The British Accounting Review xxx (xxxx) xxx

Contents lists available at ScienceDirect

The British Accounting Review

journal homepage: www.elsevier.com/locate/bar

Fintech and home bias: The power of new social capital in innovative entrepreneurial financing

Jianwei Hu [a], Xiuping Hua [b,*], Haolin Li [c], Yong Wang [d], Huayi Zhang [e]

[a] Lingnan College, Sun Yat-sen University, Guangzhou, 510275, PR China
[b] Nottingham University Business School China, University of Nottingham Ningbo China, Ningbo, 315100, PR China
[c] Faculty of Science and Engineering, University of Nottingham Ningbo China, Ningbo, 315100, PR China
[d] Institute of New Structural Economics (INSE), Peking University, Beijing, 100871, PR China
[e] University of Chicago, 5801 S Ellis Ave, Chicago, IL, 60637, United States

ARTICLE INFO

JEL classification:
G3
D22
D83
G40

Keywords:
Technology
Social capital
Financial inclusion
Investor protection

ABSTRACT

We identify that technology crowdfunding campaigns attracting more domestic investors have a higher probability of project success and examine the role of home bias in supporting online innovative entrepreneurial financing. The extent of the home bias effect among technology entrepreneurs varies and is notably linked to their social capital. When a technology entrepreneur has high "old" social capital, the home bias is strengthened and aligned with a preference-based interpretation. In contrast, technology entrepreneurs' excessive capabilities of creating "new" social capital help mitigate the home bias, reduce the dependence on local investors, and promote more diversified investment decisions, which supports an information-based interpretation. Evidence also reveals that technology entrepreneurs' home country levels of financial inclusion and investor protection influence the link between home bias and crowdfunding outcomes, indicating that the economic benefits generated in fintech are heterogeneous across different countries.

1. Introduction

In the pre-fintech era, there is a well-documented home bias puzzle. Investors tend to invest more in the assets or projects of their home countries (Chan et al., 2005; French & Poterba, 1991; Parwada, 2008), or trades are more likely to take place between parties within the same geographical region (Hortaçsu et al., 2009; Santamaría et al., 2023). Alternative definitions of home bias include more optimistic recommendations of local analysts (Lai & Teo, 2008), higher prices of local artworks (Shi et al., 2017), and the willingness to acquire projects in home cities (Zhu et al., 2023). Important factors behind the home bias include a variety of explicit or implicit barriers, such as transaction costs, networking costs, capital controls, information costs, regulatory constraints, exchange rate risks, accounting standards, behavioural biases, hedging motives, corporate culture, and language barriers (Carpio et al., 2021; Cornaggia et al., 2020; Coval & Moskowitz, 2001; Levy & Levy, 2014; Parwada, 2008).

The past two decades have witnessed unprecedented development in fintech, which has revolutionised financial services at an extraordinary pace and drawn increasing attention from entrepreneurs, investors, and many other stakeholders worldwide (Goldstein

This article is part of a special issue entitled: FinTech published in The British Accounting Review.

* Corresponding author.
E-mail addresses: hujw63@mail.sysu.edu.cn (J. Hu), Xiuping.Hua@nottingham.edu.cn (X. Hua), haolin.li@nottingham.edu.cn (H. Li), yongwang@nsd.pku.edu.cn (Y. Wang), Huayizhang@uchicago.edu (H. Zhang).

https://doi.org/10.1016/j.bar.2025.101636
Received 21 December 2022; Received in revised form 13 December 2024; Accepted 13 March 2025
Available online 14 March 2025

et al., 2019; Gomber et al., 2018; Kim & Hann, 2019; Yasar et al., 2022). The development of fintech and its impact on investment and consumption biases are significant. To date, academic studies have explored the effects of home bias in several online trading and investment platforms. Agrawal et al. (2015) examine data from an early and prominent crowdfunding platform, Sellaband, and document that the platform diminishes some distance-sensitive frictions but cannot eliminate them. Lin and Viswanathan (2016) gather detailed transaction data on loan requests and investors' bids posted on a large online crowdfunding marketplace, Prosper.com, and reveal that home bias still exists in this virtual marketplace. Bartlett et al. (2022) research into consumer-lending discrimination and find that fintech lenders' rate disparities are similar to those of non-fintech lenders for government-sponsored enterprises (GSEs) mortgages.

Reward crowdfunding is increasingly recognised as an effective way to not only promote innovation and creativity but also to fill the long-standing financing gap between large, well-endowed startups and relatively limited funding from traditional financial institutions (Mollick, 2014; Yasar et al., 2022; Yu et al., 2017). Kim and Hann (2019) claim that crowdfunding can act as an additional source of entrepreneurial finance, though disparities in socioeconomic status can hinder underprivileged individuals from fully reaping their full advantages. Interestingly, the literature indicates that although fintech infrastructures decrease networking costs considerably, home bias cannot be fully eliminated in reward crowdfunding. Jiang et al. (2022) identify the existence of home bias in Chinese reward crowdfunding due to informational needs.

