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Enhancing online visibility through strategic alliances: the case of bank-FinTech relationships

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Abstract

Purpose – This work aims to explore the effects of (equity and non-equity) strategic alliances between banks and FinTechs on FinTechs' online visibility.

Design/methodology/approach – For a sample of 124 Italian FinTechs, the authors measured online visibility through their website ranking (Google PageRank) and website traffic (Google Trends). Consistent to the historical depth of these measures, the authors separately investigated the effect of equity and non-equity (contractual) agreements on online visibility by means of ordinal logistic regressions and diff-in-diff analysis.

Findings – Strategic alliances with banks enhance FinTechs' online visibility. Although both equity and contractual agreements positively influence the popularity of FinTechs' website achieved through the activity of internal and external online content creators (websites ranking), only equity agreements are effective in attracting Internet users (website traffic).

Practical implications – When deciding to interact with banks, FinTechs' managers should consider that equity agreements may be a powerful strategic choice for enlarging the customer base and boosting visibility of FinTechs.

Social implications – Fostering strategic alliances between banks and FinTechs contributes to FinTechs' growth, generating virtuous mechanisms of innovation, financial inclusion and better allocative efficiency of the financial system.

Originality/value – This work expands marketing knowledge and literature regarding online visibility determinants, by investigating the benefits of strategic alliances and cooperation in the market, while providing an empirical strategy replicable by future marketing studies.

Keywords Online visibility, Strategic alliances, FinTech, Banks, Google trends, Google PageRank, Diff-in-diff

Paper type Research paper

1. Introduction

Technological advancement is strongly supporting the digitalization of the financial industry and new technologies and innovations are increasingly applied to every aspect of the production and distribution of financial services, moving towards online and digitalized value generation (Niemand *et al.*, 2021). The digital revolution of financial services is primarily driven by financial start-ups, i.e. FinTech firms (Elsaid, 2021).

FinTechs are internet-based companies that bring to the market digital financial services through the implementation of new technologies and information technology (IT) solutions. FinTechs only serve customers through their websites (Laidroo *et al.*, 2021) and online visibility is a strategic asset for their growth. Often in direct competition with traditional financial institutions, FinTech firms widen the range of financial services at individuals' and organizations' disposal, giving them the opportunity to access convenient, personalized and innovative solutions even when they belong to traditionally excluded or underserved customer segments (Salampasis and Mention, 2018).

Although innovative financial solutions have several benefits for customers, FinTech firms face a number of challenges when trying to expand their market presence in the financial services industry, where the level of competition is increasing strongly (Elsaid, 2021). Here, traditional financial institutions, in particular banks, still serve the largest share of the market, and competition among FinTech firms is very high as well. Furthermore,

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FinTechs are usually young financial firms and their ability to survive may be threatened by lack of reputation, limited financial resources, limited experience and, above all, lack of a sufficiently large customer base (Nguyen *et al.*, 2022; Carbó-Valverde *et al.*, 2022; Felländer *et al.*, 2018).

In this challenging context, enhancing online visibility is of the utmost importance for FinTechs to attract a greater number of prospective customers and increase sales and profitability. Also, greater online visibility might allow FinTech firms to deal with the growing competition in the financial market by attracting the attention of web users more effectively (Lee *et al.*, 2015).

In this respect, establishing strategic alliances with incumbents, particularly banks, may be a feasible way for FinTechs to enhance their online visibility (Harasim, 2021), thanks to the possibility of exploiting reputational spill-overs and the access to wider customer base, distribution channels and media coverage (Enriques and Ringe, 2020; Klus *et al.*, 2019; Bömer and Maxin, 2018). This is somewhat common in FinTechs' expectation when strategically cooperate with traditional financial institutions. For example, the equity crowdfunding platform BacktoWork24, that allows private and professional investors to fund start-ups, small-medium enterprises (SMEs) and real estate projects, decided to join the Intesa Sanpaolo Banking Group in order to support the development of its business plan and attract more investors to the platform and thus increasing the available financial resources for companies as stated by the co-founder and chief executive officer (CEO) of BacktoWork24 [1]. The same reasons are behind the partnership between Sella Banking Group and Moneyfarm, a FinTech company offering innovative advisory and investment services. The partnership was an important step for growth, gaining the opportunity to offer their innovative investment solution to new market segments [2].

Strategic alliances with banks are expected to strengthen FinTechs' ability to attract potential customers, reputation and market presence and, thus, their online visibility. This is the focus of the current study, which aims to empirically test the causal effect between bank-FinTech relationships and FinTechs' online visibility, while exploring whether equity and contractual agreements have similar effects.

The study is motivated by some gaps that we identified in the extant literature.

Starting from literature on online visibility determinants (Pant and Pant, 2018; Wang and Xu, 2017; Molla-Descals *et al.*, 2014; Nikolaeva, 2005; Drèze and Zufryden, 2004), for the first time we test if strategic alliances have any role in the enhancement of firms' online visibility. We study online visibility within the financial industry, which is underexplored by this literature stream (Cioppi *et al.*, 2019), and specifically concerning FinTech literature, we offer the first empirical evidence of the possibility to enhance FinTechs' online visibility through relationships with banks, an issue that has only been proposed in the literature from a purely theoretical point of view.

In this paper, we consider two aspects of online visibility, i.e. website ranking and website traffic (Wang and Xu, 2017; Serrano-Cinca *et al.*, 2010). The proxy used for website ranking is Google PageRank, which measures the quality of FinTechs' website through the number of references (or links) to it, giving more weight to links from high-traffic websites (Garofalakis *et al.*, 2002; Murphy and Scharl, 2007). From FinTechs' perspective, Google PageRank represents the degree of accessibility and popularity of their website achieved through internal advertising and outreach efforts, but also through the attention that external online content creators (partners, blogs, online magazines, newspapers, etc.) pay to FinTechs' business and activities. As a measure of website traffic, we employed Google Trends data, that measures how many searches have been made for a specific keyword (FinTechs' name) relative to the total number of searches over time (Ding and Hou, 2015) and that have the potential to reveal Internet users' interest (Sulong *et al.*, 2022; Liu *et al.*, 2021; Vosen and Schmidt, 2011).

By analysing a sample of 124 Italian FinTech companies, we empirically demonstrate that strategic alliances with banks enhance FinTechs' online visibility, measured through website ranking and traffic. However, we identified a significant difference between equity and non-equity (contractual) agreements. Although both types of strategic alliance positively influence FinTechs' websites ranking, we found that only equity agreements are effective in attracting users to FinTechs' websites, thus increasing website traffic.

Our results are really important for FinTechs' managers. If they wish to maximize the accessibility and popularity of their websites by increasing their networks and external links, they can opt for both equity and non-equity partnerships, but the path through equity deals, although more difficult and longer, ensures stable growth in FinTechs' web traffic and attractiveness.

From a theoretical standpoint, our work expands marketing knowledge and literature regarding online visibility determinants, by investigating the benefits of strategic alliances and cooperation in the market. In this vein, this work also offers an empirical strategy replicable by future research on online visibility studies and other marketing topics. The evidence that equity and contractual agreements have different effects on website ranking and website traffic open up a new and important theoretical stream. Indeed, the different reactions and behaviours emerging between online content creators and Internet users deserve further investigation by future studies and research. Finally, this work contributes to FinTech literature, expanding current studies on the development paths of FinTechs start-ups, highlighting the positive role of the stakeholder network and contributing to the debate on the nature and benefits of bank-FinTech relationships.

The remainder of the paper is structured as follows. In Section 2 we present the literature review and develop our hypotheses. Section 3 is dedicated to the description of samples, data and methods. Results of the analysis and robustness checks are described and discussed in Sections 4 and 5, respectively. Section 6 concludes the paper, also highlighting implications, limitations and directions for future research.

2. Literature review and hypotheses development

In this Section, we review the main contributions belonging to the online visibility and FinTech literature strands, we identify literature gaps and introduce our hypotheses. More specifically, after delving into the concept of "online visibility" and its centrality in the Internet adoption process (Section 2.1), we then discuss the importance of online visibility enhancing in the specific case of FinTech firms (Section 2.2). In line with this, we particularly stress the channels through which strategic alliances with banks may improve FinTechs' online visibility. Following the identification of literature gaps in Section 2.3, we conclude suggesting our hypotheses in Section 2.4 and 2.5.

2.1 The concept of online visibility

The literature defines firms' online visibility as "the extent to which a user is likely to come across a reference to a company's Web site in his or her online [. . .] environment" (Drèze and Zufryden, 2004). Online visibility is considered as the middle (and crucial) stage of the Internet adoption process, which follows a company's decision to create an online presence and precedes the build-up of their online reputation (Cioppi *et al.*, 2019).

Online presence, i.e. firms' decision to present themselves on the web (De Bakker and Hellsten, 2013), is a necessary but not a sufficient condition for their success in the online environment. Potentially, any organization can access the web, thus the mere decision to be present online is not enough to differentiate from competitors (Raguseo *et al.*, 2017). As also underlined by Smithson *et al.* (2011), competitive advantage depends on how Internet presence is managed and exploited, making it effective in maximizing online visibility. An effective online presence is essential for organizations to achieve higher search engine rankings, to increase Internet traffic to their websites and, finally, to boost sales and gain market shares (Chua *et al.*, 2009; Murphy and Scharl, 2007).

Indeed, once firms manage to intensify their online visibility and web traffic flow, their approach in designing and providing information and services in the online context will determine their overall online reputation (Rodríguez-Díaz *et al.*, 2018; Charest and Bouffard, 2015) and ability to attract more investors, clients, suppliers or employees and to gain long-term price, cost and performance advantages (Diana-Jens and Ruibal, 2015; Reuber and Fischer, 2011).

Naturally, even if online visibility is not enough to be fully successful in the online environment, it certainly represents the first step in the achievement of a competitive advantage (Smithson *et al.*, 2011). In the extant literature, there is empirical evidence on the association between online visibility and business performance measures. Vaughan (2004), for example, finds positive correlations between revenues and online visibility, measured through the number of inlinks to company websites for IT companies. Similarly, Vaughan and Romero-Frías (2010), focussing on the banking industry (top 50 banks in the world), find positive associations between online visibility and net income in addition to revenues. Wang and Xu (2017), Wang and Vaughan (2014) and Vaughan and Yang (2013), analysing samples of firms operating in several industries, show that web visibility positively affects short- and long-term business performance measures, including revenues, profits and Tobin's Q. Similar results are also provided by Melo *et al.* (2017) for the tourism industry, by demonstrating that greater visibility on an infomediary website positively influences business profitability.

