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ORIGINAL PAPER

Investment strategies of bank-affiliated and independent venture capitalists: a focus on innovation in the fintech sector in the wake of the global financial crisis

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Abstract

We investigate how bank-affiliated VCs (BVCs) change their investment strategy in fintech startups relative to independent VCs (IVCs) after the global financial crisis (GFC). To this end, we use the concept of mimetic isomorphism as a theoretical lens. We measure the innovation level of invested ventures by resorting to patent and patent quality data and several proxies deriving from text mining and semantic network analysis. We look at the selection dynamics of VCs based on the innovation level of their target ventures. We analyze data on VC investments in 6711 fintech ventures worldwide from 1995 to 2019. Our findings show that BVCs have changed, compared to IVCs, their patterns of investments after the exogenous shock provided by the GFC. While BVCs selected less innovative ventures compared to IVCs before the crisis, they aligned with IVCs by choosing more innovative ventures after the crisis.

Keywords Fintech · Innovation · Global financial crisis · Bank-affiliated VC · Independent VC

JEL Classification G01 · G24 · L26 · L25 · 034

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1 Introduction

The "fintech" (or financial technology)[1] industry has grown significantly in recent years, with an investment volume in fintech ventures amounting to a record of US$132 billion in 2021 and to US$114.4 billion in 2022–2023.[2] The acceleration of the financial industry's digital transformation was triggered by the onset of the global financial crisis (GFC) in 2008 (Diaz-Rainey et al. 2015; Palmié et al. 2020).[3] The GFC created new technological and entrepreneurial opportunities for new entrants, leading to a global boom in fintech startups in the years following the financial downturn (Arner et al. 2016).

The rise in the number of fintech startups following the GFC propelled investment activity by venture capitalists (VCs) across various fintech subsectors, including wealthtech, regtech, crypto, and cybersecurity (Pulse of Fintech H1 2021 2021). Interest in fintech has been boosted by both independent venture capitalists (IVCs), which have traditionally closely monitored technological progress and innovation, and bank-affiliated venture capitalists (BVCs). Indeed, banks' foray into VC in the fintech sector through BVCs is the most common way banks incorporate financial innovations developed by startups into their business.[4] This is because fintech innovation is likely to disrupt long-established banking business models, filling in functions traditionally reserved for banks (Brandl and Hornuf 2020; Lee and Shin 2018).

In this paper, we examine how an exogenous shock, such as the GFC, may affect the different investment patterns in fintech associated with IVCs and BVCs, using the concept of mimetic isomorphism as a theoretical lens. The different features characterizing these two distinct VC types (i.e., having different corporate governance structures) are expected to inspire different investment strategies and make the research question of how innovation-driven selection practices may vary over the business cycle worthy of further investigation. In general, IVCs seek out high-growth, innovative companies to maximize returns and pay close attention to assessing the technological feasibility and market viability of start-ups' innovative products (Gompers and Lerner 2001). In contrast, BVCs are characterized by the prioritization of strategic objectives over the pursuit of high financial returns and a risk-averse attitude that does not emphasize investment in innovation (Andrieu 2013; Croce et al. 2015; Hellmann 2002; Hellmann et al. 2008).

While the VC market is rather dependent on its surrounding economic environment, limited research has investigated the impact of altering economic conditions on

[1] The Financial Stability Board (FSB) defines fintech as "technology-enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on the provision of financial services" (Financial Stability Board 2019).

[2] CBInsights, State of Fintech 2021/2022/2023 Report.

[3] The GFC represented a major exogenous shock that destabilized the entire traditional financial sector. The lack of liquidity in IPO and M&A markets, the reduction of portfolio company's valuations and of the funds managed by large banks also negatively affected VCs' investment activity (Bertoni et al. 2019; Block and Sandner 2009).

[4] Banks are increasingly pressured to search for interactions with fintech startups by means of direct acquisitions (e.g., as Goldman Sachs, J.P. Morgan, and Citigroup did), strategic alliances, or through their venture capital (VC) arm (Hornuf et al. 2021).

the investment choices of different VCs. This study addresses this gap in the fintech context. The 2008 GFC offers an empirical framework for investigating the impact of crisis-induced supply shocks on the selection dynamics -based on the innovation activity of target fintech ventures- by VC firms, focusing on the distinctions between IVCs and BVCs.

Current research into fintech VC is limited to a handful of academic works (Chemmanur et al. 2020; Cumming and Schwienbacher 2018; Kolokas et al. 2022). These studies investigate the macro-foundations of fintech VC investments. However, they fail to offer valuable insights into VCs that have various governance structures and the selection dynamics that influence such investments. A comparison of the investment strategies of different types of VCs in the fintech space and the role played by the onset of the GFC[5] is still lacking. In particular, the extent to which various VC types prioritise the level of innovation in target ventures during their selection processes and how the GFC impacts this is of significant academic and practical importance. Our aim is to make a novel contribution to the limited literature on fintech VC (Cumming and Schwienbacher 2018; Kolokas et al. 2022) by exploring the patterns and attitudes towards innovation of BVCs compared to IVCs in light of the exogenous shock caused by the GFC. We draw on neo-institutional theory and the concept of mimetic isomorphism to explore how BVCs respond to the GFC and align with the selection strategies of IVCs in fintech investments.

The fintech context is appropriate for our research question because new ventures in this sector are, by definition, innovative and pursue novel technologies. We measure the level of innovation of invested ventures using two different indicators. First, we measure innovation through patent filings and patent quality (Lerner 2002; Lerner et al. 2011). Second, we construct a metric based on combined methods and tools of text mining and semantic network analysis (Wasserman and Faust 1994), which is performed on the business description of invested ventures (i.e., taking into account the products and services they offer and the other salient attributes that emerge from their business description).

We analyze data on VC investments in 6711 fintech ventures worldwide from 1995 to 2019. We explore our research hypothesis by examining both the probability of receiving BVC relative to IVC financing and the level of innovation of selected ventures at the time of the first funding round of BVCs and IVCs and whether this changes over the GFC. In addition, we provide some additional evidence by examining the impact, net of the selection effect, of both BVCs and IVCs on the level of innovation of invested ventures after they enter into the equity capital and whether their impact changes over the GFC. To this end, we use both diff-in-diff analysis and matched sample estimation as two alternative methods to explore the impact net of the selection effect.

We establish a theoretical link between the GFC, mimetic isomorphism and the investment selection strategies of BVCs compared to IVCs. Our results show that, compared to IVCs, BVCs changed their investment patterns after the exoge-

[5] Block and Sandner (2009), for example, compare the investment strategies of VCs before and after the crisis in the US and document a shift to safety also for VCs after the crisis (e.g. VCs prefer to select older companies, with later stage investments of smaller amounts involving more syndicate partners).

nous shock of the GFC. Before the crisis, BVCs selected less innovative firms than IVCs (in terms of the number of patents, patent quality, and innovation potential). We explain this result with the argument that BVCs are more tolerant of firms with lower innovation intensity (and innovation quality) than IVCs, which instead actively seek high-growth innovative firms because the ability to raise money from limited partners (and also manager compensation) is largely conditioned by future returns. Conversely, BVCs have less pressure to maximize returns than IVCs because they do not have to raise money from third parties, and they tend to pay more attention to the financial status of the firm rather than its innovation potential, acting more like banks than VCs (Croce et al. 2015). We also find that BVCs have aligned with IVCs in their selection strategy post-crisis by selecting more innovative fintech companies (compared to the pre-crisis period). Thus, we document a shift in the investment strategy of BVCs relative to IVCs that appears to be significantly correlated with the GFC: BVCs tend to align themselves with the dictates of the VC industry by adapting their selection behavior to that of IVCs, showing greater attention to the innovation capacity of target ventures compared to the pre-crisis period. We explain this shift by the increasing interest of banks in exploiting fintech-enabling technologies and enhancing their digital capabilities, which has driven the alignment of BVCs with the traditional selection approach of IVCs (i.e., paying more attention to the innovation potential of invested ventures).

The remainder of this paper is structured as follows. The next section discusses the theoretical background and puts forward a testable hypothesis. Section 3 presents our data collection and sample. Section 4 presents the results. Section 5 reports additional evidence on the impact of BVCs on innovation (compared to IVCs before and after the GFC). Section 6 discusses the results of the study in terms of contribution to previous literature, limitations and policy and managerial implications. Finally, Sect. 7 concludes.

2 Background theory

VCs' interest in innovation may vary across VC configurations and be affected by an exogenous shock like the GFC. Understanding the approach of different VCs in selecting fintech target ventures regarding firm-level innovation in the aftermath of the GFC warrants empirical investigation and has important implications for both early-stage entrepreneurs and investors. In what follows, we discuss the background literature along three lines of inquiry, which incidentally inform our specific research question: the role of VC for the fintech industry, the consequences of the GFC for the VC market, and the differences between IVCs and BVCs. We then develop our theoretical argument based on the concept of mimetic isomorphism from neo-institutional theory and introduce a testable hypothesis on how BVCs respond to the GFC and align with the selection strategies of IVCs in fintech investments. The notion of mimetic isomorphism was first articulated by DiMaggio and Powell (1983), who distinguished three types of isomorphism: mimetic, coercive, and normative. Coercive isomorphism refers to the ability of external entities to force organizations to adopt particular practices, while normative isomorphism involves the establishment of legitimate practices through authoritative definitions. However, these dimensions may not provide a useful framework for interpreting the phenomenon under study. Instead, mimetic isomorphism is useful in providing a theoretical link between the GFC and the investment selection strategies of BVCs relative to IVCs. It explains how, in the face of uncertainty, the benchmark to the group's accepted standards may become blurred, prompting organizations to align themselves with others through imitation as a strategy to gain or reinforce legitimacy within their domain (Barreto and Baden-Fuller 2006; Deephouse 1999; DiMaggio and Powell 1983; Oliver 1991, 1997; Pedersen and Dobbin 2006). Such alignment is also pursued to enhance organizational performance (Oliver 1991; Sirmon and Hitt 2009).

2.1 The role of VC in the fintech industry

Despite the significant increase in interest in fintech in the academic literature in recent years (Allen et al. 2021; Block et al. 2018; Bollaert et al. 2021; Farag and Johan 2021; Giudici et al. 2021; Goldstein et al. 2019; Ughetto et al. 2021), existing studies remain loosely connected (Goldstein et al. 2019; Kavuri and Milne 2019) and provide little insight into fintech VC. Current research on fintech VC is limited and examines either the macro drivers of fintech VC investment or the role of VCs in the emergence of the fintech market (Chemmanur et al. 2020; Cumming and Schwienbacher 2018; Kolokas et al. 2022). Some recent research emphasizes the interplay between fintechs and banks but without focusing on bank-affiliated VCs (Brandl and Hornuf 2020; Hornuf et al. 2021). This is surprising, given that VCs play an important role in fostering technological advances that are blurring industry boundaries and revolutionizing the financial industry with the introduction of new and alternative digital advisory and trading and payment systems (Farag and Johan 2021; Philippon 2016; Ughetto et al. 2021).

The study by Cumming and Schwienbacher (2018) analyzes the factors that influence the level of VC in the fintech industry. The study finds that differential regulatory enforcement between startups and large, established financial institutions after the GFC has driven VC investment in fintech. A related article is that of Haddad and Hornuf (2019), who analyze fintech startups in 55 countries and provide evidence that more fintech startups are created in more developed economies, and where VC funding is easily accessible. However, the emergence of fintech ventures is positively influenced by VC funding when there is a critical mass of fintech entrepreneurship in a country, such that VC and credit markets are substitutes, especially in countries characterized by more dynamic fintech entrepreneurship (Kolokas et al. 2022).

Two recent papers have also started to discuss how banks interact with fintechs. Hornuf et al. (2021) use hand-collected data on banks in Canada, France, Germany, and the UK to investigate the forms of collaboration between fintech startups and banks. They find that banks prefer forming alliances with startups with a well-defined digital strategy and/or employing a chief digital officer. Similarly, Brandl and Hornuf (2020) conducted a network analysis of banks and fintechs in Germany and concluded that most relationships between banks and fintechs are product-related collaborations.