The technology sector of the reward crowdfunding platform is an unconventional yet increasingly attractive channel for innovative entrepreneurial financing. It is also one of the most popular categories on crowdfunding platforms (Zhang & Chen, 2019). Duan et al. (2020) study facial trustworthiness based on Kickstarter's technology-related projects and argue that technology projects are more likely to suffer from information asymmetry problems in the early stages because of technique secrecy. The analyses in Wang et al. (2022, 2023) are also confined to technology-based campaigns because their product rewards tend to be more innovative, leading to higher information asymmetry. They argue that most potential backers are usually unfamiliar with the technology involved in entrepreneurial projects driven by technological and scientific components.

Given the global surge of technology entrepreneurial activities in fintech ecosystems, it is natural to ask whether social capital created in crowdfunding communities helps diminish home bias and, if so, how. However, academic work on the relationship between social capital and the home bias effect, particularly how different social capital influences the home bias effect on technology crowdfunding performance, is still very limited. The primary goal of our paper is to fill this gap based on theoretical connections and empirical analyses.

In this paper, we first develop a conceptual framework to explain the differentiated roles of "old" (pre-existing and out-of-the-platform) and "new" (newly-created and within-the-platform) social capitals played in strengthening or mitigating the home bias's influence. Based on the behaviour bias theory in Kahneman and Tversky (1979), Strong and Xu (2003), and Thaler (2016), we connect the first influencing channel of "old" social capital with the investment preference of a creator's pre-existing Facebook friends, most of whom come from the same country as the creator. We contemplate that the pre-existing social capital of creators, originally developed outside the crowdfunding platform, mainly influences funding performance by strengthening the home bias effect through preferences due to past experiences, familiarity, loyalty, patriotism, trust, and overconfidence of current social ties (Bailey et al., 2018; Cohen, 2009; Grinblatt & Keloharju, 2001; Huberman, 2001; Wei & Zhang, 2020; Zingales, 2015). It is labelled as a preference-based interpretation.

We propose a second influencing mechanism of newly created social capital based on the information-based theory and rational-choice framework (Brav et al., 2022; Coval & Moskowitz, 1999). Those technology entrepreneurs who are more capable of reducing networking costs, transmitting accurate information, and creating new social capital will benefit more from the interactive ecosystem in crowdfunding platforms by attracting more foreign investors. Communication efforts help reduce the monitoring costs of investors, improve the efficacy of information sharing, and increase the benefits of crowd participation (Brav et al., 2022). We conjecture that extensive interactions persuade more strangers, particularly foreign retail investors, to contribute and mitigate the effects of home bias by reducing home dependence and promoting more diversified and rational investment decisions, labelled as an information-based interpretation. Such newly created social capital in the fintech ecosystems shall significantly mitigate the effect of home bias due to familiarity, loyalty, patriotism, and information asymmetry.

We then execute our empirical analyses on a large dataset from Kickstarter's technology sector. Our dataset covers 12,055 technology crowdfunding projects on the Kickstarter platform. Following definitions of home bias in Shi et al. (2017), Cornaggia et al. (2020), Florentsen et al. (2020), and Zhu et al. (2023), we define this dependence on domestic investments existing in the technology crowdfunding sector to be home bias. We also define micro-level proxies for social capital based on the textual information of the campaigns themselves and identify a campaign-level threshold value of within-platform social networking capabilities based on text analyses.

We further identify the delivery status of the project based on the Word2Vec algorithm of Mikolov et al. (2013). We first pre-process the text data collected from Kickstarter, which includes tokenisation, removal of punctuation, stop words elimination, and lemmatisation to ensure the quality of the input data for the Word2Vec model. Using the pre-processed text, we train a Word2Vec model and map words to vectors in a continuous space based on their semantic meanings derived from the context in which they appear. Then, we construct a dictionary enriched with terms indicative of successful project execution and product/service delivery. The Word2Vec model's ability to capture semantic similarities allowed us to identify a robust set of keywords strongly associated with the delivery status.

Three sets of empirical results are presented. First, we find that technology campaigns attracting more domestic investors have higher chances of successful capital raising and project implementation, and this main result is robust to alternative variable measurements and model specifications. Second, as predicted by our conceptual framework, the home bias effect on funding and delivery success a) is strengthened when a creator has a high level of “old” (preexisting) social capital, and b) is weakened when a creator has a high level of “new” (newly created) social capital. The results align with our two key theoretical arguments, preference-based and information-based explanations, highlighting the importance of technology entrepreneurs’ excessive capabilities of creating “new” social capital in the fintech era. Third, we detect that technology entrepreneurs’ home country levels of financial inclusion and investor protection influence the link between home bias and crowdfunding outcomes. The impact of home bias is significantly stronger when an entrepreneur’s country is characterised by lower financial inclusion or weaker investor protection.