2.2 FinTech and online visibility: the role of bank-FinTech relationships

FinTechs are predominantly in start-up stage, suffering from increasing competition and limited financial resources, experience and, above all, customer base (Carbó-Valverde *et al.*, 2022; Felländer *et al.*, 2018). In this context, the enhancement of online visibility may be fundamental for FinTech firms' success. Indeed, FinTechs are similar in some respects to dot-com companies: they adopt a virtual business approach and only sell financial services through their websites (Sakas *et al.*, 2023; Serrano-Cinca *et al.*, 2010; Razi *et al.*, 2004), so the enhancement of online visibility is crucial and necessary (Drèze and Zufryden, 2004). By attracting more users towards their websites, FinTechs may have the opportunity to attract and retain a greater number of prospective customers (Cioppi *et al.*, 2019), with benefits in terms of sales, time to break-even and business scaling-up. Also, the higher the level of their website's popularity, the better its positioning in search engines (Gonzalez and Palacios, 2004). This may allow FinTechs to better deal with the growing competition in attracting the attention of web surfers, who are faced with an ever-increasing number of website alternatives and tend to exhibit a low level of patience while surfing the Internet (Drèze and Zufryden, 2004).

Many authors have theorized that FinTechs may enhance their visibility through collaborations with incumbents, in particular banks (Enriques and Ringe, 2020; Bömer and Maxin, 2018). According to the resource-based view (RBV) of the firm (Grant, 1991; Rumelt, 1997), strategic alliances play a positive role in firm's growth (Powell *et al.*, 1996), as they represent a way to overcome internal constraints by gathering the necessary resources from external strategic partners (Baum *et al.*, 2000; Henderson and Cockburn, 1994). In this perspective, strategic alliances, motivated by complementary know-how and competencies, integrate firms' resources and capabilities (Frenken, 2000; Marion and Fixson, 2014; Piva *et al.*, 2012).

Furthermore, the literature identifies some mechanisms underlying the causal effect between bank-FinTech strategic alliances and FinTechs' visibility. Banks provide a wide range of financial services (advisory, credit, payment and investment services, etc.) to different types of customers, who interact with banks in the role of entrepreneurs, investors, borrowers or information acquirers. So, banks are diversified businesses and have a huge number of stakeholders. From this perspective, strategic alliances with banks may allow FinTechs to access to banks' relational networks and stakeholders (Klus *et al.*, 2019; Milanov and Shepherd, 2013).

The establishment of bank-FinTech relationships is usually announced to stakeholders in news reports, either through the websites of the two parties to the agreement or through third-party newspapers and online magazines. As stakeholders, including potential customers, read about a firm of interest in the news, they might be persuaded to visit the corporate website to gather more information, with a positive effect on online visibility and web traffic (Pant and Pant, 2018; Nikolaeva, 2005). In addition, when banks agree to advertise or distribute FinTechs' financial products and services, the latter gain access to wider online distribution channels and, consequently, increase their online visibility (Raguseo *et al.* (2017) highlight a similar mechanism for small hotels which decide to offer rooms through online travel agencies (OTAs), such as Booking.com and Expedia).

2.3 Literature gaps

Overall, the extant literature on online visibility, on strategic alliances and FinTech exhibits some literature gaps, which are addressed and, as far as possible, filled by this study. When studying the determinants of firms' online visibility, researchers have proposed and tested several drivers, including country, industry, firm, product and buyer characteristics (Pant and Pant, 2018; Wang and Xu, 2017; Molla-Descals *et al.*, 2014; Nikolaeva, 2005). To date, the literature totally lacks of empirical contributions exploring the role of strategic alliances in enhancing firms' online visibility. At the same time, and from a managerial standpoint, the study of the effects of strategic alliances paid major attention to aspects related to financial and operational performance, competitive advantage, knowledge and resources acquisition, customer satisfaction and innovation (Kohtamäki *et al.*, 2018), leaving aside potential benefits for alliances' participants in terms of visibility. By focussing on strategic alliances between banks and FinTech firms, this study provides the first empirical evidence on the issue. The choice to focus on bank-FinTech relationships stems from three considerations. Firstly, FinTechs are internet-based service companies and results of our study concerning strategic alliances with incumbents might be interesting for other companies operating in other industries. Secondly, and specifically concerning FinTech literature, the possibility to enhance FinTechs' online visibility through relationships with banks has been proposed in the literature from a purely theoretical point of view, without offering empirical demonstrations on the issue. Thirdly, as concern online visibility, the majority of scientific contributions mainly focus on the tourism and industrial sectors, while the financial sector has received less attention (Cioppi *et al.*, 2019).

2.4 Hypotheses development: the effects of bank-FinTech relationships on FinTechs' online visibility

With the aim of filling the gaps identified in Section 2.3, and considering the line of reasoning of Sections 2.1 and 2.2, we suggest the following hypothesis:

H1. Strategic alliances with banks positively affect FinTechs' online visibility.

Online visibility is often measured through firms' website ranking and website traffic (Rossi *et al.*, 2018; Pant and Pant, 2018; Chua *et al.*, 2009; Murphy and Scharl, 2007).

Compared with other online visibility measures based on surveys (Smithson *et al.*, 2011; Drèze and Zufryden, 2004), website ranking and website traffic are simple, objective and easy to collect measures (Wang and Vaughan, 2014). They reflect two different perspectives of online visibility (Wang and Xu, 2017; Serrano-Cinca *et al.*, 2010). From the FinTechs' point of view, website ranking represents the positioning of its website during searches, so that the higher the ranking, the greater the online visibility and the probability that an Internet surfer will land on their website, which consequently gains credibility and reputation (Serrano-Cinca *et al.*, 2010; Murphy and Scharl, 2007). Search engines use proprietary algorithms to rank web pages, and are usually based on inlink counts, i.e. direct references or external links to a website that reveal it to potential visitors (Wang and Xu, 2017). Inlinks are extremely valuable for companies' online visibility and are considered equivalent to online word-of-mouth (WOM) referrals (Liu *et al.*, 2021). On the other hand, web traffic measures FinTechs' ability in attracting visitors (i.e. prospective customers) to their websites, with a potential positive effect on sales and performance (Serrano-Cinca *et al.*, 2010). Therefore, website ranking represents the degree of accessibility and popularity of FinTechs' website achieved through internal advertising and outreach efforts, but also through the attention that external online content creators (partners, blogs, online magazines, newspapers, etc.) pay to FinTechs' business and activities. Web traffic, instead, reveals Internet users' interest (Sulong *et al.*, 2022; Liu *et al.*, 2021; Vosen and Schmidt, 2011). To better address the role of bank-FinTech relationships in newcomers' online visibility, following the above line of reasoning we further divide H1 into two sub-hypotheses:

H1a. Strategic alliances with banks positively affect FinTechs' website ranking.

H1b. Strategic alliances with banks positively affect FinTechs' website traffic.

The measures of website ranking and traffic used in this paper are based on data provided by Google, as explained in Section 3.1. Given the different nature and frequency of the measures of online visibility, the testing of H1a and H1b will follow two different empirical strategies, as explained in Sections 3.2 and 3.3 for website ranking and website traffic, respectively.

2.5 Hypotheses development: the need to consider the type of bank-FinTech relationships

The literature on strategic alliances also suggests that there are major differences between equity and non-equity (contractual) agreements (Das and Teng, 2000; Yoshino and Rangan, 1995). The types of alliance are shown to have different effects on growth, innovation and performance of startups participating in the agreement (Cacciolatti *et al.*, 2020; Hagedoorn *et al.*, 2018; Plummer *et al.*, 2016). Therefore, when testing the hypotheses introduced above, it would be feasible to observe differences between equity and contractual agreements in terms of magnitude and timing of the effects on FinTechs' online visibility. This may be the result of the different degrees of interaction and integration between the parties, to which different levels of complexity in resource-sharing and synergies achievement may correspond (Todeva and Knoke, 2005; Williamson, 1991). Consequently, external stakeholders, including existing and potential customers, may have a different appreciation and understanding of the logic underlying equity and contractual agreements (Kale *et al.*, 2001). To consider this aspect, we explore the issue by considering equity and contractual agreements separately and we introduce the following hypotheses:

H2. Equity agreements with banks positively affect FinTechs' online visibility.

H3. Contractual agreements with banks positively affect FinTechs' online visibility.

As further detailed in Sections 3.2 and 3.3, these two hypotheses are simultaneously tested with H1a and H1b, by including in the empirical models both explanatory variables concerning equity and contractual agreements with banks.

3. Sample, data and methods

3.1 Sample and online visibility measures

To test our hypotheses, we analysed a sample of 124 Italian FinTechs providing payment, financing, investment and insurance services to consumers and businesses. These were identified through the "Italian FinTech ecosystem report" produced by E&Y (2020). In this paper we use three measures of FinTechs' online visibility: one is a search engine ranking and two are measures of website traffic.

To test our research hypotheses, we implemented *Google_PageRank* as the measure of FinTechs' website ranking. Google lists search results based on the PageRank algorithm (Garofalakis *et al.*, 2002), which measures the quality of a website through the number of references (or links) to it, giving more weight to links from high-traffic websites, and assigns a score from 0 to 10 (Murphy and Scharl, 2007). Accordingly, the ordinal categorical variable *Google_PageRank* assumes a value between 0 and 10, so that the higher the score, the higher a website's position. Unlike previous studies in the literature, we were unable to use data provided by Alexa (Wang and Xu, 2017; Piñeiro-Chousa *et al.*, 2021), a subsidiary of Amazon.com, since it discontinued the service on 1st May 2022 (https://www.alexa.com/).

With regard to website traffic measures, like Liu *et al.* (2021) and Molla-Descals *et al.* (2014) we measured FinTechs' website traffic through Google Trends. Launched at the beginning of 2004, the search volume index provided by Google Trends measures how many searches have been made for a specific keyword relative to the total number of searches over time (Ding and Hou, 2015). As highlighted in the literature, tools like Google Trends have the potential to reveal consumers' interests and to forecast consumption and firms' performance (Sulong *et al.*, 2022; Liu *et al.*, 2021; Vosen and Schmidt, 2011). Therefore, we introduce the following measures of FinTechs' website traffic: (1) *G_Trends*, which measures the search interest of Google users in each FinTech in the sample (we used the FinTech's name as keyword). Google Trends data range from 0 to 100, which respectively represent the lowest and the highest search volume of a specific keyword in a certain time frame, and are usually provided at weekly or monthly intervals. Therefore, we computed the yearly average of the Google Trends search volume index for each FinTech. To study the development of FinTechs' web traffic over time, we also introduce the variable (2) *G_Trends_Growth,* a web traffic growth indicator which measures the increase or decrease in the Google Trends rating compared to the year in which it first records a score different from zero (considered as base year). In order to obtain reliable data from Google Trends, we searched for FinTechs' names with topic, time and geographical filters applied, thus considering only information regarding searches in the "Finance" field, starting from the year in which FinTech firms were established and limited to the Italian context. Definitions of online visibility measures and all other variables used in this paper are provided in Table 1.

