in each model, is a dummy variable that equals 1 if there is an increase in performance measure, and 0 otherwise. The independent variable of interest is VC type which is a dummy variable that equals 1 if the FinTech is backed by a BVC, and 0 otherwise. Control variables are defined in Appendix. C Chi^2 is the C statistic Chi^2 of the endogeneity test. Hansen's J Chi^2 is the statistic of overidentifying restriction test. All standard errors are robust. Test statistics are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

10. Practical implications

The implications of this study resonate deeply with both FinTech entrepreneurs and institutional investors, shedding light on the pivotal role of bank affiliations in shaping the financial trajectory of FinTech enterprises. For entrepreneurs navigating the complex landscape of venture capital, the findings suggest that strategic alignment with bank-affiliated investors could be a game-changer. This targeted approach not only amplifies the likelihood of securing BVC investments but also augments the potential for enhanced post-investment performance. Importantly, the study intimates that entrepreneurs who engage with BVCs during periods of strong firm performance can further de-risk the investment process, thereby optimizing chances of funding while minimizing the risk of rejection.

However, it is imperative to note that the study does not corroborate the role of traditional metrics like prior equity performance or return on sales as determinants for BVC funding. This lacuna calls for a nuanced approach from policymakers, urging them to sculpt an ecosystem that is conducive to the flourishing of both BVCs and FinTech firms, beyond just the superficial financial metrics. On the investor front, the study elucidates that BVCs possess a distinct capability for astute screening, particularly in identifying FinTech firms with a robust economic track record. Thus, a focus on such high-performing firms could be a strategic move for BVCs, promising not only to enrich their investment portfolio but also to maximize its profitability. In essence, these pragmatic insights serve as a strategic compass for both FinTech entrepreneurs and investors. For entrepreneurs, the key to unlocking BVC funding may lie in a judicious blend of bank affiliation and proven economic performance. Investors, conversely, can capitalize on this knowledge to fine-tune their investment criteria, favoring FinTech firms with a demonstrable history of economic resilience and growth.

Endnotes.

1. Their data source is the Crunchbase database.
2. Their data source is Dealroom. Co (e.g., (Autio et al., 2018; Bradley et al., 2019).
3. The unavailability of financial data, in Orbis, for several FinTech from Germany, Belgium, Spain, and Italy, has considerably reduced the sample.
4. According to PwC report of March 2021 which is based on data from Dealroom. co, the funding and M&A FinTech activities in the UK represent around 38–40% of the total activity in Europe (2017–2020), and around 8–9% for France. This makes the sample of this research representative.
5. Data used from the Venture Scanner database.

Appendix

Variable	Definition

(continued on next page)

(*continued*)

Variable	Definition
Panel A. FinTech Characteristics	
Age	We use the information of foundation date from Crunchbase to calculate the age of the FinTech. The age corresponds to the number of years between the year of foundation and the year of VC announcement.
Number of employees $_{t = -1\ (t = +1)}$	Number of employees at the year preceding (following) the VC announcement. The number of employees is extracted from Diane database for French FinTech and from Orbis for other European FinTech.
Ln Size $_{t = -1}$	The log of the Number of employees $_{t = -1}$.
Total assets $_{t = -1\ (t = +1)}$	Total assets at the year preceding (following) the VC announcement in million €, extracted from Diane database for French FinTech and from Orbis for other European FinTech.
Banking segment Dummy	Banking segment Dummy is a dummy variable that equals 1 if the FinTech is classified in the banking segment according to the organization and industry descriptions identified in Crunchbase, and 0 otherwise.
Number of founders	The number of founders is the number of entrepreneurs founding the FinTech, which is identified by Crunchbase.
Active status	A dummy variable which is equal to 1 if the FinTech is still operating today, and 0 otherwise. This status is identified by Crunchbase.
Private status	A dummy variable which is equal to 1 if the FinTech is not listed, and 0 otherwise. This status is identified by Crunchbase.
Acquired by a bank Dummy	A dummy variable which is equal to 1 if the FinTech was acquired by a bank, and 0 otherwise. This status is identified by Crunchbase.
Leverage $_{t = -1}$	Ratio of total liabilities to total assets in the year preceding the VC announcement date, extracted from Diane database for French FinTech and from Orbis for other European FinTech.
Panel B. VC Characteristics	
VC size	The amount raised in the VC round in million €, identified by Crunchbase.
Ln VC size	The log of the amount raised in the VC round.
VC type	A dummy variable which is equal to 1 if the VC is bank-affiliated (i.e., one -or more- investor(s) among all investors raising the VC amount represents a bank institution(s)), and 0 otherwise. The investors are identified by Crunchbase.
Late-stage Dummy	A dummy variable which is equal to 1 if the VC funding takes place in later stages (Series C, D, E, …). The funding type (Seed, Series A, ….) is identified by Crunchbase.
Panel C. Performance Measures	
ROS $_{t = -1}$	The return on sales before the VC is the ratio of net income in the year preceding the VC announcement date to the total sales in the year preceding the VC announcement date, extracted from Diane database for French FinTech and from Orbis for other European FinTech.
ROA $_{t = -1}$	The return on assets before the VC is the ratio of operating income in the year preceding the VC announcement date to the total assets in the year preceding the VC announcement date, extracted from Diane database for French FinTech and from Orbis for other European FinTech.
ROE $_{t = -1}$	The return on equity before the VC is the ratio of net income in the year preceding the VC announcement date to the total equity in the year preceding the VC announcement date, extracted from Diane database for French FinTech and from Orbis for other European FinTech.
ROS increase	A dummy variable which is equal to 1 if the return on sales after the VC is higher than the return on sales before the VC, and 0 otherwise.
ROA increase	A dummy variable which is equal to 1 if the return on assets after the VC is higher than the return on assets before the VC, and 0 otherwise.
ROE increase	A dummy variable which is equal to 1 if the return on equity after the VC is higher than the return on equity before the VC, and 0 otherwise.

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