Our investigation of influencing mechanisms of different social capital on home bias effect and the insights regarding economic benefits generated by new social capital in technology crowdfunding put forward a novel perspective to explain the micro-macro dynamics in the fintech era. It contributes to the literature on fintech and entrepreneurship in three aspects.

Firstly, our paper highlights the power of behaviour bias theories in interpreting home bias in innovative entrepreneurial finance, contributing to the existing literature (Bailey et al., 2018; Kahneman & Tversky, 1979; Lin & Viswanathan, 2016; Strong & Xu, 2003). The behavioural bias theory was first developed by the fundamental aspects of the Prospect Theory from Kahneman and Tversky (1979). Then, a stream of literature analyses the impact of behavioural bias on investment decision-making, such as those of Grinblatt and Keloharju (2001), Strong and Xu (2003), Bailey et al. (2018), Morse and Shive (2011), Lin and Viswanathan (2016) and Cornaggia et al. (2020). For instance, Grinblatt and Keloharju (2001), Morse and Shive (2011), and Cornaggia et al. (2020) provide evidence that culture, patriotism and political environments can influence investment behaviour and lead to a home bias. Our paper provides the first detailed empirical analysis of the innovative entrepreneurial financing setting from this theoretical lens. It complements prior studies by reflecting cognitive biases due to investors’ familiarity with and trust in domestic creative ventures. It highlights the preference-based investment decisions when retail investors face the novelty and uncertainty of creative ventures.

Secondly, our study explores how entrepreneurs’ excessive communication activities influence investors’ behaviour biases in fintech communities. It contributes to the literature on the financial implications of social capital, building upon the foundational work (Covrig et al., 2007; Dahl & Sorenson, 2012; Giudici et al., 2018). These studies state that an investor’s behaviour may be connected with social capital. However, most of the prior, like Giudici et al. (2018), Kuchler et al. (2022), and Lin and Pursiainen (2022), rely on the level of social capital in the regions. Through textual analysis, our study establishes a campaign-specific threshold for the entrepreneurs’ social networking capabilities. It introduces an innovative metric for assessing new forms of social capital, advancing the field by concentrating primarily on micro-level indicators. It thus contributes to understanding the financial decision-making of crowd investors in fintech ecosystems, focusing on the dual role of social capital.

Thirdly, our research complements recent studies on fintech’s macro and micro dynamics and suggests the importance of fintech adoptions in less developed countries to enhance the likelihood of innovative entrepreneurial financing success. Several papers find that countries witness more fintech investments and activities when economies and capital markets are well-developed (An & Rau, 2021; Bertoni et al., 2022; Haddad & Hornuf, 2019; Zhao et al., 2021). In contrast, developing countries have fewer fintech opportunities due to cultural and macroeconomic factors (An et al., 2022; Haddad & Hornuf, 2019). We identify that the economic benefits of fintech are more significant for technology entrepreneurs from countries with less financial inclusion and weaker investor protection. Fintech revolutionises the financial system in developing countries and expands access to finance for small firms and start-ups. Thus, policies aiming at fintech penetration in less developed countries will help foster financial development and promote financial inclusion.

The rest of the paper is organised as follows. Section 2 discusses the theoretical framework and proposes three testable hypotheses. Section 3 describes the data and methodology. The main empirical results are then analysed in Section 4. Section 5 discusses cross-sectional heterogeneity based on entrepreneurs’ home country financial inclusion and investor protection levels. Section 6 presents the robustness check results. Finally, the conclusion is drawn in Section 7.

2. Literature review and hypotheses development

2.1. *Influence of home bias in the technology reward-crowdfunding market*

Academic studies on home bias are traced back to French and Poterba (1991), which state that people always overinvest domestically and locally. Since then, several theoretical studies have discussed home bias and its rationality, such as Cooper and Kaplanis (1994), Coval and Moskowitz (1999, 2001), and Van Nieuwerburgh and Veldkamp (2009). Their theoretical framework argues that global information access cannot eliminate the information asymmetry due to home investors choosing not to learn what foreigners know. Following the theoretical research, a strand of literature exploring different forms of home bias and its influence on investment performance has emerged, which provides sufficient empirical evidence for home bias in other markets, such as Dougal and Rettl (2021), Sialm et al. (2020), Kuchler et al. (2022).

In addition to overweighting local assets, other forms of home bias and their impacts are documented in the literature. Lai and Teo (2008) identify more optimistic recommendations of local analysts and more generous ratings among local credit analysts. Dahl and Sorenson (2012) discover a preference for local investment in the initial stages of venture location decisions and argue that this inclination takes advantage of the social capital inherent in local networks. Shi et al. (2017) find that all else being equal, artwork auctions in artists’ home cities tend to have higher prices, and thus, investors exhibit home bias in the domestic art market. Cornaggia et al. (2020) argue that home bias exists among information producers, and this observed home analyst effect indicates a behaviour bias rather than superior information. Zhu et al. (2023) examine the role of home bias in making economic decisions and find that when confronted with M&A decisions, respondents give particular priority to their hometowns.