Naturally, the three measures of online visibility differ in terms of frequency. Unlike *G_Trend* and *G_Trend_Growth*, which supply data on a yearly basis, *Google_PageRank* lacks historical depth (information on websites' ranking was retrieved from Google in December 2022). While the former suits panel data analysis, the latter only allows cross-sectional analysis. For this reason, we describe the methodology applied for FinTechs' website ranking and website traffic separately.

Variable	Description
Online visibility measures	
Google_ PageRank	Ordinal categorical variable assuming a value ranging between 0 and 10
G_Trends	Yearly average of Google Trends
G_Trends_ Growth	Yearly Google Trends growth indicator. It assumes the value of 1 until the FinTech firstly register a positive yearly average Google Trends score (base year). In subsequent years, it measures the increase or decrease compared to the base year
Bank-FinTech relationships	
Equity_Agr	Binary variable equal 1 if the FinTech has had at least a shareholder bank
Partner_Agr	Binary variable equal 1 if the FinTech has previously established a contractual agreement with at least one bank
Bank	Binary variable equal 1 for treated FinTechs (with equity or contractual agreements with at least a bank)
FinTechs' features	
Blog	Binary variable equal 1 when the FinTech includes a blog/forum on their website
Social	Binary variable equal 1 when the FinTech includes external link to social media platforms
Customer	Categorical variable with three levels: "Business", "Consumer" and "All"
Product	Categorical variable with five levels: "Payments", "Financing", "Investments", "Insurance" and "Diversified"
Age	FinTechs' years of business activity
ROA (*)	The ratio of EBIT to total assets multiplied by 100
Revenues (*)	Logarithm of revenues
Efficiency (*)	The ratio of EBIT to operating costs
Leverage (*)	The ratio of debt to total assets
Intangibles (*)	Incidence of intangibles on total assets
Size (*)	Logarithm of total assets

Note(s): (*) Variables ONLY employed for propensity score matching (PSM)
Source(s): Table was created by the authors

Table 1.
Definition of variables in the datasets

3.2 Modelling FinTechs' website ranking: methods and independent and control variables

To investigate whether strategic alliances with banks, in the form of both equity and contractual agreement, affect FinTechs' website ranking, we model the *Google_PageRank* ordinal logistic variables by representing the probability that the i-th FinTech firms will fall within the m ordered outcome through the ordinal logistic function:

Model 1.

$$\pi_{m,i} = \text{Prob}(y_{m,i} = m|\boldsymbol{x}) = \frac{1}{1 + \exp(-\kappa_m + \beta X_i)} - \frac{1}{1 + \exp(-\kappa_{m-1} + \beta X_i)}$$

for $i = 1, 2, \ldots, n$ and where $\kappa_0 = -\infty$ and $\kappa_6 = +\infty$.

Here X_i represents the vector of independent and control variables. The two independent variables of interest are: (1) *Equity_Agr*, a binary variable that takes the value of 1 if the FinTech has had at least one shareholder bank, and (2) *Partner_Agr*, a binary variable that takes the value of 1 if the FinTech has previously established a contractual agreement with at least one bank. Equity agreements are identified through FinTechs' shareholding structure available in the Aida database, while contractual agreements are identified through FinTechs' websites, in particular by looking at the press release sections, and, like Hornuf *et al.* (2020), we also carried out a Google search.

In line with the extant literature, we also include several control variables. Following the empirical evidence provided by Pant and Pant (2018), we include control variables capturing FinTechs' efforts to engage and attract more users through the inclusion of blogs, forums or links to online social media, such as Facebook, Twitter and LinkedIn (also known as information prosociality), which are shown to have a positive impact on firms' website visibility. Social media platforms and blogs are widely used by FinTech firms (Abdillah and Mukti, 2021) and are of utmost importance for collecting customers' opinions, judgements and viewpoints, which are useful in improving and suitably complete the range of financial services in offer, in improving communication on collaborations, figures, events and activities (Franco-Riquelme and Rubalcaba, 2021) and marketing efforts and in increasing website visibility and e-reputation (Moccia *et al.*, 2021; Garzaro *et al.*, 2021). Therefore, we include the following control variables: (1) *Blog*, a binary variable that takes the value of 1 when the FinTech supports experience and knowledge-sharing between current and new customers through the inclusion of a blog or a forum on their website, and (2) *Social*, a binary variable that takes the value of 1 when the FinTech's website includes external links to various social media platforms, facilitating engagement with them.

According to the study by Wang and Xu (2017), business-to business (B2B) and business-to-consumer (B2C) firms are different in terms of number, risks, experience and switching behaviour of customers. This also means that B2B and B2C firms are faced with different search and purchasing behaviour on the part of customers, with different implications for online visibility. For this reason, we also include the categorical variable *Customer*, characterized by three different levels: "Business", if the FinTech offers financial services to business customers, "Consumer", if the FinTech offers financial services to consumer customers and "All" (base level), if customers are both businesses and consumers.

In the FinTech industry, online visibility may also depend on the specialization or diversification strategy adopted by FinTechs. This choice influences the number and size of competitors, as well as the concentration and growth opportunity of the market, which are also important drivers of value creation in the digital environment (Varadarajan and Yadav, 2002). Therefore, we also control for the type of financial services offered by FinTech firms through the variable *Product*, which has the following levels: "Payments" (base level), "Financing", "Investments", "Insurance" and "Diversified" (Tanda and Schena, 2019), where the last level refers to FinTech firms operating in more than one segment.

Finally, following the empirical evidence provided by Molla-Descals *et al.* (2014), we include *Age* as control variable, i.e. FinTechs' years of business activity. Firm age has been associated to stronger brand identity, more experience and resources (Steinfield *et al.*, 2005) and, above all, more inlinks to their website from external sources (Kannan and Govindan, 2011).

When studying the determinants of online visibility, some authors, including Pant and Pant (2018) and Wang and Xu (2017), consider firm size among the control variables. However, the close link between size and visibility may arise from a strong correlation rather than a causal relationship. Indeed, some contributions in the literature actually use firms' size as a proxy for their visibility (see for example Januarti *et al.*, 2019; Rand and Tarp, 2012; Hackston and Milne, 1996). In line with this stream, our sample shows a correlation between FinTechs' size (i.e. logarithm of total assets) and their online visibility ranging between 0.3 and 0.5, depending on the measure of online visibility considered. For this reason, in order to avoid biased results, we decided to not include FinTechs' size as control variable, but rather to implement it in our robustness checks and treat it as an alternative measure of online visibility.

Descriptive statistics of the variables in our cross-sectional dataset are shown in Table 2, while the correlation matrix is displayed in Table 3.

Table 2. Summary statistics of variables implemented in Model 1 (cross-sectional sample of 124 FinTechs)

Binary and discrete variables	Mean	Median	Standard deviation	Minimum	Maximum
Google_PageRank	2.758	3	1.212	0	7
Equity_Agr	0.226	0	0.42	0	1
Partner_Agr	0.298	0	0.459	0	1
Blog	0.436	0	0.498	0	1
Social	0.734	1	0.444	0	1
Age	5	5	2.922	1	20

Categorical variables (% of cases in the sample)	
Customers	Business 33.1%, Consumer 20.2%, All 46.7%
Products	Payments 13.7%, Financing 48.4%, Investments 27.4%, Insurance 6.5%, Diversified 4%

Source(s): Table was created by the authors

Table 3. Correlation matrix of the variables implemented in Model 1

	VIF	Google_ PageRank	Equity_ Agr	Partner_ Agr	Blog	Social	Customer	Product	Age
Google_ PageRank		1							
Equity_Agr	1.108	0.316 ***	1						
Partner_Agr	1.089	0.233 ***	0.238 ***	1					
Blog	1.373	0.311 ***	0.07	−0.004	1				
Social	1.283	0.469 ***	0.151 *	0.153 *	0.419 ***	1			
Customer	1.416	−0.052	0.011	−0.117	−0.013	0.123	1		
Product	1.651	0.048	0.003	0.031	0.071	−0.004	0.12	1	
Age	1.07	0.168 *	0.166 *	0.079	−0.011	0.169 **	−0.025	−0.13	1

Note(s): Significance levels: *, **, *** for 10%, 5% and 1% respectively
Source(s): Table was created by the authors

3.3 Modelling FinTechs' website traffic: a diff-in-diff approach

To study the effect of equity and contractual agreements on FinTechs' website traffic, we exploit the longitudinal nature of our dependent variables (i.e. *G_Trends* and *G_Trends_Growth*) and use the diff-in-diff (DID) estimation method. More specifically, the DID method allows us to estimate the effects of strategic alliances with banks on website traffic by comparing FinTechs which have these alliances (treated) and those which do not (control). The DID method requires a completely random selection between treatment and control group, otherwise the estimations can be largely biased. To mitigate endogeneity problems caused by selection bias, we applied the propensity score matching (PSM) technique before implementing DID, so as to ensure accurate results regarding the effects of equity and contractual agreements on FinTechs' website traffic.

3.3.1 Propensity score matching (PSM). PSM computes the probability of a FinTech to be involved in a strategic alliance as follows:

$$P_i = P(S = T|Z_{i,t})$$

Where $S = \{T, C\}$ represents the sample of FinTech firms including both treated and control units and $Z_{i,t}$ are the matching variables that can influence the probability of a FinTech receiving the treatment. P_i, i.e. the propensity score, is estimated through a logistic regression, while PSM is computed through the nearest neighbour matching, which is the most common form of matching used by extant literature (Zakrison *et al.*, 2018). The nearest neighbour algorithm matches each treated unit with the control units that are closest in terms of propensity score difference.

PSM was carried out following strict criteria:

(1) The PSM was applied separately for equity agreements (27 treated FinTechs) and contractual agreements (36 treated FinTechs), in order to study the effect of a single version of the treatment (consistency) as requested by the assumptions underlying the DID method;

(2) To enhance the comparability of treated and control units, PSM is carried out year by year, thus avoiding that active treated FinTechs are matched with control units that have not yet been established;

(3) We consider as matching variables ($Z_{i,t}$) several economic, financial and business features, i.e. return on assets (ROA), revenues, efficiency, leverage, intangibles, size, age, customer segment and product offered to the market (see Table 1 for definitions);

(4) The 1:2 proportion is applied, thus for each treated FinTech we matched two control units. The matching is without replacement, so that each control unit can be used as a match only once;

(5) All triplets of FinTech firms matched in a specific year are excluded from the PSM of the following years.