2.2 The consequences of the GFC for the VC market

The global economic downturn led to a significant reduction in VC activity due to the close relationship between the VC market and the general economic climate (Block and Sandner 2009; Mason 2009). The VC industry was significantly and adversely affected by the crisis due to several factors, including the lack of liquidity in the IPO and M&A markets, the decline in portfolio company valuations, and the lack of funding that affected many private VC investors as a result of the financial difficulties faced by insurance companies and large banks (Bertoni et al. 2019; Block and Sandner 2009).

The onset of the GFC created a new dynamic in the VC market, forcing VCs to reduce their activities (Mason 2009) and change their investment behavior (De Vries and Block 2011). Block and Sander (2009) compared average VC investment decisions in the US before and after the GFC. They found that after the crisis, VCs, on average, selected older companies and made later-stage investments in larger syndicates. In contrast, early-stage investments were less attractive to VCs, especially corporate VCs. During the liquidity supply shock, investing in core sectors became more attractive for VCs, with core startups receiving 9.4% more funding than non-core startups compared to normal times (Conti et al. 2019). VCs reduced their propensity to syndicate investments (De Vries and Block 2011) and IPOs became less common, largely replaced by acquisition exits (Cumming and Johan 2013).

2.3 The differences between IVCs and BVCs

BVCs have been compared with IVCs regarding their selection dynamics, monitoring practices, and value-added activities (see Table 16 for an illustration of key differences). In terms of investment selection practices, it has been recognised that financial institutions that extend their knowledge to VC investments create opportunities to build future relationships with their clients. The aim is to establish a connection with a company at the VC stage with the expectation of generating potential clients for their underwriting and lending activities in the future (Andrieu 2013; Croce et al. 2015; Hellmann 2002; Hellmann et al. 2008). As such, BVCs tend to pay more attention to credit scoring variables (based on financial statement analysis) than to assessing a company's innovation potential (Croce et al. 2015). They are under less pressure than IVCs to exit early and generate abnormal returns (Manigart et al. 2002) because they can obtain additional sources of funding from the bank and do not need to raise funds from limited partners (Andrieu and Groh 2012; Croce et al. 2015). Given the generally risk-averse nature of parent banks, BVCs prefer to invest in companies that can be easily monitored (e.g., local) and from which it is easy to gain insights into the local market (Bertoni et al. 2015). They also seem to prefer to invest in more diversified and later-stage portfolios, with a lower probability of default, to reduce overall risk (Croce et al. 2015; Cumming et al. 2008; Dimov and Gedajlovic 2010; Yoshikawa et al. 2004) compared to IVCs. In contrast, IVCs actively seek high-growth innovative companies to maximise returns by betting on a particular innovative product's technological feasibility and market viability. The primary objective for IVCs is to achieve successful portfolio exits or abnormal returns as they manage funds from external investors (Dimov and Gedajlovic 2010; Gompers and Lerner 2001). In terms of monitoring practices and value-adding activities, BVCs tend to be less actively involved in the management and monitoring of their portfolio companies than IVCs, which can ultimately affect the overall performance of the firm (Baum and Silverman 2004; Hellmann and Puri 2002). BVCs are generally not involved in the day-to-day operations of the companies in which they invest and, like other captive investors, have limited decision-making autonomy. This can hinder their ability to help companies achieve a successful exit (Croce et al. 2015; Cumming et al. 2008; Yoshikawa et al. 2004).

2.4 Hypothesis development

We draw on neo-institutional theory, in particular the concept of mimetic isomorphism, to explain how BVCs respond to the GFC and align with the selection strategies of IVCs in fintech investments. Mimetic isomorphism involves the achievement of uniformity with other organisations through imitation. Institutional theorists argue that the tendency for organisations to copy each other stems from their efforts to gain or enhance legitimacy in the field (Barreto and Baden-Fuller 2006; Deephouse 1999; DiMaggio and Powell 1983; Oliver 1991, 1997; Pedersen and Dobbin 2006) and to improve their performance (Oliver 1991; Sirmon and Hitt 2009). Mimetic isomorphism is also a simple and effective response to uncertainty (DiMaggio and Powell 1983, p. 151). Indeed, one of the pressures driving the mimicry of business practices is the turbulence in the organisational and environmental environment in which organisations operate (DiMaggio and Powell 1983). In a stable and predictable environment, organisations look to their peer group and benchmark themselves against the group's recognised standards. In times of crisis, the boundaries and membership of reference groups can become blurred, affecting the dynamics of mimetic isomorphism (Davis et al. 1994). The emergence of a crisis can destabilise an organisation, undermine resource flows, and reshape the distinctive patterns and processes that characterise it, possibly redirecting its search for new points of reference. Thus, organisational efforts to emulate other organizations are intensified in times of heightened uncertainty because organizations believe that doing so reduces the costs associated with decision-making (Cyert and March 1992) and improves their performance (Oliver 1991). Additionally, emulating other organisations in turbulent times may stimulate the exploration of new opportunities that were previously out of reach or little considered (Paruchuri and Ingram 2012), and improve the ability to make complex decisions through peer observation and iteration (Lévesque et al. 2009).

Drawing on neo-institutional theory and the concept of mimetic isomorphism, we theorize that the GFC exerted mimetic isomorphic pressure on BVCs to align with the selection strategies pursued by IVCs in fintech investments. This alignment is related to the increased role that the incorporation of technological advances plays in the business of banks.

It is widely accepted that BVCs, by their nature, tend to pay more attention to credit scoring variables (based on financial statement analysis) than to assessing a company's innovation potential (Croce et al. 2015). They are under less pressure than IVCs to exit early and generate abnormal returns (Manigart et al. 2002) because they can obtain additional sources of funding from the bank and do not need to raise funds from limited partners (Andrieu and Groh 2012; Croce et al. 2015). Given the generally risk-averse nature of parent banks, BVCs prefer to invest in companies that can be easily monitored (e.g., local) and from which it is easy to gain insights from the local market (Bertoni et al. 2015). They also seem to prefer to invest in more diversified and later-stage portfolios to reduce overall risk (Cumming et al. 2008; Dimov and Gedajlovic 2010; Yoshikawa et al. 2004) compared to IVCs. As such, BVCs are more similar to banks than VCs in their selection activity, favoring firms with a lower ex-ante probability of default (based on financial data) and potentially disregarding innovation potential. This description of BVCs fits well with the pre-GFC period when technology integration was not yet central to discussions on bank stability. The notion that technological advances could improve monitoring and screening, thereby increasing resilience in times of crisis, was not prevalent during this period. The stability of the environment in those years favoured internal benchmarking practices within the group of BVCs. This meant that BVCs were less active than IVCs in investing in start-ups introducing disruptive technologies, thus favouring the selection of firms that appeared more promising in terms of financial strength rather than innovation potential compared to IVCs. In other words, BVCs were more tolerant of firms with lower innovation intensity (and innovation quality) and potentially more subject to innovation failure than IVCs.

The destabilisation caused by the GFC meant that BVCs faced external pressures that imposed difficult imperatives on how to bring technological advances to the core banking business in order to remain competitive, with little guidance on how to do so. In fact, while the banking industry has been increasingly confronted with new disruptive technologies and has been able to integrate most of them into the digital back-end, it has been much slower to internalize the digital servitization of front-end services and financial products (Navaretti et al. 2017). The GFC accelerated the overwhelming impact of technology on the financial sector, making banks aware of the importance of incorporating technology-driven configurations into their businesses. The GFC reinforced the notion that technological advancements can significantly alter how information is processed, affecting both lending and underwriting activities. We argue that the turmoil caused by the GFC exerted mimetic isomorphic pressure on BVCs, which changed their investment practices towards those of IVCs, with a tendency to select more innovative fintech firms.

The unfolding of the GFC led BVCs to pursue a strategy of imitating IVCs as a viable solution to reduce uncertainty (Ashworth et al. 2009; DiMaggio and Powell 1983; Hu et al. 2007) and bring technological advances to the core banking business, which has traditionally been characterised by low levels of innovation (Beck et al. 2016). As the fintech and innovation environment was rapidly evolving, the GFC pushed banks to reorganise their activities by improving the digital services offered to their customers in order to be more resilient in a future crisis. Banks became keen on integrating big data by leveraging fintech technologies to improve the efficiency of processing hard information and overcome the time-consuming and labour-intensive processing of soft information (Balyuk et al. 2020). In the case of fintech BVC investment, the GFC acted as a catalyst for mimetic isomorphism (DiMaggio and Powell 1983). Mimicking the IVC selection strategy towards more innovative ventures meant that BVCs could respond to the uncertainty of the changed economic environment and explore newly available technological alternatives to legitimise their parent banks' current business practices (DiMaggio and Powell 1983; Hannan and Carroll 1992; Meyer and Rowan 1977). Our overarching hypothesis is, therefore, as follows:

Hypothesis The GFC exerted mimetic isomorphic pressure on BVCs, leading them to align their investment strategies with those of IVCs by selecting more innovative fintech companies.

3 Data and methods

3.1 Sample

We obtained the data used in this paper from Crunchbase, a unique database that captures worldwide information about VC investments in high-technology ventures. For each portfolio venture, Crunchbase reports information on the date of each investment and the investing VC firms. The database provides additional details on the ventures, including the foundation year, the country of operation, a description of the industry in which the venture operates, the number of financing rounds received, the amount of money raised in each financing round, and the type of funding received. The dataset also reports information on investors that can broadly be classified as individuals and financial organizations (e.g., VC and private equity firms). The present analysis is based on data obtained from Crunchbase in November 2019.

The initial dataset contains information about 440,810 investments related to 120,427 ventures. We proceeded through several steps in the selection of the sample.

First, we only focused on fintech ventures. Following Haddad and Hornuf (2019), we resorted to the following procedure to identify fintech ventures:

(i) We started from the category variable retrieved from CrunchBase, indicating a description of the venture's industry and identified a list of keywords referring to possible fintech start-ups.[6] This filter allowed us to identify 53,971 investments in 12,087 potential fintech ventures.
(ii) We categorized fintech ventures into nine categories as reported in Table 1: Asset and Wealth Management, Exchange Services, Financing, General Fintech Services, Insurance, Loyalty Programs, Payment, Regulatory Technology, and Risk Management. In the third column of Table 1, we show all the keywords used to attribute a venture to a specific fintech category.

[6] The list of keywords used to identify fintech start-up is the following: fintech, finance, financial services, wealth management, asset management, personal finance, financial exchanges, stock exchanges, crowdfunding, crowdlending, lending, micro credit, micro lending, insurtech, risk management, angel investment, coupons, gift card, loyalty programs, Ethereum, NFC, bitcoin, cryptocurrency, payments, mobile payments, banking, funding platform, cyber security, credit.

Table 1 Definition and keywords for Fintech categories (adapted from Haddad and Hornuf 2019)

	Category of Fintech	Definition	Keywords
1	Asset and wealth management	Robo-advice, social trading, wealth management, personal financial management apps or software	Asset management/wealth management/advice/consulting/personal finance/robotics associated with finance, fintech, or financial services
2	Exchange services	Financial or stock exchange service (i.e., securities, derivatives, and other financial instrument trading)	Financial exchanges/stock exchanges
3	Financing	Crowdfunding, crowdlending, microcredit, and factoring solutions	Banking/angel investment/crowdfunding/crowdlending/micro-lending/consumer lending/credit
4	Insurance	Peer-to-peer insurance, spot insurance, usage-driven insurance, insurance contract management, brokerage services, claims, and risk management services	Insurtech/insurance associated with finance, fintech, or financial services
5	Loyalty program	Loyalty program services to customers (e.g., startups providing rewards for brand loyalty or giving customers advanced access to new products, special sales coupons, or free merchandise	Loyalty program/coupon/gift card
6	Payment	New and innovative payment solutions (e.g., mobile payment systems, e-wallets, or cryptocurrencies)	Payments/mobile payments/cryptocurrency/bitcoin/Ethereum/credit cards associated with finance, fintech, or financial services
7	Regulatory technology	Offer services based on technology in the context of regulatory monitoring, reporting, and compliance, benefiting the finance industry	Cyber security/compliance/legal/legal tech associated with finance, fintech, or financial services
8	Risk management	Services helping companies to better assess the financial reliability of their counterparties or better manage their own risk	Risk management associated with finance, fintech, or financial services
9	General fintech services	Startups operating in more than one category (e.g.providing both payment and financing)	All the remaining cases

Second, we focused on first-round investments (i.e., those in which a given venture receives financing for the first time) since follow-on investment decisions are qualitatively different from initial investment decisions (Podolny 2001). This filter reduced our dataset to 26,169 first investments, referring to 12,087 fintech ventures.