A pivotal disruption wrought by fintech is its diminution of barriers, thereby facilitating the entry of individual investors worldwide into entrepreneurial ventures. Policymakers particularly view fintech as a cost-efficient method to overcome geographical constraints and aim to partially remove the economic barriers related to distance by utilising internet-based financing platforms (Lin & Viswanathan, 2016). According to Agrawal et al. (2015), these online fintech platforms effectively diminish certain distance-related economic frictions, including monitoring projects, offering advice, and collecting information. A natural question arises: do fintech ecosystems help resolve home bias or lessen its influence?

Theoretically, online crowdfunding platforms or other fintech channels can dramatically decrease foreign investment costs and thus have great potential to ease the constraint of geographical proximity in fundraising for start-ups or micro and small firms (Kim & Hann, 2019; Levy & Levy, 2014). Because all projects on crowdfunding platforms are equally visible to potential funders irrespective of their locations, the dependence of small businesses on local lenders or investors shall be diminished, as a key disruption of fintech is that it lowers the barrier for global individual investors to access entrepreneurial projects. Nevertheless, some studies suggest that despite the decreased geographical barriers to access to finance in crowdfunding platforms, many online crowdfunders still prefer local transactions and projects (Agrawal et al., 2015; Lin & Viswanathan, 2016).

In this paper, we define dependence on domestic investment as home bias and conjecture that it plays a significant role in allocating resources in technology entrepreneurial financing due to information costs and familiarity. We propose two rationalities for home dependence in the fintech era and justify its subsequent impact on technology crowdfunding performance.

The first rationality for the influence of home bias is an informational advantage or information differential. Empirical studies show collecting “soft” information on small businesses over time through relationships with their owners is still very important in the fintech era, making local presence critical (Jiang et al., 2022; Kim & Hann, 2019; Petersen & Rajan, 2002). Hence, crowdfunding projects with a higher proportion of investors from their home country are more likely to enjoy an informational edge via better local networks and thus to win support from external backers during both the fundraising and follow-on implementation processes based on a better understanding of local culture, institutions, or soft information on small business.

The second rationality is that home bias has a behavioural explanation rooted in familiarity and trust, as people tend to invest in what they are familiar with and trust. Chan et al. (2005) argue that investors are more willing to hold securities of firms they are more familiar with. Behavioural biases such as common language, culture, loyalty, patriotism, trust, and familiarity (Cohen, 2009; Duan et al., 2020; Grinblatt & Keloharju, 2001; Huberman, 2001; Wei & Zhang, 2020; Zingales, 2015). Therefore, crowdfunding projects with a higher proportion of investors from their home country are more easily funded and supported during the follow-on implementation process due to the investors’ familiarity with and trust in the innovating entrepreneurs.

Due to more technology and innovation components, technology projects usually face higher levels of information asymmetry and unfamiliarity. Thus, we conjecture that technology projects attracting a higher proportion of domestic investors are generally more likely to succeed in raising funds and delivering products. The concentration of local investors influences online technology entrepreneurial financing performance positively. It thus drives our central hypothesis.

H1. *Home-concentrated crowdfunding projects have higher chances of funding and implementation success.*

2.2. Social capital factors that moderate the home bias effect

The concept of social capital is well-researched. Dahl and Sorenson (2012) find that firms exhibit a home bias in their location choices due to the advantages of pre-existing social capital. Lee and Persson (2016) argue that social capital, such as family and friend ties, can provide young start-ups with cheap, informal capital. Javakhadze et al. (2016) find that the social capital resident in managerial social networks is positively associated with investment sensitivity to cash flow. Duan et al. (2020) prove that entrepreneurial social capital is recognised for its significant role in conveying the credibility and goodwill of projects, influencing the success rate of crowdfunding initiatives. Kuchler et al. (2022) highlight that the social capital of regions affects firms’ access to capital, while Lin and Pursiainen (2022) identify a significant positive relationship between the social capital of an entrepreneur’s home county and the success of their crowdfunding performance. In general, this line of research supports that social capital helps to alleviate inefficiencies in financial markets caused by information asymmetry or moral hazard.

The online crowdfunding market helps entrepreneurs in the early stages start their ventures and receive a great deal of individual investor attention (Burtch et al., 2014; Jiang et al., 2022; Mollick, 2014). Many start-up businesses have limited product information or a short track record, and it is hard for them to access traditional financing markets. Naturally, entrepreneurs’ social capital helps signal projects’ trustworthiness and benevolence and affects the success of crowdfunding campaigns (Ahlers et al., 2015; Duan et al., 2020). First, social capital delivers the right and less alterable information to investors in the fintech context (Lin et al., 2013). Second, social capital influences underlying entrepreneurs’ behaviour in project fundraising and implementation (Ferris et al., 2019; Lin & Pursiainen, 2022).