Table 4 provides a yearly overview of the number of treated and control FinTechs, as well as the cumulative final number of FinTech firms belonging to two separate panel datasets: one

Year	N. of treated FinTechs	N. of control FinTechs	Total *n*. of FinTechs	Cumulative *n*. of FinTechs
Equity agreements				
2009	1	2	3	3
2013	1	2	3	6
2014	1	2	3	9
2015	2	4	6	15
2016	3	6	9	24
2017	4	8	12	36
2018	4	8	12	48
2019	6	12	18	66
2020	5	10	15	81 (*)
Contractual agreements				
2013	1	2	3	3
2015	3	6	9	12
2016	4	8	12	24
2017	2	4	6	30
2018	7	14	21	51
2019	9	18	27	78
2020	6	12	18	96
2021	4	8	12	108 (**)

Note(s): PSM is performed every year in which an equity or contractual agreement is established. For each year, treated FinTech are matched with two control units, which are excluded from the PSM of the following year. Matching variables are ROA, revenues, efficiency, leverage, intangibles, size, age, customer segment and product offered to the market

(*) Final number of FinTechs in the panel dataset focused on equity agreement, with a total of 442 records

(**) Final number of FinTechs in the panel dataset focused on contractual agreement, with a total of 560 records

Source(s): Table was created by the authors

Table 4. Yearly overview of panel datasets' construction

focused on equity agreements (81 FinTechs observed during 2009–2021 for a total of 442 records) and the other focused on contractual agreements (108 FinTechs observed during 2013–2021 for a total of 560 records).

We handle the balance test of PSM as shown in Table 5. Overall, results indicate that on average matching estimations are reliable: after the matching, the reduction of absolute value of standard deviation of covariates is strong, in particular for ROA and efficiency, and the absolute value is less than the threshold of 20 (Rosenbaum and Rubin, 1985). Furthermore, treated and control FinTech firms are highly comparable, as shown in Table 6. Indeed, if we consider the 5% significance level as threshold, the treated and

Variable	Before/After matching	Group Treated	Group Control	Avg bias	Balance test Reduction Avg bias (%)
Equity agreements					
ROA	Before	−20.214	−18.505	80.958	77.9%
	After	−20.214	−14.442	18.674	
Revenues	Before	4.396	4.106	1.983	13.4%
	After	4.396	3.987	1.718	
Efficiency	Before	−0.652	−39.186	1367.042	99.9%
	After	−0.652	−0.328	1.762	
Leverage	Before	0.397	0.527	0.785	58.6%
	After	0.397	0.462	0.325	
Intangibles	Before	0.353	0.288	0.617	60.1%
	After	0.353	0.355	0.246	
Size	Before	5.810	5.550	94.620	99.2%
	After	5.810	5.482	0.790	
Age	Before	1.539	3.083	3.032	55.9%
	After	1.539	1.294	1.336	
Customer	Before	1.989	1.863	1.179	17.9%
	After	1.989	2.012	0.968	
Product	Before	1.806	1.827	0.771	27.8%
	After	1.806	1.759	0.557	
Contractual agreements					
ROA	Before	−18.728	−24.036	83.988	77%
	After	−18.728	−19.870	19.313	
Revenues	Before	3.430	4.350	1.972	6%
	After	3.430	3.720	1.854	
Efficiency	Before	−1.022	−59.770	1360.272	99.9%
	After	−1.022	−0.429	2.009	
Leverage	Before	0.405	0.572	0.829	34.6%
	After	0.405	0.495	0.542	
Intangibles	Before	0.264	0.349	1.177	3.7%
	After	0.264	0.374	1.134	
Size	Before	5.403	5.571	0.847	7.3%
	After	5.403	5.365	0.785	
Age	Before	1.863	3.204	2.944	29.5%
	After	1.863	2.068	2.075	
Customer	Before	1.843	1.991	1.169	15.1%
	After	1.843	1.935	0.993	
Product	Before	1.568	1.743	0.773	3.6%
	After	1.568	1.748	0.745	

Note(s): Results for equity agreements represents the average value of the statistics computed through PSM in the years 2009 and from 2013 to 2020. Results for contractual agreements represent the average value of the statistics computed through PSM in the years 2013 and from 2015 to 2021
Source(s): Table was created by the authors

Table 5. Balance test of variables before and after PSM

	Treated (1)	Control (2)	*t*-Test (1–2)
Equity agreements			
ROE (%)	−49.322	−22.584	−1.304
ROA (%)	−16.541	−10.701	−0.869
Revenues (*1000 euro)	407	119	1.287
Efficiency	−0.449	−0.334	−0.582
Leverage	0.472	0.394	1.103
Intangibles	0.372	0.338	0.478
Age	1.348	0.779	1.397
Size (*1000 euro)	1,347	442	1.817
Fisher exact test			
Customer	0.948		
Product	0.419		
Contractual agreements			
ROE (%)	−53.281	−46.777	−0.304
ROA (%)	−24.306	−17.019	−0.872
Revenues (*1000 euro)	197	739	−1.125
Efficiency	−0.825	−5.616	0.901
Leverage	0.499	0.518	−0.219
Intangibles	0.267	0.277	−0.228
Age	1.556	1.604	−0.107
Size (*1000 euro)	1,509	1,283	0.257
Fisher exact test			
Customer	0.525		
Product	0.423		

Note(s): This Table displays the average values of FinTechs' characteristics in the years before the formation of strategic alliances with banks. For continuous variables we tested differences between treated and control units through a two-sample *t*-Test, while for categorical variables, i.e. *Customer* and *Product*, we carried out a Fisher Exact Test. All differences are not statistically significant at the 5% level
Source(s): Table was created by the authors

Table 6. Summary statistics of pre-treatment characteristics of treated and control FinTech firms

control samples are not statistically different from each other, excluding a possible selection bias.

3.3.2 DID baseline models. The width of the time window considered in our analysis is $(-4, 4)$, where 0 represents the year in which the strategic alliance is established. Formally, the DID estimator with multiple time periods $t = -4, \ldots, t^* \ldots, 4$ and for observations $i = 1, \ldots, N$ is:

$$DID = E\left[\overline{Y^1_{\{t>t^*\}}} - \overline{Y^0_{\{t>t^*\}}}\right] - E\left[\overline{Y^1_{\{t<t^*\}}} - \overline{Y^0_{\{t<t^*\}}}\right]$$

Where E is the average value, Y is the outcome variable (*G_Trends* or *G_Trends_Growth*), t^* is the year of strategic alliance formation and the indices 1 and 0 refer to treated and control FinTech firms, respectively. The baseline models are the following:

Model 2a.

$$y_{i,t} = \beta_1 * Post_t + \beta_2 * Bank\_Equity_i + \beta_3 * Post_t * Bank\_Equity_i + \beta_4 * post_t * age_{i,t} + \mu_i + \delta_t + \varepsilon_{it}$$

Model 2b.

$$y_{i,t} = \beta_1 * Post_t + \beta_2 * Bank\_Partner_i + \beta_3 * Post_t * Bank\_Partner_i + \beta_4 * post_t * age_{i,t} + \mu_i + \delta_t + \varepsilon_{it}$$

Where $y_{i,t}$ are the outcome variables (*G_Trends* and *G_Trends_Growth*) for the *i*-th FinTech in time *t*, $Post_t$ is a binary variable equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−4 to −1) [3], $Bank\_Equity_i$ and $Bank\_Partner_i$ are binary variable equal to 1 for treated FinTechs, while β_3, i.e. the coefficient of the interactions of $Post_t * Bank\_Equity_i$ and $Post_t * Bank\_Partner_i$, is the parameter of interest. This coefficient measures the effect of strategic alliances on the website traffic of treated FinTech firms compared to control units. Therefore, it can only be estimated when considering both pre- and post-treatment periods. With regard to other control variables, we do not include time-invariant information (i.e. *Blog, Social, Customer* and *Product*) which is automatically dropped by fixed-effects estimation, but we still include the interaction $post_t * age_{i,t}$ to account for the effect of the amount of business activity on website traffic and FinTechs' online visibility. Finally, μ_i are firm fixed effects, introduced in the model in order to deal with potential omitted variables bias, δ_t are time fixed effects and ε_{it} is the error term.

4. Results

4.1 Website ranking

Table 7 provides the results of Model 1, in which we study the determinants of FinTechs' website ranking as a proxy of their efforts to improve website popularity and online visibility. In all specifications, the two main assumptions of ordinal logistic regression are satisfied: there is no evidence of multicollinearity problems, as suggested by the low value of the variance inflation factor (VIF) reported in Table 3 (VIF <5 for each independent variable), and the proportional odds assumption holds, as indicated by the Brant test (Brant, 1990) reported at the bottom of Table 7 (*p*-value >0.05). Furthermore, reverse causality should not be a concern for the analysis. Indeed, as explained in Section 3.2, *Google_PageRank* refers to December 2022, while the independent variables *Equity_Agr* and *Partner_Agr* concern strategic alliances established before 2022, in particular between 2009–2021 for equity agreements and between 2013–2021 for contractual agreements. Hence, there is no reason to assume that our measure of website ranking influences the establishment of strategic alliances between banks and FinTechs.

Both equity and contractual agreements are strategic in increasing external links to the website, which actually improve online visibility. The full model (specification 5 of Table 7) reveals that FinTech firms with at least one shareholder-bank show, *ceteris paribus*, 1.027 points higher log odds of gaining a Google ranking position than FinTechs that do not receive capital infusions from banks, an effect significant at the 5% level. For FinTech firms that establish contractual agreements with banks, the log odds are equal to 0.689, significant at the 10% level.

In line with previous studies, we also provide empirical evidence that FinTechs' information prosociality, i.e. their efforts to engage and attract more users through the inclusion of blogs, forums or links to online social media, positively influences firms' website visibility. This holds in particular for links to online social media (*Social*), which shows the largest positive and significant log odds in all specifications of Table 7.