Third, we restricted the analysis to fintech ventures financed by VCs, thus excluding individual investors. More in detail, we included in our sample BVC investors and, for comparison purposes, IVC investors. Thus, we only considered fintech ventures that received their first financing round from an IVC or a BVC, thus excluding rounds syndicated by the two types of VC investors. This filter is motivated by the aim of comparing the selection strategies of these two VC types in terms of the innovation level of invested ventures. The presence of co-invested ventures in our sample would influence and bias our results. We obtained 7175 first investments in fintech ventures, 225 of which (3.14%) were financed by BVC investors, and the remaining 6950 (96.86%) were financed by IVC investors.

Finally, we excluded observations for which we had missing data for the control variables used in our econometric model. The final sample consists of 6711 fintech ventures invested by either IVCs (6509 ventures, 96.99% of the sample) or BVCs (202 ventures, corresponding to 3.01% of the sample).

Table 2 reports the distribution of our samples in terms of foundation year, country of operation, fintech services category, and investment year. Both total distribution and distribution by typology of VC investors are reported.

Looking at the total sample, almost 11.43% relates to investments made in the years before 2008 (i.e., the starting year of the GFC), while the remaining 88.57% refers to investments made in the years following the GFC. This is driven by the fact that the

Table 2 Distribution of the sample by foundation year, country, fintech category, and investment year

	BVC-backed		IVC-backed		Total sample	
	n. ventures	%	n. ventures	%	n. ventures	%
Foundation year						
Before 2000	53	26.238	899	13.812	952	14.186
2001–2005	22	10.891	529	8.127	551	8.210
2006–2010	27	13.366	968	14.872	995	14.826
2011–2015	73	36.139	2589	39.776	2662	39.666
2016–2019	27	13.366	1524	23.414	1551	23.111
Continent						
Africa	7	3.465	145	2.228	152	2.265
Asia	26	12.871	1166	17.914	1192	17.762
Europe	75	37.129	1570	24.120	1645	24.512
North America	87	43.069	3353	51.513	3440	51.259
Oceania	4	1.980	121	1.859	125	1.863
South America	3	1.485	154	2.366	157	2.339
Fintech services						
Asset and wealth management	11	5.446	340	5.224	351	5.230
Exchange services	6	2.970	98	1.506	104	1.550
Financing	47	23.267	1012	15.548	1059	15.780
General Fintech services	72	35.644	2258	34.690	2330	34.719
Insurance	11	5.446	320	4.916	331	4.932
Loyalty program	6	2.970	262	4.025	268	3.993
Payment	25	12.376	1184	18.190	1209	18.015
Regulatory technology	22	10.891	790	12.137	812	12.100
Risk management	2	0.990	245	3.764	247	3.681
Investment year						
Pre-GFC: before 2008	31	15.347	736	11.307	767	11.429
Post-GFC: after 2008	171	84.653	5773	88.693	5944	88.571
Total	202	100	6509	100	6711	100

Crunchbase coverage has increased over the years. As to the geographical distribution, 51.26% of sample ventures are located in the U.S., while most of the remaining ventures are located in Europe (24.51%), with 618 U.K. ventures (9.21%) and the remaining 1027 from countries belonging to the European Union (15.30%). Sample ventures provide different fintech services, even if the largest majority (34.72%) operate in the General Fintech Services sector. Payment (18.01%) and Financing (15.78%) represent other significant categories of fintech services providers in our sample. Significant differences exist between companies backed by BVCs and those backed by IVCs based on χ^2 tests comparing their foundation year, location, and fintech services. This implies the importance of adding these variables as controls in our selection model, which will be detailed in Sect. 5. The same reasoning holds for the amount received by VCs in the first round of financing, with BVC-backed companies receiving significantly higher financing than IVC-backed ones. As a result, we will also incorporate the received amount in our control variables.

3.2 Metrics to capture firm-level innovation

We measured innovation by resorting to the number of patents and forward patent citations as a proxy of patent quality. In the fintech sector, patent filings have increased steadily over the years, although the quality of these patents has often been reported to be low (Lerner et al. 2015). The innovative potential of a venture is often signaled to investors by means of the patents owned (Lerner 2002). Besides being an exclusive right that grants legal protection to an invention from imitation by competitors, a patent can be an important devise to signal that the firm has innovation capabilities and a specific technological positioning (Chang 2012; Hoenig and Henkel 2015) and that an invention is worth being protected (Caviggioli et al. 2017; Caviggioli and Ughetto 2016).

Patents are a reliable indicator of a company's innovation endeavors for two main reasons. Firstly, applying for a patent is expensive and requires significant resources, implying that only highly valuable innovations are likely to be patented. Secondly, patenting activity is typically associated with product innovation rather than process innovation (Teece 1988). However, the effectiveness of patents in protecting technological innovations is contingent upon the product's characteristics, which varies across different sectors. For instance, certain innovations that form the basis of digital products, such as computer code, may not be effectively protected by patents. Other digital products that are novel or distinct may be instead effectively protected by patents (Boudreau et al. 2022).

Research has shown that startups filing patents have a greater likelihood of receiving VC financing (Hoenen et al. 2014; Mann and Sager 2007; Munari and Toschi 2015) and that patents are associated with favorable firm valuations by VCs (Baum and Silverman 2004; Hsu and Ziedonis 2013). For VCs, the fact that startups own patents indicates the presence of collaborative R&D, inventiveness, and technological dynamicity of the firm.

We identified all patents associated with sample ventures by resorting to the proprietary patent search database Derwent Innovation provided by Clarivate. We collected information on patents and patent quality for each venture over time. The innovation measures are based on the patent application year (i.e., the year in which the patent application is filed) since this is closer to the time of the actual innovation (Griliches et al. 1987). The patent count is measured as the number of patent applications filed (and subsequently granted) by the venture in a given year. To capture the importance (technical merit) of each patent, we constructed two measures of quality based on forward-citation counts. The technological worth of an innovation is often estimated in scientific literature by analyzing forward patent citations, which are indicative of the patent's value and technical significance. The use of forward citations as indicators of patent value was first introduced by Trajtenberg in 1990. Since then, numerous empirical studies have validated the usefulness of forward citations in assessing the value of patents (e.g., Harhoff et al. 2003; Jaffe and De Rassenfosse 2017; Reitzig 2003; Sapsalis et al. 2006). Following Hall et al. (2001, 2005), the citation truncation problem was corrected using citation-lag distribution. Consistent with the literature, we used two variables: (1) forward 4-year citation, defined as the number of forward citations within four years of filing for all patents filed in a given year, and (2) citation per patent– defined as the average number of forward citations received by each patent. Natural log transformation was used to counter the right-skewness of the variables.

As shown in Table 3, out of 6711 ventures (total sample), 1016 resulted in having at least one patent (15.14% of the total sample), both before and/or after the investment round. More in detail, patenting ventures comprise 991 IVC-backed ventures (15.23% of the IVC-backed sample) and 25 BVC-backed ventures (12.38% of the BVC-backed sample).

We observe 3441 patents filed by these 1016 patenting ventures, 72 of which are associated with BVC-backed ventures (2.09%), while the remaining 3369 refer to IVC-backed ventures (97.91%). Out of the total 3441 patents, 537 (15.61%) are filed before the entry of the VC in the venture's equity capital, 325 (9.44%) are filed in the same year of the receipt of VC financing, while the remaining 2579 (74.95%) relate to patents filed after the entry of the VC in the venture's equity capital. The availability of data about patents and patent quality in the post-investment period allows us to provide some evidence of the impact of VC investments on the innovation rate of invested ventures, as shown in Sect. 6.

Our final sample is thus composed of 6711 observations relative to investment years (325 of which are also patenting years) plus 3116 observations relative to

Table 3 Descriptive statistics on patenting ventures

	BVC-backed		IVC-backed		Total sample	
n. patenting ventures	25	12.38%	991	15.23%	1016	15.14%
n. non-patenting ventures	177	87.62%	5518	84.77%	5695	84.86%
Total	202	100.00%	6509	100.00%	6711	100.00%
n. total patents registered	72	2.09%	3369	97.91%	3441	100.00%
of which:						
n. patents registered before VC investment	12	16.67%	525	15.58%	537	15.61%
n. patents registered in the year of VC investment	6	8.33%	319	9.47%	325	9.44%
n. patents registered after VC investment	54	75.00%	2525	74.95%	2579	74.95%

additional patenting years before or after the investment year, for a total of 9827 observations.

Secondly, we complemented our data with information about the innovation level of the invested ventures by resorting to different proxies deriving from text mining and semantic network analysis.

First, we considered a measure of innovation based on semantic text analysis performed on the business description of ventures invested by BVCs and IVCs (i.e., considering the products and services they offer and the other prominent attributes emerging from their business description). For this analysis, we combined methods and tools of text mining and network analysis (Wasserman and Faust 1994). In particular, we used the SBS BI app (Fronzetti Colladon and Grippa 2020) to pre-process the textual data by removing stopwords (i.e., words that add little meaning to each description, such as the terms "and" or "the), punctuation, links, and special characters, transforming all the text into lowercase, and removing word affixes. This last procedure is known as stemming (Porter 2006); it makes sure that related terms (such as "mystery" and "mysterious") map to the same word stem.

After preprocessing, we transformed the corpus into semantic networks, where each node represents a word/concept, and links among words are weighted based on their co-occurrence in the text (Diesner 2013). This procedure is preliminary to identifying the main topics emerging from the different venture descriptions, which we carried out following a network topic modeling approach. This choice is aligned with past research that showed the advantage and reliability of adapting methods from community detection in networks (Lancichinetti et al. 2015).[7] Specifically, we identified the main topics by finding the most meaningful clusters in the semantic network using the Louvain algorithm (Blondel et al. 2008). In addition, we used the formula proposed by Fronzetti Colladon and Grippa (2020) to identify the most representative words for each topic and their importance scores. In particular, we valued more terms

Table 4 Semantic network analysis—topic description

Topic number and title	Relevance (%)	Top keywords
1. Technology and Innovation	38.8	Machine learning, blockchain, security, cyber, data, cloud, technology, innovative, analytics, advanced, threats, protection, intelligence, risk, attacks, applications, detection, network, systems, devices
2. Trading and Payment Systems	19.7	Payment, card, platform, online, mobile, credit, money, app, digital, pay, loans, trading, exchange, merchants, process, peer, debit, buy, transactions, lending, cash
3. Customers and Team	16.5	Business, customers, help, experience, need, work, team, people, world, decisions, efficient, loyalty
4. Financial Services	24.9	Services, provides, financial, management, solutions, bank, insurance, offers, products, finance, software, industry, institutions, clients, asset, corporate, retail, group

[7] We also tested well-known alternative approaches for topic modeling—such as LDA (Blei et al. 2003)—which did not lead to better results or topic representations.

with strong links within their cluster and weak external connections. This process led to the identification of four main topics, described in Table 4. At the same time, we obtained information to carry out a reverse fit and evaluate how much each venture description was related to the different topics.