Based on the theories of behaviour bias and rational choice, we differentiate two types of social capital: an “old” one, namely, pre-existing social relations of technology entrepreneurs before raising capital from the crowd, and a “new” one, namely, newly created social relationships by entrepreneurs’ extensively engaging in fintech platform networking with the crowd. We argue that these two types of social capital affect the link between home bias and crowdfunding performance in diverged directions, with one enhancing the home bias effect and the other weakening it.

2.2.1. The theory of behaviour bias and a preference-based interpretation

Behavioural bias refers to the tendency of individuals to make decisions based on cognitive and emotional factors rather than rational analysis, such as a preference for local investments based on familiarity, loyalty, trust, or over-optimism (Cohen, 2009;

Huberman, 2001; Lin & Viswanathan, 2016; Strong & Xu, 2003; Zingales, 2015). The behavioural bias theory suggests investors tend to be relatively optimistic about the outlook for their domestic economies, leading them to overweight domestic projects in their portfolios (Strong & Xu, 2003). Lin and Viswanathan (2016) find that behavioural motivations, rather than economic reasons alone, play an important role in driving home bias in the online crowdfunding market.

Domestic investors strongly prefer domestic versus foreign markets, suggesting that "home bias" derives in part from increased confidence (Maroney et al., 2008). Social networks usually play an important role in delivering confidence to investors. Pre-existing social relationships, most of which are comprised of friend and family ties, act as the mechanism through which geographic distance matters. In early-stage platform financing, friend and family relationships build up a certain trustworthiness of the creator, which helps identify worthwhile investments (Lee & Persson, 2016).

In the behavioural preference view, confidence and trustworthiness are essential in investors' evaluation process of technology entrepreneurs because the information costs incurred in new technology's development and commercialisation process are rather high. For technology reward crowdfunding, crowdfunders look up high-tech projects or services online and choose what they want to invest in (Mollick, 2014). Investors must make decisions based on the description of products and risks uploaded by creators along with some videos or other subjective materials, which provide high uncertainty about the future and cause information asymmetry.

Thus, we contemplate that the pre-existing social capital of creators, measured by the number of Facebook friends not cultivated inside the crowdfunding platform, which was originally developed outside the online crowdfunding platform, is mainly influencing the crowdfunding performance by strengthening the home bias effect through preferences due to past experiences, familiarity, trust and overconfidence of pre-existing social ties. Investors are reluctant to invest in foreign campaigns due to perceived risks or lack of information, and such investments may not offer the best financial returns or diversification benefits. Hence, pre-existing social relationships strengthen the impact of home bias on crowdfunding performance. This leads to our second hypothesis.

H2. *The home bias effect is strengthened when the creator has a higher level of "old" social capital, namely, pre-existing social relations such as family and friend ties.*

2.2.2. The theory of rational choice and an information-based explanation

According to the information-based/rational theory, investors prefer specific types of securities because they have better access to information about them (Brav et al., 2022; Coval & Moskowitz, 1999, 2001). Social networking within the platform allows crowdfunders to communicate with each other and with funding recipients effectively (Agrawal et al., 2015). Gedajlovic et al. (2013) argue that entrepreneurs usually develop "new" social connections when running a new venture. Belleflamme et al. (2014) also regard community benefits as a key determinant for crowdfunding and document that crowd investors use online social networks to monitor and enjoy the improvement of product quality. Courtney et al. (2017) argue that online signals through start-up actions such as using various media and creators' prior crowdfunding experiences mitigate information asymmetry concerns about project quality and founder credibility and, thus, enhance the project's likelihood of attaining funding.

Given the large number of crowd investors in a crowdfunding platform, investor management is challenging (Kim & Hann, 2019), and the dynamic interactions between entrepreneurs and investors are important for project development. Wessel et al. (2016) document that the information displayed in "comments" can serve as a quality signal and help consumers assess the quality of goods before purchasing better. Cornelius and Gokpinar (2020) find that entrepreneurs in reward crowdfunding are faced with a crowd of investors who try to impact product development and can benefit from this influence because greater investor involvement increases funding success. Cai et al. (2021) document that social networks generated by creators in extensive communication efforts to persuade strangers, the crowd, to back up their campaigns as internal, which resulted in social capital creation by generating backers' psychological ownership of a project and enhancing their commitment, or even a shared culture within the online crowdfunding community. Yasar et al. (2022) show that higher levels of open communication increase the likelihood of project funding success, and project creators can engage backers and use the "wisdom of the crowd" in product development.

In our paper, platform social networking ability refers to a creator's excessive capacity to engage in social interactions on crowdfunding platforms, such as posting comments and communicating with potential investors. This ability can reduce information costs and help creators build "new" social capital. In online technology crowdfunding, technology entrepreneurs' extensive communications within platforms are essential to overcome information asymmetry and to enhance backers' trust in strangers. Technology entrepreneurs, who usually face a high level of innovation risk, must engage many contributors regularly to create platform-specific social capital to enhance their chances of success.