Dependent variable: Google_PageRank	(1)	(2)	(3)	(4)	(5)
Equity_Agr	1.516***	1.16***			1.027**
	(0.43)	(0.439)			(0.434)
Partner_Agr			1.054***	0.846**	0.689*
			(0.382)	(0.386)	(0.388)
Blog		0.824*		1.041**	0.917**
		(0.443)		(0.434)	(0.444)
Social		1.894***		1.68***	1.769***
		(0.596)		(0.57)	(0.605)
Customer: Business		−0.84*		−0.811*	−0.83*
		(0.428)		(0.438)	(0.425)
Customer: Consumer		−0.652		−0.502	−0.586
		(0.588)		(0.602)	(0.58)
Product: Diversified		1.437*		1.393	1.282*
		(0.754)		(0.85)	(0.709)
Product: Financing		0.027		−0.273	−0.081
		(0.563)		(0.588)	(0.571)
Product: Insurance		0.594		0.381	0.544
		(0.657)		(0.748)	(0.683)
Product: Investments		0.054		−0.224	−0.025
		(0.642)		(0.631)	(0.646)
Age		0.087		0.11*	0.088
		(0.061)		(0.066)	(0.06)
N° observations	124	124	124	124	124
LR test	14.018***	56.003***	8.467***	53.59***	59.182***
Cox and Snell's R2	0.107	0.363	0.066	0.351	0.38
Nagelkerke's R2	0.112	0.38	0.069	0.367	0.397
AIC	387.289	363.303	392.84	365.716	362.124
Residual deviance	371.289	329.303	376.84	331.716	326.124
Brant test (*p*-value)	0.24	0.52	0.99	0.94	0.3

Note(s): Ordinal logistic regressions for the dependent variable *Google_PageRank*. Log odds ratio is displayed. Standard errors are clustered at firm level. For the definition of all variables see Table 1. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 7. Determinants of website ranking: results of Model 1 when implementing Google_PageRank as dependent variable

As we expected, the choice to focus on the business segment is associated with a lower probability of gaining Google ranking positions (with log odds of almost −0.8): therefore, targeting a broader and more diverse customer base is the key to greater online visibility.

Similarly, FinTechs which diversify their offerings (i.e. which operate in multiple product segments) are able to exploit greater growth opportunities and target a larger market share, with a positive effect on online visibility (specifications 2 and 5, Table 7). Finally, there is no evidence (specification 5 Table 6) that the age of FinTech firms have effects on probability of gaining ranking positions.

4.2 Website traffic

In Tables 8 (Model 2a) and 9 (Model 2b) we report the baseline results of DID analysis, which also include firm fixed effects, time fixed effects and the *Post*Age* interaction as controls.

It can be seen that FinTech firms with at least one shareholder-bank show, on average, a higher level of website traffic, in terms of both volume and growth. Indeed, for all the time intervals considered in the analysis, coefficient of the interaction *Post*Bank_Equity* is

Time intervals	−4 to 0	−4 to 1	−4 to 2	−4 to 3	−4 to 4
Panel A – Dependent variable: G_Trends					
Post*Bank_Equity	0.346***	0.533***	0.589***	0.564***	0.586***
	(0.132)	(0.153)	(0.176)	(0.171)	(0.171)
Post*Age	−0.083**	−0.089*	−0.131**	−0.144**	−0.149**
	(0.042)	(0.054)	(0.060)	(0.059)	(0.058)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.055	0.092	0.102	0.092	0.091
F-stat	4.989***	11.99***	16.336***	16.478***	17.471***
Treated pre-treatment average (*): 13.270					
Control pre-treatment average (*): 8.838					
Panel B – Dependent variable: G_Trends_Growth					
Post*Bank_Equity	0.109**	0.219**	0.321**	0.368**	0.451**
	(0.047)	(0.087)	(0.134)	(0.166)	(0.221)
Post*Age	−0.017*	−0.023	−0.045	−0.059*	−0.073
	(0.010)	(0.019)	(0.028)	(0.036)	(0.045)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.054	0.059	0.043	0.033	0.021
F-stat	4.916***	7.529***	6.564***	5.577***	3.681**
Treated pre-treatment average (*): 5.228					
Control pre-treatment average (*): 0.759					

Note(s): The coefficient of the interaction *Post*Bank_Equity* (β_3) measures the effect of equity agreements with banks on the website traffic of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy *Post* equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−4 to −1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
(*) Pre-treatment average of the dependent variable for treated and control FinTech firms
Source(s): Table was created by the authors

Table 8.
Diff-in-diff baseline results: effect of equity agreements with banks on FinTechs' website traffic (Model 2a) for different time intervals

statistically significant at the 1 and 5% level for *G_Trends* and *G_Trends_Growth,* respectively (Table 8). Interestingly, the coefficients increase as the time window considered lengthens, showing that the differential benefits arising from equity agreements with banks increase over time. Contractual agreements and partnerships, on the other hand, do not contribute to an improvement in website traffic (Table 9).

4.2.1 Exogeneity assumption. The DID approach requires strict exogeneity, that is the establishment of equity or contractual agreements (treatment) must not be determined by the level of FinTechs' website traffic (outcome) at baseline. At this stage, it cannot be excluded that banks decide to establish strategic alliances with FinTech firms that already reached a strong online visibility. To address this possible violation of the exogeneity assumption, we carried out Granger causality test, a statistical test usually employed for determining whether a variable Y is useful in forecasting X. Y is said to "Granger cause" X if the historical information of Y is useful in predicting the behaviour of X. On the contrary, if Y does not Granger cause X, then Y is said to be strictly exogenous (Granger, 1969).

In our specific case, we tested if *Bank_Equity* and *Bank_Partner* Granger cause our measures of website traffic, i.e. *G_Trends* and *G_Trends_Growth*. Results of the tests are

Time intervals	−4 to 0	−4 to 1	−4 to 2	−4 to 3	−4 to 4
Panel A – Dependent variable: G_Trends					
Post*Bank_Partner	0.054	0.125	0.228	0.210	0.232
	(0.099)	(0.124)	(0.175)	(0.149)	(0.155)
Post*Age	−0.034	−0.051	−0.062	−0.063	−0.065
	(0.036)	(0.037)	(0.041)	(0.041)	(0.041)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	367	447	502	534	558
R2	0.011	0.024	0.036	0.028	0.025
F-stat	1.138	3.596**	6.348***	5.294***	5.144***
Treated pre-treatment average (*): 11.671					
Control pre-treatment average (*): 4.080					
Panel B – Dependent variable: G_Trends_Growth					
Post*Bank_Partner	−0.004	0.015	0.062	0.031	0.038
	(0.027)	(0.042)	(0.075)	(0.091)	(0.123)
Post*Age	−0.011	−0.018	−0.023	−0.023	−0.024
	(0.010)	(0.012)	(0.015)	(0.014)	(0.015)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	367	447	502	534	558
R2	0.007	0.023	0.026	0.006	0.004
F-stat	0.954	2.788*	4.589**	1.048	0.819
Treated pre-treatment average (*): 2.974					
Control pre-treatment average (*): 1.888					

Note(s): The coefficient of the interaction *Post*Bank_Partner* (β_3) measures the effect of contractual agreements with banks on the website traffic of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy *Post* equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−4 to −1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1% respectively
(*) Pre-treatment average of the dependent variable for treated and control FinTech firms
Source(s): Table was created by the authors

Table 9. Diff-in-diff baseline results: effect of contractual agreements with banks on FinTechs' website traffic (Model 2b) for different time intervals

reported in Table 10. By considering the typical statistical significance threshold of 5%, we concluded that exogeneity assumption is satisfied in our DID analysis.

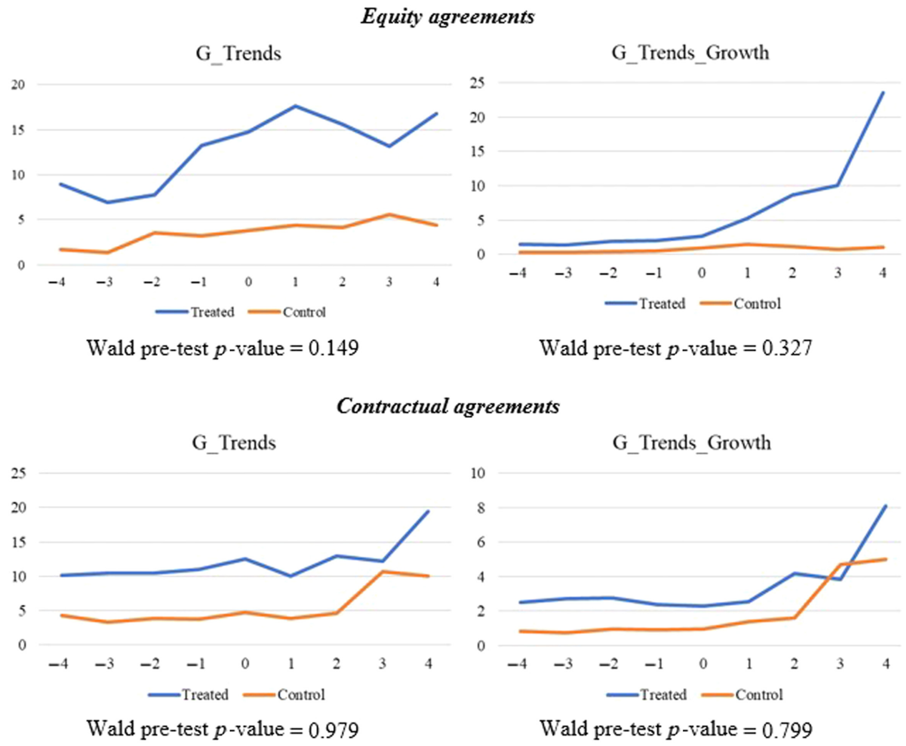
4.2.2 Parallel trend assumption (PTA). The DID method is robust only when the parallel trend assumption (PTA) is satisfied, i.e. the assumption that without strategic alliances with banks, treated and control FinTech firms would have followed the same time paths. As in Bronzini *et al.* (2020), to verify this hypothesis, we first visually test the similarity of web traffic trends for treated and control firms before treatment. The results are plotted in Figure 1.