Our semantic network analysis of the venture descriptions led to identifying four significant topics, described in Table 4. As shown in the table, Topic 1 is the most relevant and concerns the most innovative traits of the analyzed ventures. It includes information about the advanced technologies they use and the systems/devices they developed to offer innovative products and services—for example, related to cyber security, data protection, machine learning, or business intelligence and analytics. Topics 2 and 3 are less relevant in the corpus. The former concerns trading and payment systems offered by some ventures, including online platforms used for e-commerce or other financial transactions, such as money lending. Topic 3 is focused on people, both employees and customers. In this case, descriptions relate to how ventures can satisfy customers' needs, improve their loyalty, or provide solutions to support teamwork and improved decision-making. Topic 4 is the second most relevant topic, and it is related to financial services and products, software, and management

Table 5 Description of the variables

Variable	Description
Innovation topic	Weight of the matching of a company's description with Topic 1. Topic 1 is the most relevant and concerns the most innovative traits of the analyzed ventures. It includes information about the advanced technologies they use and the systems/devices they developed to offer innovative products and services—for example, related to cyber security, data protection, machine learning, or business intelligence and analytics
Top innovator	Dummy indicating ventures for which the value assigned by semantic network analysis to the Innovation topic exceeds the 90° percentile of the distribution
Patent count (logs)	Number of patents registered by the focal fintech venture in year t (in logs)
Forward 4-years citations (logs)	Number of forward 4-year citations in year t (in logs) of patents registered by the focal fintech venture
Average citations per patent (logs)	Number of average citations in year t (in logs) of patents registered by the focal fintech venture
Financed amount	Amount of thousand euros received in the first funding round (in logs)
Age (logs)	Age of fintech venture in year t (in logs)
d_after GFC	Dummy taking value 1 for ventures receiving VC investments in the years following the GFC (i.e., investment year from 2008 onwards)
BVC-backed	Dummy taking value 1 for BVC-backed ventures and 0 for IVC-backed ones
BVC-backed before inv	Dummy taking value 1 for BVC-backed ventures in the years before the investment
BVC-backed after inv	Dummy taking value 1 for BVC-backed ventures in the years after the investment
IVC-backed after inv	Dummy taking value 1 for BVC-backed ventures in the years after the investment

systems designed for banks and financial institutions. Among all these topics, only the first one is related to the innovative traits of venture activities. We thus resorted to Topic 1 as a measure of innovation in ventures invested by BVCs and IVCs investors.[8] Through the SBS BI app, we matched the words used in the company descriptions with those most representative of each topic. In this way, we could measure the weight of Topic 1 in the text and assign to all ventures a metric of innovation (*Innovation topic*). Moreover, we also defined a high-innovative dummy (*Top innovator*) indicating ventures for which the value assigned to the Innovation topic exceeded the 90th percentile of the distribution. See Table 5 for a complete description of the variables used in this study.

4 Empirical analysis

Table 6 provides a preliminary univariate analysis of the innovation activity of the invested ventures before the entry of a VC investor. Results related to the overall period, reported in the first columns of Table 6, suggest that BVC-backed ventures have significantly lower forward 4-year citations and average citations than IVC-backed ones before the financing round. Conversely, BVC-backed ventures do not show a significant difference with respect to IVC-backed ones in terms of innovation level, as indicated by the Innovation topic and the number of patents, before the entry in the equity capital of the invested venture.

Interesting results emerge when we disentangle between ventures invested before and after the GFC, as shown in the following columns of Table 6. More in detail, ventures invested by BVCs before the GFC show a lower innovation activity (expressed by a lower number of patents and patents with lower quality and lower incidence of high values in the Innovation topic) than IVC-backed ventures.

Conversely, ventures invested by BVCs after the GFC do not show significant differences in innovation levels compared with IVC-backed ventures. Taken together, these results seem to suggest a shift in the BVCs' investment strategy after the GFC in terms of the selection of innovative ventures and alignment with IVCs' selection approach. While, before the GFC, BVCs selected less innovative ventures than IVCs, after the crisis, they aligned with IVCs (i.e., by picking ventures with innovation levels comparable to the ones invested by IVCs).

As additional evidence, Table 7 provides a preliminary univariate analysis of the innovation activity of invested ventures after the entry of a VC investor in terms of patent and patent quality, for which we have data in the post-investment period. This provides a first description of the analysis of the impact of VC investments on innovation that will be reported as additional evidence in Sect. 6. Results related to the overall period, reported in the first columns of Table 7, suggest that BVC-backed ventures have both significantly lower forward 4-year citations and average citations

[8] For the sake of completeness, we also performed the analysis by considering the other three Topics deriving from semantic network analyses. No significant effects result from these analyses related to the investment strategy of BVCs across the GFC. Analyses are not reported in the text for the sake of brevity but are available from the authors upon request.

Table 6 Univariate analysis on selection: innovation level at investment year

	Innovation levels at investment year								
	Overall			Before GFC			After GFC		
	BVC-backed	IVC-backed	Diff	BVC-backed	IVC-backed	Diff	BVC-backed	IVC-backed	Diff
Patent count (logs)	0.188	0.232	− 0.044	0.120	0.377	− 0.256*	0.201	0.213	−0.012
Forward 4-years citations (logs)	0.296	0.450	− 0.154*	0.363	1.101	− 0.738**	0.283	0.361	−0.077
Average citations per patent (logs)	0.127	0.208	− 0.082*	0.134	0.477	− 0.343*	0.125	0.172	−0.046
Innovation topic	54.404	53.713	0.691	55.562	62.373	− 6.811	54.193	52.61	1.583
Top innovator	0.200	0.2029	− 0.003	0.129	0.251	− 0.122*	0.2163	0.1933	0.023

** Significance at 5% level. * Significance at 10% level than IVC-backed ventures after the financing round, even though no significant differences emerge in terms of the number of patents. When we disentangle between ventures invested before and after the GFC, no significant differences emerge comparing the two periods: it appears that BVC-backed ventures have significantly lower citations after the entry of the investor both before and after the GFC (except for forward 4-year citations in the total sample after the GFC, which becomes not significant anymore).

In order to verify the evidence provided by this univariate analysis, we proceed by estimating several econometric models.

Focusing on selection, we first estimated a probit model for the sub-sample of observations related to the years before the investment. As the dependent variable, we used a dummy variable set to 1 if the venture was funded by a BVC and 0 if funded by an IVC. As to the independent variables, we included the different proxies of innovation (related to patent, patent quality data, and Innovation Topic distribution) to test whether BVCs select (or not) more innovative ventures than IVCs.

More in detail, in Table 8, we used patents and patent quality to proxy firms' innovation level. In Table 9, we resorted to semantic network analysis results using *Innovation topic* and *Top innovator* as independent variables. We incorporated a series of controls such as: i) venture age, measured as the calendar time in years between year t and the founding year of the venture; ii) financed amount, measured by thousand euros (in logs) received in the financing round; iii) fintech services dummies, representing the different categories of fintech service provided by the invested venture iv) country and year dummies. Moreover, to explore the role of the GFC, we estimated these models on the overall sample and split between investments performed before and after the GFC.

More in detail, we use as independent variables the different proxies of innovation, respectively in columns I-III (number of patents), IV to VI (forward 4-years citations), and VII to IX (average citations per patent) of Table 8. For each proxy of innovation, we report estimates on the overall sample (columns I, IV, and VII), the sample of investments before the GFC (columns II, V, and VIII), and the sample of investments undertaken after the GFC (columns III, VI, and IX).

Overall, BVC-backed ventures do not seem to show significant differences compared to IVC-backed ones in terms of innovation level before the investment, as indicated by the non- significant coefficients of patent data and patent quality variables in columns I, IV, and VII. However, when splitting the sample, the difference becomes negative and significant for investments made before the GFC (estimates in columns II, V, and VIII), while it is not significant for investments undertaken after the GFC (estimates in columns III, VI, and IX). We interpret these results as follows: while in the years before the GFC, BVCs seem to choose ventures with a lower innovation level than IVCs, this difference disappears in the years following the GFC. In other words, our findings suggest a positive role of the GFC in influencing BVC investment strategies toward selecting ventures with an innovation level aligned to the one required by IVCs. In fact, before the GFC, the level of innovation activity has a negative and significant impact on the probability of receiving BVC financing. The Average Marginal Effect of innovation activity proxies in all the models reported in Table 8 are negative and significant in the period before crisis. Specifically, a 1%

Table 7 Univariate analysis on impact: innovation level in the years following the investment

	Innovation levels in the years following the investment								
	Overall			Before GFC			After GFC		
	BVC-backed	IVC-backed	Diff	BVC-backed	IVC-backed	Diff	BVC-backed	IVC-backed	Diff
Patent count (logs)	1.564	1.596	− 0.032	1.441	1.768	− 0.327	1.678	1.492	0.186
Forward 4-years citations (logs)	0.771	1.516	− 0.745**	1.169	2.546	− 1.377**	0.406	0.890	− 0.484
Average citations per patent (logs)	0.610	0.946	− 0.336*	0.949	1.437	− 0.488*	0.299	0.648	−0.349*

** Significance at 5% level. * Significance at 10% level increase in the number of patents reduces the probability of receiving BVC financing by 3.62%. Similarly, a 1% increase in the number of forward 4-year citations results in a 1.23% decrease in the probability of receiving BVC financing. Finally, a 1% increase in average citations reduces the probability of receiving BVC financing by 2.45%.

To provide a clearer idea of the economic impact, when the innovation activity level increases from the 5th percentile of its distribution (equal to 0 for both the number of patents and patent quality) to the 95th percentile (equal to 1.61, 3.83, and 1.71 for the number of patents, forward 4-year citations, and average citations, respectively), the probability of receiving BVC financing, before the crisis,decreases by more than 50% (− 65.73%, − 57.6%, and − 53.05%, according to the different proxies of innovation activity).

Conversely, after the GFC, the level of innovation activity has positive, but not significant impact on the probability of receiving BVC financing: the Average Marginal Effects of innovation activity proxies in all the models related to the post crisis period reported in Table 8 are positive (equal to 0.44%, 0.31%, and 0.72% for the number of patents, forward 4-year citations, and average citations, respectively) but not significant.

A graphical representation of Average Marginal Effects, both before and after crisis, according to the three proxies used for innovation activity (patent count, forward 4-years citations and average citations per patent) is provided in Fig. 1.

Similar results are reported in Table 9, using innovation-related variables as a proxy of innovation.

The results are in line with those previously commented. Overall, BVC-backed ventures do not show significant differences compared to IVC-backed ones in innovation output before the investment, as indicated by the non-significant coefficients of innovation-related variables in columns I and IV. However, splitting the sample makes the difference negative and significant for investments made before the GFC (estimates in columns II and V). At the same time, it is not significant for investments undertaken after the GFC (estimates in columns III and VI).

The Average Marginal Effects of both innovation-related variables are negative and significant in the period before GFC. Specifically, a 1% increase in the metric of innovation (*Innovation topic*) significantly reduces the probability of receiving BVC financing by 0.04%. When considering *Top innovator*, the Average Marginal Effects is negative and significant before GFC (− 11.19%) indicating that Top Innovator has a significantly lower probability of receiving BVC financing before the crisis.

Again, to provide an idea about the economic impact, when the metric of innovation (*Innovation topic*) increases from the 5th percentile of its distribution (equal to 2.45) to the 95th percentile (equal to 145.92), the probability of receiving BVC financing decreases by 61.76%. This reduction is even more remarkable when considering *Top innovator*, i.e., the high-innovative dummy indicating ventures for which the value assigned to the Innovation topic exceeded the 90th percentile of the distribution: the probability of receiving BVC decreases by 85.55%, from 7.73% when Top Innovator takes value 0–1.11% for high-innovative startups.

Table 8 Estimates on selection effect: probability of receiving BVC financing.