Therefore, we argue that extensive communication efforts to persuade strangers to contribute help mitigate the effects of home bias and promote more rational and diversified investment decisions. Because of great uncertainty in technology projects, when crowd investors raise problems and concerns, excessive comments made by creators represent a positive signal of problem-solving and help enhance social interaction with the community by promoting investors' engagement, decreasing monitoring costs and improving emotional connections. This leads to higher informational social value and creates new social capital.

We highlight the importance of extensive and effective interplays between entrepreneurs and investors and hence conjecture that there is a threshold in the networking efforts. When the level of communication, proxied by the number of comments, is lower than the threshold value, the communications may not convey enough information, and the new social capital may not be well established. The preference-based investment dominates, and, at this stage, the project relies more on the support of local investors. When the level of communications exceeds the threshold value and extensive information is created, preference-based investment decreases. With the enhancement of excessive social networking ability, creators can reduce information costs and establish new social contacts, broadening their funding sources and reducing their dependence on local investors.

Thus, we anticipate that technology entrepreneurs with a high capability of platform networking and conveying more precise project-specific information can obtain foreign investment more effectively, thus mitigating investors' home bias. This new mechanism of "new" social capital creation due to extensive communications leads us to the third hypothesis.

H3. *The impact of home bias is weakened when a creator has an excessive capability of within-platform networking that reduces information costs and creates "new" social capital.*

3. Data and methodology

3.1. Data and variables

Kickstarter, an international fundraising website located in the U.S., is one of the largest reward crowdfunding platforms in the world. Since its establishment in April 2009, this crowdfunding platform has emerged as a major online crowdfunding marketplace for various creative projects (Kim & Hann, 2019). Our dataset for the current study consists of detailed technology campaign data from the Kickstarter platform from the second quarter of 2009, when Kickstarter was founded, to December 2019. All the information is available at the campaign level. The Kickstarter platform contains information on 41,171 technology crowdfunding projects launched until the end of the data collection period, namely, December 2019.

In our study, we use 12,055 technology projects which contain the most complete information. The database contains three data files: (i) the campaign owner-specific characteristics, including the creators' name, location, and Facebook friend number; (ii) the campaign-specific characteristics, including goal amount, pledged amount, category, and project location; and (iii) the campaign backer-specific characteristics, including the comments of the backers, the top ten countries where most backers come from and the number of backers from each of the countries. Detailed statistics of the number of campaigns and main backers initiated from each country are provided in panels A and B ofAppendix A. As shown, the U.S. backers take up a large proportion of all backers.

Table 1 shows the industry and year distribution of the sampled technology reward campaigns. The proportion of campaigns successfully funded in the web, apps, and software industries is relatively small. Technology, robots, DIY electronics, camera equipment, sound, and space exploration campaigns whose rewards are more mature and thus have limited scalability are rarely initiated but relatively easier to obtain funding for.

The performance of technology reward crowdfunding is our main interest in this study. Some new ventures are likely to fail to deliver the products even after raising capital successfully. Thus, we proxy crowdfunding performance in two dimensions: fundraising success and campaign implementation success. Fundraising success is measured by the campaign survival dummy *Success*, which takes a value of 1 when the initiator successfully reaches its goal during the time duration and 0 otherwise. Campaign implementation success is measured by *Delivery* to distinguish whether the campaign delivers the product and service as promised. The dummy variable is equal to 1 if the campaign delivers the product and service as promised and equal to 0 otherwise. We also employ the *Success rate* as an alternative measure of crowdfunding success to test whether the findings might be sensitive to the specific measures chosen. Definitions of variables are provided in Appendix B.

We are interested in the changes in performance concerning the dependence on domestic investment within the examination period. Variables to distinguish whether the campaign is mainly supported by domestic or international investors are defined. *Samecountry* is a dummy variable that equals 1 when the campaign is domestic, as the largest group of funders for the crowdfunding campaign is from the creator's home country, and 0 otherwise. For robustness check, we also proxy the dependence of domestic investment by an alternative definition, namely *Samecountry%,* which is defined as the number of backers from the creator's home country divided by the total number of campaign backers.

We are also interested in how different types of social networks add value to technology reward campaigns. Pre-existing and platform social networks differ in several aspects, including information content, participant structure, and impact on the home bias effect. *Facebook* and *Comment* are the two moderation variables used to measure the two factors that transfer information about the quality of the project and moderate investors' beliefs in public and private information. *Facebook* is measured by the natural logarithm of the number of Facebook friends of the founder shown on the campaign website, which is included to measure the pre-existing social relationship. *Comment* is calculated using the natural logarithm of the number of comments on the campaign website where the founder and investor can communicate with each other. This variable represents the size of the inner social community, i.e., the platform social network.

Four control variables are included in the analysis, namely*, FAQ, Website, Backed,* and *Collaborator*. These characteristics and quality of the campaigns are summarised from the existing literature to control for their effects on fundraising success and campaign implementation of technology reward crowdfunding. We also employ two variables, *Financial inclusion* and *Investor protection*, to examine heterogeneity based on the backers' home country's financial inclusion level and investor protection level, respectively. *Backer openness* and *Backer terrorism* are the instrumental variables used in our instrumental variable strategy to address endogeneity concerns.