As you can see from the plots, pre-treatment trends of *G_Trends* and *G_Trends_Growth* seem to be similar for treated and control FinTechs, for both equity and contractual agreements. To further investigate the issue, we first performed a Wald pre-test for the PTA, as proposed by Callaway and Sant'Anna (2021). The results of Wald pre-test (p-values >0.05), included in Figure 1 as well, confirm that PTA holds in our DID setting. Secondly, following other studies in extant literature, we further addressed PTA by adding the interactors of *Pre*, a dummy variable equal to 1 for the years prior to the treatment, and the treatments, i.e. *Bank_Equity* and *Bank_Partner* (Zhang, 2022; Cao *et al.*, 2022). If the added interactors are

Time intervals	1 lag	*Bank_Equity* Granger causes *G_Trends* 3 lags	5 lags	1 lag	*Bank_Equity* Granger causes *G_Trends_Growth* 3 lags	5 lags
Panel A – Equity agreements						
−4 to 0	0.863	0.889	0.498	0.053	0.111	0.124
−4 to 1	0.643	0.882	0.329	0.094	0.198	0.273
−4 to 2	0.595	0.859	0.463	0.126	0.439	0.485
−4 to 3	0.635	0.839	0.509	0.148	0.533	0.318
−4 to 4	0.603	0.850	0.511	0.187	0.616	0.804
Time intervals	1 lag	*Bank_Partner* Granger causes *G_Trends* 3 lags	5 lags	1 lag	*Bank_Partner* Granger causes *G_Trends_Growth* 3 lags	5 lags
Panel B – Contractual agreements						
−4 to 0	0.517	0.866	0.826	0.244	0.510	0.661
−4 to 1	0.539	0.799	0.395	0.276	0.436	0.458
−4 to 2	0.500	0.798	0.804	0.227	0.425	0.563
−4 to 3	0.579	0.865	0.919	0.449	0.543	0.632
−4 to 4	0.573	0.863	0.929	0.508	0.663	0.740

Note(s): Null hypothesis of "no Granger Causality" between dependent and independent variable. The table reports the *p*-values for Granger Causality tests with *Bank_Equity* (Panel A) and *Bank_Partner* (Panel B) for all time intervals considered in the baseline diff-in-diff analysis and considering 1, 3 and 5 lags
Source(s): Table was created by the authors

Table 10.
Granger causality results for diff-in-diff analysis



Source(s): Figure created by the authors

Figure 1.
Average trends in FinTechs'website traffic measures before and after the establishment of strategic alliances (treated vs control group) and evaluation of parallel trend assumption

insignificant, the DID model setting satisfies the PTA. Results of this additional test are provided in Tables 11 and 12.

As you can see, the coefficients of DID effects persist compared to the baseline model, while the pre-DID effects are insignificant, demonstrating that model satisfies the PTA and that our fundamental estimations are reliable.

4.2.3 Stable unit treatment values assumption (SUTVA). The stable unit treatment assumption (SUTVA) is satisfied under two conditions. First, SUTVA holds when there no different forms or versions of the treatment (consistency), which is the case of our study: we test the effect of equity and contractual agreements on online visibility separately and in two different specifications, so that there are not different versions or changes of the treatment over time. Second, spillover effects are not allowed, thus a FinTech's potential outcome should not be affected by other FinTechs' exposure to the treatment. As concern this point, we do not exclude potential spillover effects between FinTech firms providing similar financial services. Indeed, there is the possibility that Internet surfers, once they become aware of a strategic alliance involving a particular FinTech, become interested not only in the financial services offered by this one, but are also eager to explore similar and alternative financial

Time intervals	−4 to 0	−4 to 1	−4 to 2	−4 to 3	−4 to 4
Panel A – Dependent variable: G_Trends					
Post*Bank_Equity	0.621**	0.822**	0.845***	0.836***	0.843***
	(0.313)	(0.323)	(0.319)	(0.324)	(0.324)
Pre*Bank_Equity	0.296	0.312	0.278	0.295	0.279
	(0.264)	(0.273)	(0.274)	(0.279)	(0.279)
Post*Age	−0.084**	−0.090*	−0.132**	−0.146**	−0.150***
	(0.042)	(0.054)	(0.060)	(0.059)	(0.058)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.063	0.097	0.105	0.095	0.093
F-stat	3.860**	8.530***	11.240***	11.354***	11.967***
Panel B – Dependent variable: G_Trends_Growth					
Post*Bank_Equity	0.226**	0.356***	0.422***	0.442***	0.479**
	(0.089)	(0.135)	(0.153)	(0.164)	(0.180)
Pre*Bank_Equity	0.126	0.149	0.109	0.081	0.030
	(0.086)	(0.098)	(0.100)	(0.112)	(0.136)
Post*Age	−0.017*	−0.023	−0.046*	−0.060*	−0.073
	(0.010)	(0.019)	(0.028)	(0.035)	(0.045)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.074	0.065	0.044	0.033	0.021
F-stat	4.551***	5.523***	4.454***	3.737**	2.449*

Note(s): Test of PTA through the additional interaction term *Pre*Bank_Equity*. The coefficient of the interaction *Pre*Bank_Equity* (β_3) measures the effect of equity agreements with banks on the website traffic of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy *Post* equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−4 to −1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 11. Effect of equity agreements: test of parallel trend assumption (PTA)

Time intervals	−4 to 0	−4 to 1	−4 to 2	−4 to 3	−4 to 4
Panel A – Dependent variable: G_Trends					
Post*Bank_Partner	0.336	0.401	0.486	0.467	0.482
	(0.281)	(0.262)	(0.371)	(0.381)	(0.374)
Pre*Bank_Partner	0.340	0.327	0.304	0.302	0.293
	(0.223)	(0.223)	(0.226)	(0.227)	(0.229)
Post*Age	−0.037	−0.054	−0.065	−0.065	−0.068
	(0.037)	(0.038)	(0.042)	(0.042)	(0.042)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	367	447	502	534	558
R2	0.023	0.032	0.039	0.030	0.027
F-stat	1.970	3.639**	5.238***	4.377***	4.107***
Panel B – Dependent variable: G_Trends_Growth					
Post*Bank_Partner	0.084	0.100	0.133	0.101	0.102
	(0.086)	(0.086)	(0.092)	(0.106)	(0.122)
Pre*Bank_Partner	0.106	0.101	0.084	0.082	0.076
	(0.088)	(0.088)	(0.090)	(0.094)	(0.100)
Post*Age	−0.012	−0.019	−0.024	−0.024	−0.025*
	(0.011)	(0.013)	(0.015)	(0.015)	(0.015)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	367	447	502	534	558
R2	0.019	0.023	0.026	0.006	0.004
F-stat	1.618	2.668**	3.510**	0.813	0.613

Note(s): Test of PTA through the additional interaction term *Pre*Bank_Partner*. The coefficient of the interaction *Pre*Bank_Partner* (β_3) measures the effect of contractual agreements with banks on the website traffic of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy *Post* equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−4 to −1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1%, respectively

Source(s): Table was created by the authors

Table 12. Effect of contractual agreements: test of parallel trend assumption (PTA)

services offered by other FinTechs. For this reason, we carried out an additional analysis by following an empirical strategy similar to Sinclair *et al.* (2012). In particular, we control the presence of possible spillover effects by including a control variable that, for a specific FinTech in a particular year, considers if other sampled FinTechs offering similar financial services (i.e. "Payment", "Financing", "Investment" or "Diversified") are involved in an equity or a contractual agreement. We named these control variables "Spillover_Equity_Agr" and "Spillover_Partner_Agr". Results of this additional analysis are provided in Tables 13 and 14.

As you can see, the analysis excludes the existence of spillover effects among FinTech firms. Indeed, the coefficients of *Spillover_Equity_Agr* and *Spillover_Partner_Agr* are never statistically significant. Hence, the baseline models satisfy the SUTVA and provide reliable results.

4.3 Overview of results

Overall, although with some differences between equity and contractual arrangements, strategic alliances with banks appear to have a positive effect on FinTechs' online visibility,

Time intervals	−4 to 0	−4 to 1	−4 to 2	−4 to 3	−4 to 4
Panel A – Dependent variable: G_Trends					
Post*Bank_Equity	0.370***	0.548***	0.592***	0.565***	0.589***
	(0.130)	(0.153)	(0.176)	(0.171)	(0.171)
Post*Age	−0.090**	−0.095*	−0.132**	−0.145**	−0.150***
	(0.043)	(0.054)	(0.060)	(0.060)	(0.058)
Spillover_Equity_Agr	0.086	0.100	0.026	0.009	0.035
	(0.059)	(0.069)	(0.057)	(0.061)	(0.057)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.063	0.099	0.102	0.092	0.091
F-stat	3.815**	8.742***	10.908***	10.959***	11.717***
Panel B – Dependent variable: G_Trends_Growth					
Post*Bank_Equity	0.113***	0.223**	0.314**	0.359**	0.450**
	(0.037)	(0.087)	(0.131)	(0.161)	(0.220)
Post*Age	−0.018*	−0.025	−0.043	−0.057*	−0.073
	(0.011)	(0.019)	(0.026)	(0.034)	(0.045)
Spillover_Equity_Agr	0.014	0.032	−0.058	−0.075	−0.007
	(0.020)	(0.023)	(0.052)	(0.063)	(0.029)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.057	0.063	0.048	0.037	0.021
F-stat	3.438**	5.327***	4.799***	4.183***	2.449*

Note(s): Test of spillover effects of equity agreement (SUTVA assumption) through the additional control variable *Spillover_Equity_Agr*, a binary variable which, for a specific FinTech observed in a specific year, is equal to 1 when other FinTechs operating in the same market segment are involved in an equity agreement in the same year. The coefficient of the interaction *Post*Bank_Equity* (β_3) measures the effect of equity agreements with banks on the website traffic of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy *Post* equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−4 to −1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 13. Effect of equity agreements: test of SUTVA assumption (spillover effects)

measured through their website ranking and traffic. Therefore, our results support Hypotheses 1a and 1b. Strategic alliances based on equity investments improve the accessibility and popularity of FinTechs' website (ranking), while also effectively attracting and retaining new and old customers, thus recording an increase in website traffic volumes. This evidence supports H2, in which we stated that equity agreements with banks positively affect FinTechs' online visibility. Contractual agreements, on the other hand, are strategic in improving FinTechs' ranking, but are not effective in attracting a greater number of website users. For this reason, H3 is only partially supported.