	Probability of receiving BVC financing								
	Overall	Before GFC	After GFC	Overall	Before GFC	After GFC	Overall	Before GFC	After GFC
	I	II	III	IV	V	VI	VII	VIII	IX
Patent count (logs)	− 0.016	− 0.348**	0.071						
	(0.063)	(0.193)	(0.067)						
Forward 4-years Citations (logs)				− 0.016	− 0.118**	0.050			
				(0.029)	(0.051)	(0.035)			
Average citations per patent (logs)							− 0.019	− 0.235***	0.114
							(0.054)	(0.080)	(0.071)
Financed amount	0.017***	0.005	0.017***	0.017***	0.011	0.016***	0.017***	0.007	0.017***
	(0.005)	(0.014)	(0.005)	(0.005)	(0.014)	(0.005)	(0.005)	(0.015)	(0.005)
Age (logs)	0.196***	0.105	0.222***	0.196***	0.103	0.224***	0.195***	0.081	0.224***
	(0.030)	(0.092)	(0.032)	(0.029)	(0.090)	(0.031)	(0.029)	(0.092)	(0.031)
Const	− 3.181***	− 2.562***	− 3.300***	− 3.180***	− 2.529***	− 3.301***	− 3.179***	− 2.493***	−3.310***
	(0.540)	(0.487)	(0.618)	(0.540)	(0.485)	(0.617)	(0.540)	(0.493)	(0.618)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fintech types dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6805	558	5926	6805	558	5926	6805	558	5926

Metric: patents and patent quality

This table reports the regression results of the probit estimation in the years before VC investments. The dependent variable is the probability of receiving BVC in the future. Heteroskedasticity corrected robust standard errors clustered at the firm level are reported in parenthesis. *** Significance at 1% level. ** Significance at 5% level. * Significance at 10% level

The same statistics estimated in the period after GFC, suggest an estimation of Average Marginal Effects that are slightly positive (0.002% for Innovation Topic and 0.01% for Top Innovator) but not significant.

A graphical representation of Average Marginal Effects of innovation-related variables (Innovation topic and top innovator), both before and after crisis, is provided in Fig. 2.

As to control variables, all models suggest that BVC-backed ventures are older at the time of the first financing round and receive a higher amount of financing from their investors.

As a robustness check and to provide further insights about the innovation trend of VC-backed companies across the GFC, we resort to an alternative model to test our selection effect by BVCs. More in detail, we estimate a model including, as the dependent variable, the innovation level at the investment year (measured by patent, patent quality data and innovation level variables), and as independent variables: a) time period (d_after GFC) that allows us to understand whether the innovation level of selected ventures has changed after the GFC for IVC-backed ventures; b) BVC-backed dummy, indicating whether differences exist between IVC- and BVC-backed ventures before the GFC in terms of innovation level of invested ventures; c) the interaction between BVC-backed dummy and d_after GFC dummy, indicating whether, after the GFC, BVCs change their selection by aligning their strategy to that of IVCs.

Results are reported in Table 10. We report OLS estimates by using, as dependent variables: the number of Patents in logs (column I), Forward 4-year citations in logs (column II), and Average Citations per year (column III). In the remaining columns, we report results using Innovation level variables used as a further proxy of innovation, i.e., *Innovation topic* in column IV, while, in column V, we report probit estimates using *Top Innovator* as the dependent variable.

Results indicate that, for IVC-backed ventures, the innovation level of selected ventures after the GFC has significantly increased in terms of patent and patent quality, as indicated by the positive and significant coefficient of d_after GFC dummy in models I, II, and III. The coefficient of the BVC-backed dummy is negative and significant in all models, confirming that, before the GFC, BVCs selected ventures characterized by a lower level of innovation than IVCs. This result holds whatever proxy is used for innovation. For the purpose of our study, it is more interesting to look at the interaction between BVC-backed and d_after GFC dummies, representing the marginal effect of the GFC for BVC-backed ventures. This indicates whether and how BVCs changed their investment strategy after the GFC. Results confirm that, after the GFC, BVCs aligned with IVCs by selecting more innovative ventures: the interaction coefficient is positive and significant in all models. In order to provide further insights, we resorted to a Wald test on the sum of coefficients of BVC-backed and its interaction with d_after GFC to estimate whether, after the crisis, BVCs invested in ventures characterized by higher levels of innovation compared to IVCs. Results are reported in the bottom part of Table 10 and indicate the marginal effects of being BVC-backed after the GFC on the innovation level of invested companies: the non-significance of the estimated coefficients suggests that, after the GFC, BVCs aligned with IVCs in selecting innovative fintech ventures. Interestingly, in

Table 9 Estimates on selection effect: probability of receiving BVC financing

	Probability of receiving BVC financing					
	Overall	Before GFC	After GFC	Overall	Before GFC	After GFC
	I	II	III	IV	V	VI
Innovation topic	− 0.000	− 0.004**	0.001			
	(0.001)	(0.002)	(0.001)			
Top innovator				− 0.093	− 1.130***	0.002
				(0.085)	(0.274)	(0.091)
Financed amount	0.017***	0.012	0.016***	0.017***	0.011	0.016***
	(0.005)	(0.014)	(0.005)	(0.005)	(0.014)	(0.005)
Age (logs)	0.194***	0.082	0.228***	0.195***	0.087	0.229***
	(0.029)	(0.090)	(0.031)	(0.029)	(0.090)	(0.031)
Const	−3.1791***	− 2.391***	−3.313***	−3.176***	− 2.594***	−3.303***
	(0.541)	(0.506)	(0.622)	(0.540)	(0.512)	(0.619)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fintech types dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	6805	558	5926	6805	558	5926

Metric: innovation topic

This table reports the regression results of the probit estimation in the years before VC investments. The dependent variable is the probability of receiving BVC in the future. Heteroskedasticity corrected robust standard errors clustered at the firm level are reported in parenthesis. *** Significance at 1% level. ** Significance at 5% level. * Significance at 10% level

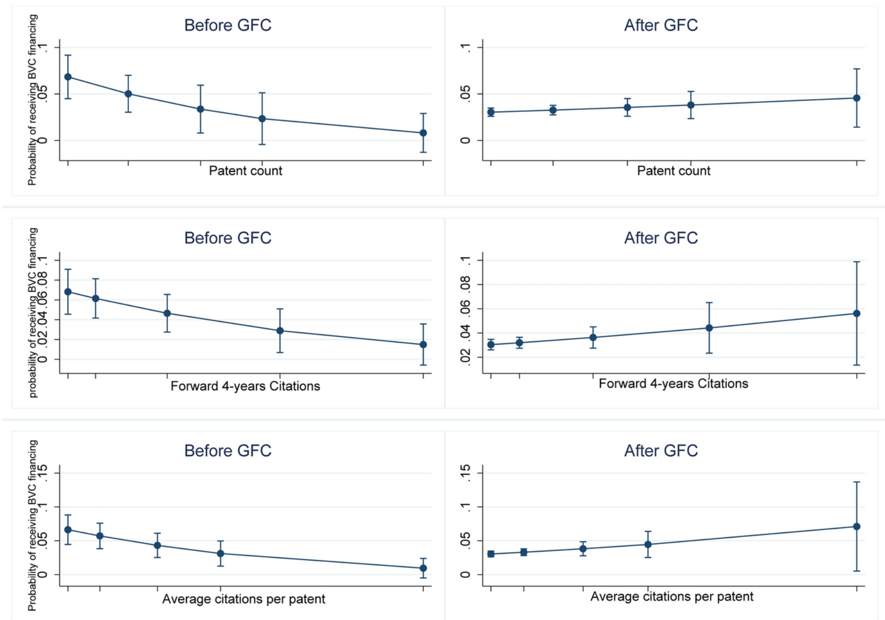

Fig. 1 Marginal effects of innovation activity (patent) variables on the probability of receiving BVC financing

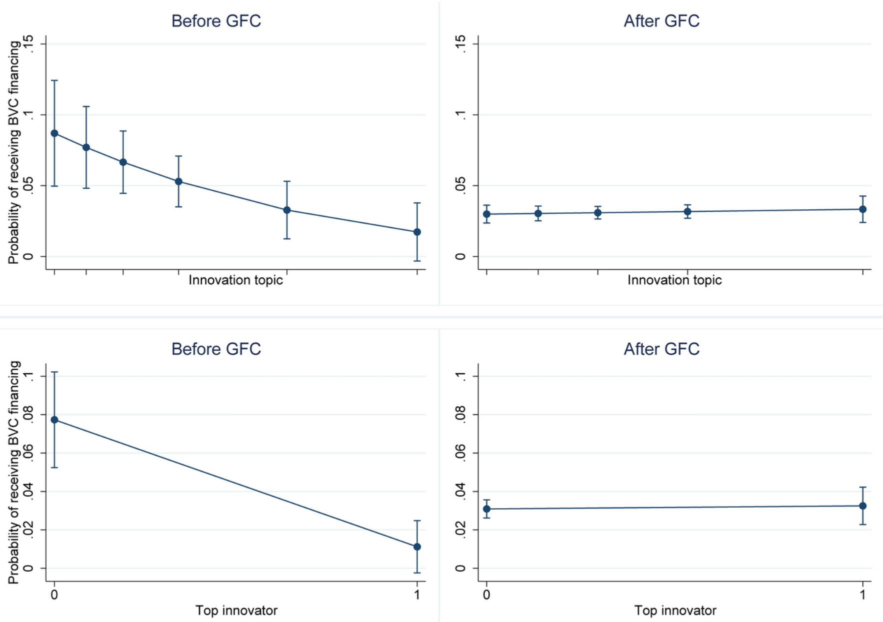

Fig. 2 Marginal effects of innovation-related variables on the probability of receiving BVC financing

terms of citations (columns II and III), results of the Wald test indicate that BVCs get to supersede IVCs after the GFC, selecting ventures with higher patent quality than those selected by IVCs (both in terms of Forward 4 years citations that in terms of average citations per year).

5 Additional evidence on the impact of VC investments on innovation

VC activity is also associated with the ability of VC managers to nurture ventures and to create value through innovation, for example, by stimulating patent creation (Kortum and Lerner 2000), thus enabling firms to quickly transform ideas into marketable products (Pierrakis and Saridakis 2017). A substantial amount of academic research has examined how VCs contribute to value creation through innovation (e.g., Arqué-Castells 2012; Bertoni et al. 2010; Bertoni and Tykvová 2015; Chemmanur et al. 2014; Dimitrova and Eswar 2019; Dutta and Folta 2016; Faria and Barbosa 2014; Gompers and Lerner 2001; Hellmann and Puri 2000; Kortum and Lerner 2000; Lerner and Nanda 2020; Pierrakis and Saridakis 2017; Popov and Roosenboom 2012; Tian and Wang 2014). Most of this research has focused on how VCs contribute to innovation at the regional, country, or industry level (Popov and Roosenboom 2012; Safari 2016; Samila and Sorenson 2010), while less research has dealt with firm-level analyses (Dutta and Folta 2016). In general, research points to a positive effect on innovation with evidence that VC-backed ventures bring more radical innovation to the market

Table 10 Estimates on selection effect: innovation levels

	Patent count (logs)	Forward 4-years citations (logs)	Average citations per patents (logs)	Innovation topic	Top innovator
	I	II	III	IV	IV
d_after GFC	0.798***	1.139***	1.140***	2.903	0.023
	(0.066)	(0.203)	(0.127)	(3.069)	(0.120)
BVC_backed	− 0.224***	− 0.727***	− 0.328***	− 11.536*	− 0.756**
	(0.078)	(0.214)	(0.078)	(6.915)	(0.315)
d_after GFC*BVC_backed	0.269***	0.847***	0.407***	13.273*	0.779**
	(0.092)	(0.226)	(0.087)	(7.703)	(0.338)
Financed amount	− 0.018***	− 0.021***	− 0.016***	0.117	0.006**
	(0.001)	(0.002)	(0.001)	(0.079)	(0.003)
Age (logs)	0.104***	0.122***	0.039***	2.121***	0.019
	(0.009)	(0.017)	(0.009)	(0.571)	(0.018)
Const	0.544	− 1.014	− 1.576***	− 25.862**	− 1.273***
	(0.043)	(0.124)	(0.071)	(9.420)	(0.300)
Year dummies	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes
Fintech types dummies	Yes	Yes	Yes	Yes	Yes
N	7524	7524	7524	7524	7404
Marginal effects of BVC-backed	0.004	0.119*	0.078**	1.737	0.023
After GFC	(0.049)	(0.071)	(0.031)	(3.384)	(0.119)