The Kickstarter dataset offers us an excellent opportunity to study technology reward crowdfunding backer allocations worldwide. First, we classify campaigns into domestic and international campaigns. Domestic campaigns have most of their backers from the creators' home country. Otherwise, the campaigns are classified as international campaigns.

Table 1
Category and year distribution of the sample.

Panel A: Category distribution of the sample			
Campaign category	No. of observations	No. of observations funded	Percentage of funded obs.
3D Printing	334	147	44.01 %
Apps	2026	395	19.50 %
Camera Equipment	276	158	57.25 %
DIY Electronics	599	350	58.43 %
Fabrication Tools	124	44	35.48 %
Flight	151	43	28.48 %
Gadgets	1878	837	44.57 %
Hardware	1839	630	34.26 %
Makerspaces	142	71	50.00 %
Robots	311	190	61.09 %
Software	1349	313	23.20 %
Sound	443	245	55.30 %
Space Exploration	192	106	55.21 %
Technology	201	201	100.00 %
Wearables	652	277	42.48 %
Web	1538	244	15.86 %
Total	12055	4446	35.36 %

Panel B: Year distribution of the sample			
Year	No. of observations	No. of observations funded	Percentage of funded obs.
2009	18	6	33.33 %
2010	87	31	35.63 %
2011	117	55	47.01 %
2012	243	111	45.68 %
2013	549	189	34.43 %
2014	1618	394	24.35 %
2015	3124	681	21.80 %
2016	2053	548	26.69 %
2017	1583	807	50.98 %
2018	1400	706	50.43 %
2019	1263	723	57.24 %
Total	12055	4251	35.26 %

Table 2 presents the descriptive statistics of all the variables used in this paper.[1] Overall, 35 % of the campaigns initiated successfully received funding. The share of domestic investors within the total backers of the top ten countries is averaged at 47 %. The largest campaign aims to raise US$55,000,000. Correspondingly, the natural logarithm value is 17.823. The number of comments for each campaign ranges from 0 to 1,634, and the number of Facebook books ranges from 0 to 5000. Hence, the values for the natural logarithm of “Comment” and “Facebook” range from 0 to 7.719 and 0 to 8.517, respectively.

3.2. *Research design*

To avoid the endogeneity problem, we employ the propensity score matching (PSM) method before running the logit regressions. The PSM method is developed by Rosenbaum and Rubin (1983), aiming to randomise the sample selection procedure. Following Chen et al. (2017), we match a domestic crowdfunding project to a non-domestic campaign with the nearest neighbour with a proportion of 1:3. In our regression models, *Samecountry* is employed as the treatment variable, while *Success* or *Delivery* is the dependent variable of the first PSM model. The variables *Goal, FAQ, Collaborator* and *Loved* are included in the propensity score matching model. The *Year* effect, *Industry* effect, and *Country* effect have been controlled.

Tables 3 and 4 report the characteristics of the treatment and control campaigns based on the dependent variables of *Success* and *Delivery*, respectively. The difference in the average treatment effects (ATTs) on *Success* and *Delivery* between the treatment and control groups is 0.196 with a *t* value of 6.30 and 0.114 with a *t* value of 6.310 after propensity score matching, respectively. There is no selection bias between the two groups. As indicated, after PSM, the difference in the mean values of the variables between the two groups was eliminated. We use the Abadie-Imbens (AI) method to calculate standard errors. Appendix C provides density plots to verify that assumptions related to the PSM methodology are fully met.

Following Mollick (2015), Lin and Viswanathan (2016) and Regner and Crosetto (2021), we employ logistic regressions on *Success* to test the home bias hypotheses on the PSM samples empirically. In addition, the delivery of the crowdfunding campaigns is only observed if the campaign is successful. Hence, to account for potential sample selection bias in this context with non-linear models, we apply the Heckman-probit model when the dependent variable is *Delivery*. We use “*Created*” as the identify variable, since when the

[1] The correlation matrix is available upon request.

Table 2
Descriptive Statistics.
This table reports the number of observations, mean, maximum value, minimum value, standard deviation for all the variables used in this paper. The main pooled sample consists of 12055 campaign observations from Year 2009–2019. Variables are defined in Appendix B.