5. Robustness tests

To test the robustness of DID analysis, we first focus on the circumstance that strategic alliances in the sample are established in different years that is the treatment occurs with different timing for treated FinTechs. In this regard, it is worth noting that the 75% of bank-FinTech relationships considered are established over the period 2017–2020,

Time intervals	−4 to 0	−4 to 1	−4 to 2	−4 to 3	−4 to 4
Panel A – Dependent variable: G_Trends					
Post*Bank_Partner	0.132	0.172	0.592	0.251	0.274
	(0.156)	(0.135)	(0.152)	(0.155)	(0.171)
Post*Age	−0.033	−0.051	−0.061	−0.061	−0.064
	(0.053)	(0.037)	(0.041)	(0.042)	(0.042)
Spillover_Partner_Agr	0.048	0.024	0.022	0.066	0.085
	(0.054)	(0.048)	(0.048)	(0.051)	(0.053)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	367	447	502	534	558
R2	0.013	0.025	0.036	0.029	0.029
F-stat	1.078	2.776**	4.778***	4.271***	4.316***
Panel B – Dependent variable: G_Trends_Growth					
Post*Bank_Partner	0.008	0.018	0.064	0.039	0.043
	(0.047)	(0.042)	(0.06)	(0.091)	(0.125)
Post*Age	−0.010	−0.018	−0.023	−0.022	−0.024
	(0.008)	(0.012)	(0.015)	(0.015)	(0.015)
Spillover_Partner_Agr	0.022	0.004	−0.003	0.053	0.017
	(0.029)	(0.018)	(0.018)	(0.035)	(0.024)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	367	447	502	534	558
R2	0.009	0.017	0.024	0.008	0.004
F-stat	0.832	1.876	3.095**	1.095	0.582

Note(s): Test of spillover effects of contractual agreement (SUTVA assumption) through the additional control variable *Spillover_Partner_Agr*, a binary variable which, for a specific FinTech observed in a specific year, is equal to 1 when other FinTechs operating in the same market segment are involved in a contractual agreement in the same year. The coefficient of the interaction *Post*Bank_Partner* (β3) measures the effect of contractual agreements with banks on the website traffic of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy Post equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−4 to −1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 14.
Effect of contractual agreements: test of SUTVA assumption (spillover effects)

percentage that remains high at 48% even when considering a shorter time period from 2019 to 2021. The concentration of strategic alliances in a short time window makes the average difference in treatment timing almost irrelevant, reducing problems arising from a possible non-comparability between early-treated and late-treated FinTech firms. Despite this, there could be still specificities characterizing the different cohort (year) of treated FinTechs, thus we perform a robustness test controlling for the year of establishment of strategic alliances through the interactors *Post*Cohort_Equity_Agr* and *Post*Cohort_Partner_Agr*, added to the baseline Model 2a and Model 2b, respectively. *Cohort_Equity_Agr* and *Cohort_Partner_Agr* are factor variables indicating the year of establishment of strategic alliances. The aim is to check if main findings concerning the effects of equity and contractual agreements of FinTechs' website traffic persist even when cleansed from cohort specificities. The results are reported in Tables 15 and 16 and confirm our fundamental estimations.

Time intervals	−4 to 0	−4 to 1	−4 to 2	−4 to 3	−4 to 4
Panel A – Dependent variable: G_Trends					
Post*Bank_Equity	0.363***	0.542***	0.599***	0.558***	0.577***
	(0.131)	(0.156)	(0.189)	(0.184)	(0.185)
Post*Age	−0.100**	−0.103*	−0.144**	−0.150**	−0.154**
	(0.048)	(0.060)	(0.069)	(0.067)	(0.066)
Post*Cohort_Equity_Agr	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.074	0.106	0.116	0.108	0.107
F-stat	1.311	2.737***	3.677***	3.864***	4.118***
Panel B – Dependent variable: G_Trends_Growth					
Post*Bank_Equity	0.114**	0.221**	0.331**	0.379**	0.473***
	(0.049)	(0.088)	(0.139)	(0.172)	(0.180)
Post*Age	−0.019	−0.026	−0.048	−0.062	−0.082
	(0.013)	(0.021)	(0.032)	(0.040)	(0.053)
Post*Cohort_Equity_Agr	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.083	0.097	0.072	0.058	0.035
F-stat	1.476	2.463***	2.175**	1.952**	1.250

Note(s): Robustness check controlling for the year of establishment of equity agreements through the interaction *Post*Cohort_Equity_Agr*, where *Cohort_Equity_Agr* is a factor variable indicating the year of establishment of equity agreements. The coefficient of the interaction *Post*Bank_Equity* (β_3) measures the effect of equity agreements with banks on the website traffic of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy *Post* equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−4 to −1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 15. Robustness check: controlling for the year of establishment (cohort) of equity agreements

Also, since the results of DID estimations may be influenced by the length of the time intervals considered, we re-run Models 2a and 2b for the time window (−1,4). In this way, we check whether the positive difference between treated and control FinTech firms in terms of website traffic persists even comparing the year before the establishment of strategic alliances with the following years. As Tables 17 and 18 shows, the main results of Models 2a and 2b hold.

In addition, we test the robustness of our results by using an alternative measure of online visibility, i.e. FinTechs' size. As stated in Section 3.2, we decided to implement FinTechs' size as a proxy of online visibility because the close link between the two may arise from a strong correlation rather than a causal relationship. Therefore, we re-run Models 1, 2a and 2b with *Size* (i.e. logarithm of total assets) as dependent variable. The results of this robustness check (Tables 19 and 20) are very similar to the baseline results commented on in Section 4.

Finally, we also carried out a robustness test for the variable *Social*, which is the variable with the largest and positive effect on website visibility among the explanatory variables capturing FinTech's information prosociality. In particular, we re-run Model 1 introduced in Section 3.2 by replacing the variable *Social* with the variable *N_Social*, which represent the number of social medias to which FinTechs provide external links on their websites. Results

Time intervals	−4 to 0	−4 to 1	−4 to 2	−4 to 3	−4 to 4
Panel A – Dependent variable: G_Trends					
Post*Bank_Partner	0.151	0.187	0.284	0.259	0.277***
	(0.146)	(0.130)	(0.175)	(0.158)	(0.176)
Post*Age	−0.040	−0.054	−0.065	−0.063	−0.066
	(0.036)	(0.038)	(0.042)	(0.042)	(0.042)
Post*Year_Partner_Agr	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.045	0.051	0.061	0.058	0.050
F-stat	1.290	1.963**	2.767***	2.800***	2.554***
Panel B – Dependent variable: G_Trends_Growth					
Post*Bank_Partner	0.002	0.013	0.059	0.017	0.016
	(0.035)	(0.042)	(0.059)	(0.091)	(0.125)
Post*Age	−0.012	−0.019	−0.023	−0.018	−0.017
	(0.012)	(0.013)	(0.016)	(0.015)	(0.016)
Post*Year_Partner_Agr	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.011	0.027	0.041	0.031	0.035
F-stat	0.300	1.001	1.809*	1.465	1.745*

Note(s): Robustness check controlling for the year of establishment of contractual agreements through the interaction *Post*Cohort_Partner_Agr*, where *Cohort_Partner_Agr* is a factor variable indicating the year of establishment of contractual agreements. The coefficient of the interaction *Post*Bank_Partner* (β3) measures the effect of contractual agreements with banks on the website traffic of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy *Post* equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−4 to −1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 16. Robustness check: controlling for the year of establishment (cohort) of contractual agreements

of this robustness test are provided in Table 21 and confirm the effectiveness of FinTechs' information prosociality in enhancing website visibility.

6. Conclusions, implications and limitations

In the last decade, the financial industry has witnessed an increase in the level of competition, due to the entrance of FinTech firms into the market. Thanks to technological innovations and a favourable regulatory framework, FinTechs can develop effective and innovative financial service delivery processes and can address a broader customer base, which includes excluded and underserved market segments (Salampasis and Mention, 2018). Although FinTech firms are gaining importance worldwide, many of them struggle to survive: they are new in the financial market, so they typically lack reputation and cannot rely on a large customer base, which is crucial for profitability and growth (Carbó-Valverde *et al.*, 2022; Felländer *et al.*, 2018). For these reasons, online visibility is of the utmost importance for FinTechs. It is the first step in reaching a greater number of potential customers, building reputation and, overall, ensuring a less risky development path (Enriques and Ringe, 2020; Bömer and Maxin, 2018). The current study aims to empirically test the causal effect between

Time intervals	−1 to 0	−1 to 1	−1 to 2	−1 to 3	−1 to 4
Panel A – Dependent variable: G_Trends					
Post*Bank_Equity	0.100	0.244*	0.278*	0.271*	0.306**
	(0.129)	(0.133)	(0.156)	(0.159)	(0.119)
Post*Age	−0.054	−0.053	−0.088**	−0.098**	−0.104***
	(0.034)	(0.037)	(0.041)	(0.041)	(0.040)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	156	225	277	315	341
R2	0.038	0.036	0.037	0.032	0.033
F-stat	1.494	2.617*	3.721**	3.811**	4.328**
Panel B – Dependent variable: G_Trends_Growth					
Post*Bank_Equity	0.042	0.142*	0.270*	0.358	0.489
	(0.042)	(0.087)	(0.160)	(0.235)	(0.337)
Post*Age	−0.017*	−0.025	−0.053	−0.072	−0.092
	(0.010)	(0.020)	(0.036)	(0.049)	(0.065)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	156	225	277	315	341
R2	0.034	0.028	0.026	0.024	0.017
F-stat	1.327	2.008	2.558*	2.811*	2.188

Note(s): The coefficient of the interaction *Post*Bank_Equity* (β_3) measures the effect of equity agreements with banks on the website traffic of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy *Post* equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 17. Diff-in-diff robustness check: effect of equity agreements with banks on FinTechs' website traffic (Model 2a) for the time window (−1, 4)

bank-FinTech relationships and FinTechs' online visibility, while exploring whether equity and contractual agreements have similar effects.

The general conclusion supported by our analysis is that cooperation with banks enhances FinTechs' online visibility, measured through website ranking and traffic. Therefore, relationships with banks are strategic in enabling FinTechs to enlarge their presence in the digital environment and attract a greater number of prospective customers, with potential benefits in terms of sales, time to break-even and business scaling-up. This also is an important conclusion for marketing literature on online visibility because we point out the relevance of strategic alliances on firms' online visibility and the positive role of cooperation policies.

However, we identified an important difference between equity and non-equity (contractual) agreements. Although both types of strategic alliance positively influence the volume and relevance of direct external links to FinTechs' websites (measured through Google PageRank), we found that only equity agreements are effective in increasing interest in FinTechs' activities and attracting users to FinTechs' websites, thus increasing website traffic (measured through Google Trends). This difference is a valuable insight for the formulation of managerial implications and opens up new avenues of investigation from a theoretical perspective.