This table reports the regression results of the OLS estimation. The dependent variables are the innovation proxies: natural logs of patent count, forward 4-year citation, citation per patent, and *Innovation topic*. Probit estimations are reported in column IV when using the dummy *Top Innovator* as the dependent variable. *** Significance at 1% level. ** Significance at 5% level. * Significance at 10% level

(Dushnitsky and Lenox 2006; Hellmann and Puri 2000; Kortum and Lerner 2000) and are associated with greater patenting rates (Faria and Barbosa 2014).[9]

As additional evidence, we performed a multivariate test to isolate an investor's relative ability to impact (or treat) ventures' innovation and ensure that it is not confounded with an investor's relative ability to select ventures (that we showed in our principal results as being significantly related to both the type of investor and the time period). The empirical challenge in exploring the relative contribution of different

[9] Different explanations have been advanced to the argument that VCs may enhance innovation (Dushnitsky and Lenox 2006; Dutta and Folta 2016; Kortum and Lerner 2000). These explanations range from implementing efficient governance and monitoring mechanisms to the role played by VCs in lowering information asymmetry problems that impede new technology ventures to establishing a position in the industry (Dutta and Folta 2016; Hsu 2006). The first explanation is that VCs contribute to fostering innovation of their portfolio firms through active monitoring, coaching (with their organizational and managerial capabilities), providing complementary assets, such as access to distribution, social, and professional networks. Indeed, the enforcement of decision-making through efficient governance and monitoring bestows VCs a significant influence on a venture's strategic decisions, including innovation (Chemmanur et al. 2014; Hsu 2006). The second explanation is that the endorsement of a VC represents a signal of quality that increases a venture's market visibility and potential of cooperation with commercial or research partners (Hsu 2006), which in turn spurs ventures' innovation output.

VCs on innovation is tied to correctly separating selection (i.e., the decision to pick a venture) from treatment effects (i.e., the active involvement after the investment) in order to deal with the potential endogenous relationship (Bertoni et al. 2011; Croce et al. 2013; Popov and Roosenboom 2012; Samila and Sorenson 2011). Indeed, the real effects of VC on innovation are difficult to predict (Dessí and Yin 2012) and involve several empirical issues linked to the causality relationship between VC and innovation (Faria and Barbosa 2014), so a positive relationship might be found not because VC leads to innovation but because innovative firms select VCs as a source of finance.

Given the relevance of selection effects, we had to estimate the impact of BVCs compared to IVCs, net of the difference in the selection that emerges from our analyses. First, to consider both selection and impact effects, following Dutta and Folta (2016), we resorted to a difference-in-differences estimation in which the number of patents is used as the dependent variable.[10] As to the independent variables, we included a dummy *BVC-backed before inv* taking value 1 in the years before the entry of the BVC in the venture's equity capital and 0 afterward. This dummy is included to control for selection effects. A dummy *BVC-backed after inv* is used to estimate the impact of BVCs and takes the value 1 starting from the year following the investor's entry in the venture's equity capital onwards and 0 in the years before. A dummy *IVC-backed after inv* is used to control for the impact of IVCs and takes the value 1 starting from the year following the investor's entry in the venture's equity capital onwards and 0 in the years before.

We incorporated a series of controls to capture the characteristics of sample ventures and the market that could affect ventures' innovation output. Venture age is controlled because prior research suggests an association with the patenting behavior of the firm (Sørensen and Stuart 2000). Venture age is measured as the calendar time in years between year t and the founding year of the venture. We also control for the amount received at the time of financing by VC investors (in logs). Fintech services provided by the ventures and venture location are controlled using indicator variables. We also controlled for market fluctuations using country and year dummies.

In order to explore the role played by the GFC on the investment strategies of VC investors, we resorted to Model 2, in which we included a dummy *d_after GFC* that takes value 1 in the years following the GFC (i.e., from 2008 onwards). We interacted this dummy with *BVC-backed before inv* to test whether the GFC influenced the selection strategy of BVCs and with *BVC-backed after inv* and *IVC-backed after inv* to test whether the GFC influenced the impact of BVCs and IVCs on the innovation activities of invested ventures.

The results of these estimates are reported in the first two columns of Table 11.

In Table 11, the dependent variables in columns I–II are the natural logs of the patent count. Column I refers to Model 1, while column II relates to Model 2, exploring the role exerted by the GFC on the investment strategy of VCs in fintech ventures in the total sample of observations. As to the estimates of Model 1, results indicate that BVCs seem to select ventures with a not significantly different number of patents

[10] Please note that we are not considering citations as dependent variable because they are affected by truncation effects.

Table 11 Difference in difference estimations

	Total sample		Matched sample	
	Model 1	Model 2	Model 3	Model 4
BVC-backed before inv	− 0.026	− 0.252***		
	(0.063)	(0.094)		
BVC-backed before inv*d_after GFC		0.270**		
		(0.114)		
BVC-backed after inv	0.796***	0.878***	1.061***	1.029***
	(0.159)	(0.227)	(0.146)	(0.249)
BVC-backed after inv *d_after GFC		0.147		0.228
		(0.302)		(0.325)
IVC-backed after inv	1.015***	1.419***	0.925***	1.176***
	(0.053)	(0.108)	(0.084)	(0.131)
IVC-backed after inv *d_after GFC		− 0.436***		− 0.313**
		(0.122)		(0.141)
d_after GFC		0.437***		0.266
		(0.089)		(0.188)
Financed amount	− 0.020***	− 0.018***	− 0.015***	−0.014***
	(0.001)	(0.001)	(0.003)	(0.003)
Age (logs)	0.141***	0.143***	0.047**	0.049**
	(0.023)	(0.022)	(0.024)	(0.024)
Const	0.648*	− 0.641***	0.470**	− 0.181*
	(0.349)	(0.144)	(0.288)	(0.260)
Year dummies	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes
Fintech types dummies	Yes	Yes	Yes	Yes
N. obs	9691	9691	1321	1321

Impact of VC investment on patenting activity

This table reports the regression results of diff-in-diff estimation in the total and matched samples. The dependent variables are natural logs of the patent count. Heteroskedasticity corrected robust standard errors clustered at the firm level are reported in parenthesis. *** Significance at 1% level. ** Significance at 5% level. * Significance at 10% level

than IVCs. In terms of impact, results suggest a positive and significant effect of both BVCs and IVCs in terms of the number of patents filed by the invested venture, thus indicating that both types of VCs can favor a significant increase in innovation activity after the entry into the venture's equity capital.

However, the advent of the GFC significantly changed the investment strategy of BVCs and its impact on the innovation activity of invested ventures. We first focus on selection. Looking at Model 2 estimations, results suggest that, in accordance with our principal results, BVCs changed their selection strategy by choosing more innovative ventures, as shown by the positive and significant coefficients of the interaction between *BVC-backed before inv* and *d_after GFC*. Results confirm that BVCs changed their attitude after the GFC. Indeed, the coefficient of *BVC-backed before inv*, indicating selection in the years before the GFC, is negative and significant, confirming that, before the GFC, BVCs selected less innovative firms than IVCs. However, after the GFC, their investment strategy changed toward selecting more innovative ventures, thus aligning with IVCs. In order to correctly estimate

Table 12 Difference in difference estimations (selection and impact)

Total sample		Matched sample	
Model 2		Model 4	
Selection			
BVC versus IVC before GFC	− 0.252***		
A: BVC-backed before inv	(0.094)		
BVC versus IVC after GFC	0.017		
*B: BVC-backed before inv+BVC-backed before inv *d_after GFC*	(0.069)		
Effect of GFC	0.269**		
*C=B-A: BVC-backed before inv *d_after GFC*	(0.114)		
IMPACT (net of selection)		Impact	
BVC versus IVC before GFC	− 0.288	BVC versus IVC before GFC	− 0.146
D: BVC-backed after inv—BVC-backed before inv—IVC-backed after inv	(0.247)	*G: BVC-backed after inv—IVC-backed after inv*	(0.236)
BVC versus IVC after GFC	0.024	BVC versus IVC after GFC	0.395*
*E: BVC-backed after inv+BVC-backed after inv *d_after GFC-BVC-backed before inv- BVC-backed before inv *d_after GFC-IVC-backed after inv—IVC-backed after inv *d_after GFC*	(0.201)	*H: BVC-backed after inv+BVC-backed after inv *d_after GFC-IVC-backed after inv—IVC-backed after inv *d_after GFC*	(0.210)
Effect of GFC	0.313	Effect of GFC	0.541*
*F=E-D: (BVC-backed after inv- BVC-backed before inv-IVC-backed after inv) *d_after GFC*	(0.318)	*I=H-G: (BVC-backed after inv-IVC-backed after inv) *d_after GFC*	(0.325)

Marginal effects

*** Significance at 1% level. ** Significance at 5% level. * Significance at 10% level the impact of the GFC on the difference between BVCs and IVCs in terms of selection, we performed tests on the linear combinations of the estimated coefficients in our models. More specifically, in the upper part of Table 12 (column I), we reported the estimates (based on Wild tests on the linear combinations of coefficients) of the difference between BVCs and IVCs in terms of selection effect, both before (A) and after the crisis (B). The difference (i.e., C, estimated as B-A) indicates the impact of the GFC.

Results confirm what was discussed in our principal estimates: while before the GFC, BVC investors chose ventures with lower innovation activity, after the GFC, they significantly changed their selection strategy by picking more innovative ventures so that the difference with IVCs becomes not significant. Accordingly, the effect of the GFC is positive and significant, indicating a shift in BVC investment selection practices towards more innovative ventures.

We then focus on the impact of VC investments on the innovation rate of invested ventures, controlling for selection effects. Looking at coefficients in Table 11, estimates suggest that, while IVCs reduced, after the GFC, their impact on the innovation rate of invested ventures, the same result does not hold for BVCs. However, in order to evaluate the impact of BVCs with respect to IVCs (net of selection effects), looking at the coefficients of the interaction with *d_after GFC* is not enough to test whether there is a change in the propensity of BVCs to oversee their investments effectively and efficiently and to enhance the innovation activity and the performance of funded ventures in the aftermath of the GFC. To correctly estimate differences between BVCs and IVCs, we need to look at the linear combinations reported in Panel B, estimating differences between VC investors, net of selection effects, before and after the GFC. More in detail, D represents the difference in the impact of BVCs versus IVCs, net of selection effects, before the GFC, while E estimates the same difference after the GFC. The coefficient F, estimated as the difference between E and D, measures the effect of the GFC in influencing the differential impact of BVCs with respect to IVCs.

We first focus on D, for which results offer interesting insights. When we control for selection before the GFC, the difference between BVCs and IVCs in fostering the innovation of invested ventures is not significant. Controlling for selection, we may state that the lower impact of BVCs (in comparison with IVCs) in fostering innovation of the invested ventures disappears: BVCs, even though they invest in less innovative ventures, do not show significant differences, before GFC, in influencing the innovation rate of invested ventures. In other words, net of selection effects, there is no difference in the impact of BVCs and IVCs on fostering innovation at the firm level before the GFC. When we estimate the differential impact of BVCs with respect to IVCs after the GFC, tests on the coefficient E show that, after the GFC, the difference between BVCs and IVCs remains not significant in terms of number of patents. In other words, net of selection effects, there is no difference in the impact of BVCs and IVCs on fostering innovation at the firm level after the GFC. We interpret this result by considering that BVCs seem to have not completely profited from their improved selection abilities in strengthening their ability to foster innovation in the invested ventures after the investment, aligning but not exceeding IVCs.[11]Looking at coefficient F, the GFC does not have a significant role in influencing this result.