Bearing in mind that website ranking measures the degree of accessibility and popularity of FinTechs' website achieved through internal and external online content creation, while

Time intervals	−1 to 0	−1 to 1	−1 to 2	−1 to 3	−1 to 4
Panel A – Dependent variable: G_Trends					
Post*Bank_Partner	0.004	0.059	0.143	0.135	0.164
	(0.113)	(0.101)	(0.109)	(0.114)	(0.120)
Post*Age	−0.036	−0.044**	−0.050**	−0.048**	−0.050**
	(0.024)	(0.022)	(0.022)	(0.022)	(0.022)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	207	287	342	374	398
R2	0.035	0.031	0.029	0.018	0.015
F-stat	1.748	2.809*	3.401**	2.331*	2.104
Panel B – Dependent variable: G_Trends_Growth					
Post*Bank_Partner	−0.038	−0.031	0.004	−0.018	−0.005
	(0.028)	(0.035)	(0.046)	(0.068)	(0.089)
Post * Age	−0.013***	−0.017***	−0.018***	−0.014*	−0.012
	(0.005)	(0.006)	(0.006)	(0.008)	(0.009)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	207	287	342	374	398
R2	0.086	0.034	0.018	0.002	0.001
F-stat	4.564**	3.109**	2.118	0.229	0.117

Note(s): The coefficient of the interaction *Post*Bank_Partner* (β_3) measures the effect of contractual agreements with banks on the website traffic of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy *Post* equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 18.
Diff-in-diff robustness check: effect of contractual agreements with banks on FinTechs' website traffic (Model 2b) for the time window (−1, 4)

website traffic reveals Internet users' interest (Sulong *et al.*, 2022; Liu *et al.*, 2021; Vosen and Schmidt, 2011), FinTechs' managers should consider that equity agreements are a powerful strategic choice for enlarging a FinTech's customer base and boosting interest in its brand. Equity agreements with banks allow FinTechs to benefit from reputational spill-overs and are a strong quality signal for customers, promoting FinTechs' trustworthiness and customers' propensity to take a look at FinTechs' financial products and services.

The creation of commercial partnerships and contractual agreements helps to expand the access network and the dissemination of links but does not originate positive signalling mechanisms. It is feasible that the missing link between a website's ranking and traffic improvement stems from customers' difficulty in understanding the high professional standards and soundness which FinTech firms must demonstrate to be selected as partners by banks, given the high reputational risk associated to these agreements.

Furthermore, we advise FinTechs' managers to support the creation of online communities, allowing a variety of customers to share experience and knowledge through blogs, forums and social media platforms. As our analysis reveals, prosocial behaviour is repaid in stakeholder attention, leading to greater online visibility.

In a theoretical perspective, our work contributes to the extant literature. First, it expands marketing knowledge and literature regarding online visibility determinants investigating the benefits of strategic alliances and cooperation in the market. This is a new and very important theoretical stream as it links online visibility to strategies and organizational behavioural studies.

Time intervals	−4 to 0	−4 to 1	−4 to 2	−4 to 3	−4 to 4
Panel A – Dependent variable: size					
Post*Bank_Equity	0.338***	0.291***	0.300***	0.320***	0.315***
	(0.109)	(0.108)	(0.108)	(0.112)	(0.114)
Post*Age	−0.102***	−0.094***	−0.094***	−0.100***	−0.102***
	(0.020)	(0.022)	(0.021)	(0.022)	(0.023)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	257	326	378	416	442
R2	0.097	0.090	0.094	0.092	0.081
F-stat	9.268***	11.833***	14.922***	16.602***	15.469***
Panel B – Dependent variable: size					
Post*Bank_Partner	0.150	0.164	0.204	0.207	0.228
	(0.106)	(0.129)	(0.140)	(0.141)	(0.145)
Post*Age	−0.036**	−0.040**	−0.042**	−0.044**	−0.046**
	(0.018)	(0.018)	(0.019)	(0.020)	(0.021)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N° observations	367	447	502	534	558
R2	0.028	0.033	0.037	0.035	0.037
F-stat	3.711**	5.735***	7.502***	7.642***	8.397***

Note(s): The coefficient of the interactions *Post*Bank_Equity* and *Post*Bank_Partner* (β_3) measures, respectively, the effect of equity agreements and contractual with banks on the *Size* of treated FinTech firms compared to control units and can only be estimated when considering also post-treatment periods. All the specifications include firm fixed effects, time fixed effects and the interaction *Post*Age*. The columns show the results of separate panel regressions for each time interval, with the dummy *Post* equal to 1 in the years when we want to evaluate the effect of strategic alliances with banks and 0 in pre-treatment period (−4, −1). Standard errors are clustered at firm level. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 19. Diff-in-diff robustness check: effect of equity and contractual agreements with banks on FinTechs' Size, implemented as an alternative measure of website traffic. Estimations for the time window (−4, 4)

Another important theoretical stream is opened up by the evidence that equity and contractual agreements have different effects on website ranking and website traffic; the former captures the communication activities of internal and external online content creators following the establishment of strategic alliances (in terms of links and news dissemination), while the latter captures their effects on the interest and searches carried out by Internet users. Thus, the different reactions and behaviours emerging between online content creators and Internet users deserve further investigation by future studies and researches.

Turning to the financial field, we study online visibility within the financial industry, which is underexplored in the literature (Cioppi *et al.*, 2019), by also providing an empirical strategy to future research which is replicable for online visibility studies and other marketing topics. Concerning FinTech literature, the empirical demonstration of the possibility to enhance FinTechs' online visibility through strategic alliances with banks expands current studies on the development paths of FinTechs in the early stages of the life cycle, highlighting the positive role of the stakeholder network and contributes to the debate on the nature and benefit of the relationship between FinTechs and incumbents, in particular banks.

From a societal point of view, the development of FinTech firms has important implications in terms of financial innovation, financial inclusion and efficiency of the financial system and, therefore, in resource allocation and development of the economic system. Authorities and policymakers should aim to foster strategic alliances between FinTechs and

Dependent variable: Size	(1)	(2)	(3)	(4)	(5)
Intercept	−0.001	−1.232***	0.088	−1.129***	−1.265***
	(0.098)	(0.297)	(0.112)	(0.344)	(0.288)
Equity_Agr	1.218***	0.977***			0.909***
	(0.194)	(0.176)			(0.166)
Partner_Agr			0.624***	0.46**	0.286*
			(0.202)	(0.177)	(0.149)
Blog		−0.161		−0.058	−0.13
		(0.201)		(0.213)	(0.199)
Social		0.751***		0.693***	0.695***
		(0.194)		(0.2)	(0.193)
Customer: business		0.187		0.219	0.204
		(0.17)		(0.193)	(0.167)
Customer: consumer		0.303		0.423*	0.351*
		(0.202)		(0.228)	(0.197)
Product: diversified		1.211**		1.325**	1.147**
		(0.478)		(0.601)	(0.466)
Product: financing		0.233		0.073	0.205
		(0.244)		(0.286)	(0.233)
Product: insurance		0.881***		0.793*	0.874***
		(0.316)		(0.425)	(0.314)
Product: investments		0.349		0.124	0.324
		(0.274)		(0.308)	(0.266)
Age		0.073***		0.09***	0.073***
		(0.026)		(0.025)	(0.027)
N° observations	124	124	124	124	124
F-stat	36.27***	9.185***	9.476***	6.125***	8.739***
Adjusted R2	0.223	0.4	0.064	0.294	0.409

Note(s): Linear regressions for the dependent variable *Size*. Standard errors are clustered at firm level. For the definition of all variables see Table 1. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 20. Robustness check: Model 1 implementing *Size* as an alternative measure of online visibility

banks, contributing to increasing FinTechs' online visibility and development, while generating virtuous innovation mechanisms for traditional financial intermediaries and for the financial system in general.

Despite its valuable insights and implications, this study has some limitations, which open up future research directions. In particular, we used Google data to measure online visibility, that, if on one side it allows to carry out quantitative analysis on a sufficiently large sample of FinTechs, on the other it does not consider the online behaviour of Internet surfers, which is important in assessing the effectiveness of online presence. Basing on a case-study approach, future research may investigate if strategic alliances with banks have some effect on customers' behaviour while navigating FinTechs' website, by considering, for example, the number and which pages they have visited, the time of usage and the actual purchase of financial services. Furthermore, future research may include FinTechs' advertising efforts and other forms of driving traffics among explanatory variables, which are not included in this study because of the difficulties in sourcing data. Regarding the generalizability of the results, it is important to underline that this study focuses on the Italian market, thus future research could expand the sample and provide cross-country evidence on the topic. Finally, our work can be extended by studying the association between FinTechs' online visibility and their performance, while considering a possible mediator role for strategic alliances with banks.

Dependent variable: Google_PageRank	(1)	(2)	(3)	(4)	(5)
Equity_Agr	1.516****	1.236***			1.096**
	(0.43)	(0.442)			(0.439)
Partner_Agr			1.054***	0.829**	0.646*
			(0.382)	(0.387)	(0.383)
Blog		0.878**		1.105**	0.964**
		(0.433)		(0.424)	(0.439)
N_Social		0.473***		0.41***	0.442***
		(0.131)		(0.123)	(0.133)
Customer: business		−0.641		−0.635	−0.65
		(0.421)		(0.429)	(0.423)
Customer: consumer		−0.343		−0.236	−0.301
		(0.551)		(0.588)	(0.55)
Product: diversified		0.965		0.972	0.864
		(0.828)		(0.9)	(0.763)
Product: financing		−0.000		−0.313	−0.099
		(0.566)		(0.606)	(0.574)
Product: insurance		0.695		0.456	0.649
		(0.672)		(0.771)	(0.684)
Product: investments		−0.214		−0.483	−0.265
		(0.617)		(0.6)	(0.615)
Age		0.091		0.118	0.093
		(0.071)		(0.076)	(0.068)
N° observations	124	124	124	124	124
LR test	14.018***	59.008***	8.467***	55.478***	61.757***
Cox and Snell's R2	0.107	0.379	0.066	0.361	0.392
Nagelkerke's R2	0.112	0.396	0.069	0.378	0.411
AIC	387.289	360.299	392.84	363.829	359.55
Residual deviance	371.289	326.299	376.84	329.829	323.55
Brant test (*p*-value)	0.24	0.73	0.99	0.83	0.43

Note(s): Ordinal logistic regressions for the dependent variable *Google_PageRank*. Log odds ratios are displayed. Standard errors are clustered at firm level. For the definition of all variables see Table 1. Significance levels: *, **, *** for 10%, 5% and 1%, respectively
Source(s): Table was created by the authors

Table 21. Robustness check: Model 1 implementing *N_Social* as an alternative measure of information prosociality

Notes

1. Source: https://www.fintechdistrict.com/backtowork24-intesa-sanpaolo-investment/
2. Source: https://www.milanofinanza.it/news/partnership-tra-moneyfarm-e-banca-sella-per-i-clienti-digitali-201810151340314439
3. For example, if we want to evaluate the effect in the time window (−4,2), then the variable $post_t$ is equal 1 in the periods 0, 1 and 2 and 0 otherwise.

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