Given the relevance of selection effects, we estimate the impact on innovation by performing the analysis on a matched sample as a robustness check. More in detail, we performed a matching procedure to identify, out of the IVC-backed sample, a group of ventures that more closely resemble BVC-backed ones (i.e., the "treated" companies) regarding observable characteristics. Specifically, we resorted to propensity score matching (PSM) (Rosenbaum and Rubin 1983). PSM selects matched companies based on a propensity score, i.e., the probability to "be treated" (in this case, to be a BVC-backed venture) estimated based on a set of matching variables. The PSM is then used to identify ventures with the highest propensity score of being similar to BVC-backed ones. We estimated the propensity score with a probit model in which the dependent variable is 1 for BVC-backed ventures and 0 for IVC-backed ones. In order to control differences across GFC, we perform two different matchings, before and after GFC, looking for IVC-backed ventures that are more similar to BVC-backed ones financed in the two different periods. Regarding the matching variables, we included the amount of financing received by the venture at the time of financing, patents filed (in logs) before BVC investment to control for differences in selection in terms of innovation performance, venture foundation year, financing year, fintech types, and country dummies. Based on the probit model results, we computed a propensity score, and for every BVC-backed venture, we picked the 5 IVC-backed ventures with the closest propensity score ("nearest neighbors"). We ended up with 1006 matched ventures, 196 of which were BVC-backed and 810 IVC-backed,[12] which entered into our estimates on the matched sample.

Moreover, to assess the appropriateness of our matching algorithm, we test the balancing of matching variables after matching, including the amount financed, patents filed (in logs) before BVC investment, age of the company at the time of financing, foundation year, investment year, fintech category and country dummies. Rubin's R, i.e., the ratio of the variances of the propensity score in the two groups, is 1.54 before matching,0.98 after matching in the matching before crisis, 2.15 before matching, and 1.29 after matching in the matching after crisis. Values of Rubin's R between 0.5 and 2 are generally considered indicators of balanced matching (Rubin 2001).

As expected, according to the matching procedure, all the differences between IVC and BVC-backed ventures disappear in the matched sample according to the amount received at the time of first funding, patents filed (in logs) before BVC investment, foundation year, geographical location, fintech services sectors, and investment year. Table 13 reports the distribution of the matched sample in terms of foundation year, country of operation, fintech services category, and investment year. Both total distribution and distribution by typology of VC investors are reported.

[11] We also estimated the same models by disentangling investments undertaken before and after the GFC. Results are in line with those discussed in this section and are not reported in the text for the sake of brevity but are available from the authors upon request.

[12] Six BVC-backed ventures are excluded by the matching procedure based on the common support option that drops treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls.

Table 13 Distribution of the matched sample by foundation year, country, fintech category, and investment year

	Matched sample					
	BVC-backed		IVC-backed		Total sample	
	n. ventures	%	n. ventures	%	n. ventures	%
Foundation year						
Before 2000	49	25.00	166	20.49	215	21.37
2001–2005	22	11.22	64	7.90	86	8.55
2006–2010	27	13.78	131	16.17	158	15.71
2011–2015	72	36.73	292	36.05	364	36.18
2016–2019	26	13.27	157	19.38	183	18.19
Continent						
Africa	7	3.57	17	2.10	24	2.39
Asia	25	12.76	115	14.20	140	13.92
Europe	72	36.73	273	33.70	345	34.29
North America	86	43.88	378	46.67	464	46.12
Oceania	4	2.04	19	2.35	23	2.29
South America	2	1.02	8	0.99	10	0.99
Fintech services						
Asset and wealth management	11	5.61	46	5.68	57	5.67
Exchange services	6	3.06	22	2.72	28	2.78
Financing	45	22.96	160	19.75	205	20.38
General Fintech services	69	35.20	287	35.43	356	35.39
Insurance	11	5.61	48	5.93	59	5.86
Loyalty program	6	3.06	27	3.33	33	3.28
Payment	25	12.76	92	11.36	117	11.63
Regulatory technology	21	10.71	116	14.32	137	13.62
Risk management	2	1.02	12	1.48	14	1.39
Investment year						
Pre-GFC: before 2008	31	15.82	128	15.80	159	15.81
Post-GFC: after 2008	165	84.18	682	84.20	847	84.19
Total	196	100.00	810	100.00	1006	100.00

We then estimate our model on the matched sample as reported in the last column of Table 11. In Table 11, the dependent variables in columns III–IV are the natural logs of the patent count. Column III refers to Model 3 estimating the impact of VC investment on the innovation level, as measured by patent count (logs) on the matched sample. Column IV relates to Model 4, exploring the role exerted by the GFC on the investment strategy of VCs in fintech ventures on the matched sample. As to the estimates of Model 3, we focus on the impact of VC investments on the innovation rate of invested ventures (after having controlled for selection effects through the matching procedure). Results confirm what was discussed in the estimates of the total sample. Looking at coefficients in Table 11, estimates suggest a positive and significant effect of both BVCs and IVCs in terms of the number of patents filed by the invested venture after the investment, thus indicating that both types of VCs can favor a significant increase in innovation activity after the entry into the venture's equity capital.

When we include the moderator related to the GFC, results are again in line with what we commented before on estimates on the total sample, suggesting that, while IVCs reduced, after the GFC, their impact on the innovation rate of invested ventures, the same result does not hold for BVCs. Again, to correctly estimate differences between BVCs and IVCs, we need to look at the linear combinations reported in Panel B, estimating differences between VC investors before and after the GFC. More in detail, G represents the difference in the impact of BVCs versus IVCs before the GFC, while H estimates the same difference after the GFC. The coefficient I, estimated as the difference between H and G, measures the effect of the GFC in influencing the differential impact of BVCs with respect to IVCs.

We first focus on G, for which results align with what was found before in the analyses on the total sample: before the GFC, the difference between BVCs and IVCs in fostering the innovation of invested ventures is not significant. When we estimate the differential impact of BVCs with respect to IVCs after the GFC, results are still in line with those obtained in the total sample by becoming slightly significant: the test on the coefficient H shows that, after the GFC, the difference between BVCs and IVCs becomes significant in terms of number of patents, this indicating that BVCs seem actually to have profited from their improved selection abilities in strengthening their ability to foster innovation in the invested ventures after the investment, getting to exceed IVCs. In line with this assumption, looking at coefficient I, the GFC has a slightly significant role in influencing this result.

Finally, as a final robustness check, we applied an endogenous switching regression approach to control for selection. Specifically, we examined the VC treatment effect by analyzing how innovation would advance if a venture that received a specific VC investment (BVC or IVC) had not received such an investment. In other words, the analysis aims to answer two questions: (i) what would the innovation of a venture that did not receive IVC investment (but received BVC financing) have been, had it received IVC financing? and (ii) what would the innovation of a venture that did not receive BVC investment (but received IVC financing) have been, had it received BVC financing?

We adopted a generalized Heckman model (Heckman 1979; Maddala 1983) that sorts the ventures over two different investment states (BVC-backed and IVC-backed) with one regime being observed for any given venture and accounts for the effect of unobservable heterogeneity by using the inverse Mills ratio. In the two-step analysis, the first-stage reduced form dynamic probit estimation predicts the probability of receiving the specific VC investment that reflects the focal VC selection equation and calculates the inverse Mills ratios.

The first stage regression includes variables that could affect BVC selection: venture age at the time of the first investment, patents filed (in logs) before BVC investment, amount received at financing round, venture location, industry, and *d_after GFC* dummy. In addition, it includes exogenous variables correlated with the supply of BVC financing that affect the likelihood of receiving BVC investment but are independent of the future venture's innovation: the percentage of BVC investments in the focal country and in the focal fintech category over the total BVC investments in the same year.

Table 14 Switching regressions: first and second stages

Dependent variable	First stage	Second stage	
	BVC-backed	Patent count (logs)	
		BVC-backed	IVC-backed
	(1)	(2)	(3)
Age (logs) at investment year	0.257***	0.096	− 0.055
	(0.039)	(0.246)	(0.060)
Patent count (logs) before investment	− 0.053	0.648***	1.507***
	(0.066)	(0.188)	(0.067)
Financed amount	0.016***	0.007	0.011*
	(0.005)	(0.024)	(0.006)
Percentage of BVC inv per country	0.826**		
	(0.334)		
Percentage of BVC inv per industry	2.399***		
	(0.895)		
IMR lambda		0.184	− 2.331**
		(1.071)	(1.112)
d_after GFC	− 0.268	− 0.187	− 1.412***
	(0.184)	(0.574)	(0.150)
Const	− 2.158***	− 0.566	2.715***
	(0.719)	(2.696)	(1.047)
Country dummies	Yes	Yes	Yes
Fintech dummies	Yes	Yes	Yes
N.obs	4378	202	4176

Stage 1 dependent variable (BVC-backed) is a dummy variable that takes the value of "1" whether the venture is BVC-backed and "0" otherwise. The dependent variables in stage 2 are innovation variables (log of patent coun). Stage 2 includes the inverse Mills ratio obtained from Stage 1. Heteroskedasticity corrected robust standard errors are reported in parenthesis. *** Significance at 1% level. ** Significance at 5% level. * Significance at 10% level

In the second stage, ventures' innovation is regressed on the inverse Mills ratio (obtained from the first stage) and the control variables, separately for BVC- and IVC-backed ventures. Because we are interested in the difference in innovation between BVC- and IVC-backed ventures, the expected value of innovation is conditional on receiving the specific VC investment. Therefore, we should assess the estimates' properties for BVC- and IVC-backed ventures separately.

Table 14, column I, reports the first-stage probit estimation assessing the determinants of VC investment. Columns II and III report the second-stage regressions for BVC-backed and IVC-backed ventures and include the inverse Mills ratio calculated from the first stage. The second-stage results show that while the inverse Mills ratio is negative and significant for the regression of IVC-backed ventures, it remains insignificant for BVC-backed ventures. This suggests that, compared to IVCs, BVCs may also rely on unobservable factors when selecting ventures.

Table 15 reports the results of the counterfactual analysis for BVC-backed versus IVC-backed ventures. Results show that, on average, there is a significant difference in the actual patent counts for BVC-backed ventures compared to what they could (hypothetically) have achieved had they instead received IVC financing, suggesting that BVCs are more able to foster the innovation level of invested ventures. Conversely, there is no significant difference in the actual patent counts for IVC-backed ventures compared to what they could (hypothetically) have achieved had they instead received BVC financing. This suggests that there is no superiority between

Table 15 Switching regressions: counterfactual analysis

	Actual value of BVC-backed venture	Predicted value of BVC-backed venture if they had received IVC investment instead of BVC investment	Difference between (1) and (2)	Actual value of IVC-backed venture	Predicted value of IVC-backed venture if they had received BVC investment instead of IVC investment	Difference between (4) and (5)
	(1)	(2)	(3)	(4)	(5)	(6)
Overall sample years[a]						
Patent count (logs)	0.360	− 0.321	0.682**	0.503	0.515	− 0.011
	(0.117)	(0.230)	(0.237)	(0.035)	(0.016)	(0.035)
Before GFC[b]						
Patent count (logs)	1.017	1.659	− 0.641	1.789	0.631	1.159***
	(0.521)	(0.448)	(0.638)	(0.262)	(0.135)	(0.273)
After GFC[c]						
Patent count (logs)	0.241	0.207	0.034	0.357	0.415	− 0.058**
	(0.099)	(0.063)	(0.088)	(0.026)	(0.015)	(0.025)

[a]This table reports the counterfactual analysis based on the results of the second-stage switching regression. Columns 1, 2, and 3 present, respectively, the mean of the actual innovation measure for BVC-backed ventures, the mean of the counterfactual (hypothetical) innovation measure of BVC-backed ventures if they had not received IVC investment (obtained from column 3 from Table 11) and the difference between the means. Columns 4, 5, and 6 present the means of the actual innovation measure for IVC-backed ventures, the mean of the counterfactual (hypothetical) innovation measure of IVC-backed if they had received BVC investment (obtained from column 2 from Table 11), and the difference between the means. *** Significance at 1% level for t-test of the mean difference. ** Significance at 5% level for t-test of the mean difference. * Significance at 10% level for t-test of the mean difference

[b]This table reports the counterfactual analysis based on the results of the second-stage switching regression only for ventures invested before the GFC. Columns 1, 2, and 3 present, respectively, the mean of the actual innovation measure for BVC-backed ventures, the mean of the counterfactual (hypothetical) innovation measure of BVC-backed ventures if they had not received IVC investment (obtained from column 3 from Table 11) and the difference between the means. Columns 4, 5, and 6 present the means of the actual innovation measure for IVC-backed ventures, the mean of the counterfactual (hypothetical) innovation measure of IVC-backed if they had received BVC investment (obtained from column 2 from Table 11), and the difference between the means. *** Significance at 1% level for t-test of the mean difference. ** Significance at 5% level for t-test of the mean difference. * Significance at 10% level for t-test of the mean difference

[c]This table reports the counterfactual analysis based on the results of the second-stage switching regression only for ventures invested after the GFC. Columns 1, 2, and 3 present, respectively, the mean of the actual innovation measure for BVC-backed ventures, the mean of the counterfactual (hypothetical) innovation measure of BVC-backed ventures if they had not received IVC investment (obtained from column 3 from Table 11) and the difference between the means. Columns 4, 5, and 6 present the means of the actual innovation measure for IVC-backed ventures, the mean of the counterfactual (hypothetical) innovation measure of IVC-backed if they had received BVC investment (obtained from column 2 from Table 11), and the difference between the means. *** Significance at 1% level for t-test of the mean difference. ** Significance at 5% level for t-test of the mean difference. * Significance at 10% level for t-test of the mean difference

BVCs and IVC groups in nurturing innovation rates. Interestingly, if we repeat the same analysis only on investments made in the years before the GFC, IVC-backed ventures show a higher level of patents compared to what they could (hypothetically) have achieved had they instead received BVC financing, while following the GFC, the opposite results are obtained. Results suggest that there is an improvement in BVC contribution to the patent activity of invested ventures in line with the analysis shown in Tables 11 and 12, which is significant for the matched sample.[13]

Summarizing, in line with our principal results, after the GFC, results suggest that BVCs could improve, with respect to IVCs, in their task of nurturing innovation rates.

6 Discussion

6.1 Contribution to the literature

Despite the growing interest in fintech and some preliminary evidence on fintech VC (Chemmanur et al. 2020; Cumming and Schwienbacher 2018; Kolokas et al. 2022), little is known about the relative attention that different VC types devote to the degree of innovation of target ventures in their selection processes and how this is affected by the GFC. The literature has shown that different governance configurations may affect the risk attitude, investment preferences, and expected returns of VC investors (Bertoni et al. 2015; Croce et al. 2015), in a way that can vary with changing market conditions (Bertoni et al. 2019).

Given the highly innovative nature of the fintech sector, our main focus was examining how BVCs compare to IVCs in their selection dynamics of innovative ventures before and after the GFC. Our study offers several contributions to the stream of research on entrepreneurial finance and crisis response. On the theoretical forefront, we extend the applicability of the theory of mimetic isomorphism to the equity finance sector and add insights by disentangling the pre- and post-crisis periods. An important extension of previous studies on VC financing is the development of the basic argument that different VC types can uniform to each other in their investment practices following an exogenous shock. By establishing a link between the notion of mimetic isomorphism, the GFC and the investment selection strategies of VCs, the comparison between the investment strategies of BVCs and IVCs becomes a novel angle to study. Similarly, we inform neo-institutional theory more generally by proposing a novel application context beyond the conventional discourse within international business management (e.g. to explain firms' decisions on offshore outsourcing or entry strategies into foreign markets).

Our results indicated that, in the pre-crisis period, BVCs did not seem to pay exclusive attention to the innovation potential of target firms and selected less innovative firms (in terms of innovation potential, number of patents, and patent quality)

[13] Results of the second-stage switching regression on which the counterfactual analyses are based on focusing only on ventures invested before and after the GFC are not reported in the text for the sake of brevity but are available from the authors upon request.

compared to IVCs. This attitude is explained by the tendency of BVCs to be less subject to pressures determined by time-oriented performance, as it happens with IVCs (Andrieu 2013; Croce et al. 2015; Hellmann 2002; Hellmann et al. 2008). Accordingly, BVCs endorse a longer-term investment horizon that makes them more tolerant of innovation failures or quality. We then developed theoretically grounded arguments based on the concept of mimetic isomorphism from neo-institutional theory. The GFC exerted mimetic isomorphic pressure on BVCs which changed their investment practices towards those of IVCs, with a tendency to select more innovative fintech firms. This change in attitude is linked to the fact that after the crisis, banks went under greater pressure to endorse a digital transformation and enhance their digital capabilities. Banks became aware: i) that advances in fintech allow the implementation of faster, more customer-centric, and user-friendly operations, which ultimately increase the overall efficiency and transparency of banking services (Barrett et al. 2015; Brandl and Hornuf 2020; Chemmanur et al. 2020; Sangwan et al. 2019); ii) of the need to rapidly adapt their financial services offerings to evolving demand in order to remain competitive and to face the entry of new fintech players, which are increasingly taking over functions that were traditionally within their domain (Hornuf et al. 2021; Jakšic and Marinc 2019; Sangwan et al. 2019). Mimicking the IVC selection strategy towards more innovative firms was seen as a viable solution to reduce uncertainty and nurture banks' core business banks with technology-driven solutions.

6.2 Limitations and future research

Some possible limitations of our study and areas for future research merit consideration. Firstly, the study focuses on the fintech sector, which, while appropriate given its innovative nature, may limit the generalizability of our findings to other industries. Future research could explore whether similar patterns hold in other high-tech sectors or traditional industries. Secondly, the study relied on patents and a novel metric incorporating text mining and semantic network analysis to capture the innovation potential of fintech startups. While these metrics provide valuable insights, they may not capture the full innovation potential of startups within the rapidly evolving fintech landscape. Future research could explore alternative metrics, or a combination of indicators, to offer a more comprehensive understanding of innovation in this context. Furthermore, our innovative methodology could be employed to analyze various textual documents pertaining to the company, extending beyond its description. This includes scrutinizing project documents, examining patent content, or delving into the knowledge exchanged among employees through email communications. For example, researchers could consider patent citations or use text mining to derive measures of patent impact (Arts et al. 2021; Kelly et al. 2018). This would enable a classification of the innovative capabilities of fintech startups based on the characteristics of their patent outputs.

Additionally, the study predominantly focused on the GFC, leaving room for further investigation into the dynamics of VC selection strategies during other economic downturns or periods of financial instability—such as the COVID-19 pandemic, which represented another significant exogenous shock to the global economy. Moreover, our research highlights the shift in the behavior of BVCs towards more innovative ventures post-crisis. However, the specific mechanisms and internal changes within BVCs that facilitated this transformation remain unexplored. Future studies could delve into the organizational structures, decision-making processes, and internal adaptations within BVCs that enable a shift towards greater innovation focus. New methods, such as experimental approaches (e.g., Lohrke et al. 2010), may allow researchers to delve deeper into these issues, as has been seen in other types of venture financing—see, for example, Ademi et al. (2023) in the corporate venture capital (CVC) context, or Block et al. (2019) in VCs, BAs, and family offices.

Lastly, while our study distinguishes between BVCs and IVCs, it does not fully account for the potential heterogeneity within these categories. For instance, BVCs affiliated with different types of banks (e.g., commercial vs. investment banks) or IVCs with varying strategic focuses might exhibit different investment behaviors. Future research could delve into more granular categorizations of VCs and consider additional types, such as CVCs and family offices.

6.3 Policy and managerial implications

Our study has important policy and managerial implications for fintech entrepreneurs looking for financing and BVCs investing in the fintech industry. First, it seems that a good innovation potential (number of patents and quality) is important when searching for BVC financing after the GFC, as it is for IVCs. Thus, besides solid financial statements, fintech ventures must also be aware that BVCs are concerned about innovation. This is conducive to the idea that the potential opportunities for fintech entrepreneurs supported by BVCs are broad, as with IVCs. Besides receiving capital resources and value-added services to fuel innovation, BVC-backed fintech ventures may have the possibility of accessing banks' broader customer base, receiving better credit conditions from banks afterward, getting access to banks' advice on how to cope with regulation, extensive social relations, industrial hub contacts. From an investor's point of view, our results offer insights into how the shift in the investment strategy of BVCs after the crisis can potentially affect their portfolios' risk/return profile. Moreover, a broader question is how the banking industry will be reshaped as banks increasingly absorb technological breakthroughs of fintechs through their VC arms.

Exploring the patterns and attitudes to innovation of BVCs compared to IVCs in the light of the exogenous shock caused by the GFC in fintech is relevant and timely because it presents both a challenge and an opportunity for policy: a challenge in terms of moving beyond the conventional wisdom that VC types have different investment strategies that fail to adapt to the dictates of a changing economic environment and an opportunity in terms of transforming the VC'ecosystem' into a more vibrant and competitive environment. Since fintech startups are increasingly growing in number, there is a pressing need for policymakers to develop regulatory initiatives that can enhance the development and application of digital technologies in the financial sector. A deeper understanding of the conditions under which VCs select innovation in the fintech sector and how BVCs are paving the way is important for policymakers who want to enhance the funding opportunities for fintech startups, promoting the fintech industry and, at the same time, setting the boundaries so that innovations can be compliant with regulations without losing their enabling technological power.

7 Conclusion

In this paper, we used the theoretical lens of mimetic isomorphism to examine how the GFC affected the different investment patterns in fintech associated with IVCs and BVCs. We analysed a comprehensive dataset of 6711 fintech ventures globally, spanning the period from 1995 to 2019. We looked at the selection dynamics of VCs based on the innovation level of their target ventures. As done in several works (Dutta and Folta 2016; Lerner 2002; Pierrakis and Saridakis 2017), we used patents (and patent quality proxied by citations) as metrics for innovation. In addition to patents, we introduced a new metric based upon combined methods and tools of text mining and semantic network analysis to capture the innovation potential of invested firms. As additional evidence, we also explored how BVCs contribute to value creation through innovation for fintech startups, controlling for selection effects, compared to IVCs before and after the GFC. Our results suggest that BVCs changed their investment strategies relative to IVCs in response to the GFC; whereas pre-crisis BVCs favoured less innovative firms relative to their IVC counterparts, post-crisis they began to align themselves with IVCs by investing in more innovative firms.

Appendix

Academics have been largely interested in the governance structure of VC investors, which can influence their investment strategies, objectives, investment portfolios, expected returns, and the performance of the companies they invest in (Bertoni et al. 2015; Croce et al. 2015; Da Rin et al. 2013). Several studies have examined the relationship between different VC governance mechanisms and their investment patterns. Table 16 lists the main differences between IVCs and BVCs identified in the literature.

Table 16 Main differences between IVCs and BVCs

	IVC	BVC	Literature
Primary objective	Financial objective: achieve successful portfolio exits or abnormal returns More pressure to exit early and generate abnormal returns	Strategic objective: generate potential clients for the underwriting and lending activities of associated banks Less pressure to exit early and generate abnormal returns	Andrieu (2013), Andrieu and Groh (2012), Croce et al. (2015), Dimov and Gedajlovic (2010), Gompers and Lerner (2001), Hellmann (2002), Hellmann et al. (2008), Manigart et al. (2002)
Investment selection focus	Focus on the innovation potential of high-growth companies	Focus on the creditworthiness of high-growth companies Preference for later-stage companies, with a lower probability of default	Andrieu and Groh (2012), Croce et al. (2015), Cumming et al. (2008), Dimov and Gedajlovic (2010), Hellmann et al. (2008), Yoshikawa et al. (2004)
Monitoring and value-added activities	Active monitoring of portfolio companies Active involvement in guidance and mentoring	Less active monitoring of portfolio companies Less active involvement in day-to-day operations and mentoring	Baum and Silverman (2004), Bertoni et al. (2015), Croce et al. (2015), Cumming et al. (2008), Hellmann and Puri (2002), Yoshikawa et al. (2004)

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