Variables	No. of Obs.	Mean	Std. Dev.	Min	Max
Success	12055	0.353	0.478	0.000	1.000
Delivery	12055	0.309	0.462	0.000	1.000
Samecountry	12055	0.527	0.499	0.000	1.000
Samecountry%	12055	0.474	0.367	0.000	1.000
Comment (log)	12055	1.507	1.760	0.000	7.719
Facebook (log)	12055	2.224	2.961	0.000	8.517
Goal (log)	12055	9.502	1.668	0.577	17.823
Website (log)	12055	0.800	0.543	0.000	2.079
FAQ (log)	12055	0.505	0.857	0.000	3.091
Loved	12055	0.056	0.231	0.000	1.000
Backed (log)	12055	0.678	0.984	0.000	3.892
Created (log)	12055	0.874	0.381	0.693	2.708
Reward (log)	12055	1.946	0.604	0.693	3.135
Collaborator (log)	12055	0.186	0.433	0.000	1.792

Table 3
PSM Treatment and Control Sample with respect to Success.
This table reports the characteristics of treatment and control campaigns. Difference of ATT with respect to *Success* between the two groups of crowdfunding projects equals 0.196 and the *t*-value is 6.30 after propensity score matching. Panel B and C present the comparison between treatment and control campaigns using a pooled and a propensity score-matched sample, respectively. Variables are defined in Appendix B.

Panel A: Average treatment effect

Variables	Treated projects	Control projects	Differences	S.E.	t-statistics
Success(ATT)	0.445	0.249	0.196***	0.017	6.30
Success(ATE)			0.114***	0.012	9.09

Panel B: Before matching

Variables	Treated projects	Control projects	Differences	%bias	t-statistics	p-value
	Mean	Mean				
Goal	9.456	9.560	−0.104***	−6.400	−3.530	0.000
FAQ	0.602	0.396	0.206***	24.300	13.250	0.000
Created	0.880	0.875	0.025	1.300	0.700	0.487
Loved	0.060	0.052	0.008**	3.800	2.080	0.038
Year	YES	YES				
Industry	YES	YES				
Country	YES	YES				

Panel C: After matching

Variables	Treated projects	Control projects	Differences	%bias	t-statistics	p-value
	Mean	Mean				
Goal	9.456	9.419	0.037	2.200	1.280	0.201
FAQ	0.602	0.613	−0.011	−1.300	−0.660	0.510
Collaborator	0.880	0.869	0.011	2.700	1.570	0.117
Loved	0.060	0.055	0.005	2.200	1.220	0.224
Year	YES	YES				
Industry	YES	YES				
Country	YES	YES				

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

initiator had created more campaigns before, they had more successful experiences. However, there is no evidence that this will guarantee the delivery of the project. For Hypothesis 1, we adopt the first regression model, and the *Year* effect, *Industry* effect and *Country* effect have been controlled. In this model, we examine the positive relationship between domestic investment and the fundraising/implementation success of technology crowdfunding. *Samecountry* is employed as the key independent variable to measure the overall level of domestic investors within the total backers. If the coefficient is significant and positive, the home bias effect is discovered.

$$Success_i \, / \, Delivery_i = \beta_0 + \beta_1 Samecountry_i + \beta_2 Control_i + \beta_3 Year_i + \beta_4 Industry_i + \beta_5 Country_i + \varepsilon_i \quad (1)$$

For Hypothesis 2, we adopt the regression model in Equation (2). The moderation effects of pre-existing social networking on the positive relationship between domestic investment and the performance outcomes of technology crowdfunding are investigated.

Table 4
PSM Treatment and Control Sample with respect to Delivery.
This table reports the characteristics of treatment and control campaigns. The difference of ATT with respect to *Delivery* between the two groups of crowdfunding projects equals 0.114 and the *t*-value is 6.310 after propensity score matching. Panel B and C present the comparison between treatment and control campaigns using a pooled and a propensity score-matched sample, respectively. Variables are defined in Appendix B.

Panel A: Average treatment effect						
Variables	Treated projects	Control projects	Differences	S.E.	t-statistics	
Delivery(ATT)	0.494	0.380	0.114***	0.018	6.310	
Delivery(ATE)			0.135***	0.015	8.840	
Panel B: Before matching						
Variables	Treated projects	Control projects	Differences	%bias	t-statistics	p-value
	Mean	Mean				
Backed	0.972	0.355	0.617***	65.900	33.060	0.000
Video	0.810	0.480	0.330***	73.400	36.420	0.000
Created	0.899	0.850	0.049***	12.800	6.410	0.000
Loved	0.068	0.041	0.027***	12.100	6.060	0.000
Year	YES	YES				
Industry	YES	YES				
Country	YES	YES				
Panel C: After matching						
Variables	Treated projects	Control projects	Differences	%bias	t-statistics	p-value
	Mean	Mean				
Backed	0.949	0.950	−0.001	−0.100	−0.050	0.963
Video	0.808	0.809	−0.001	−0.300	−0.170	0.865
Created	0.899	0.892	0.007	1.800	0.840	0.398
Loved	0.068	0.064	0.004	1.700	0.740	0.459
Year	YES	YES				
Industry	YES	YES				
Country	YES	YES				

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Communication among friends and family and the pre-existing social community formed is measured by the number of Facebook friends. The interaction term of *Samecountry* and *Facebook* is included to catch the moderation effect. *Facebook* will help the process of identifying worthwhile investments and making investment decisions in the earlier stage due to different information owned by friends

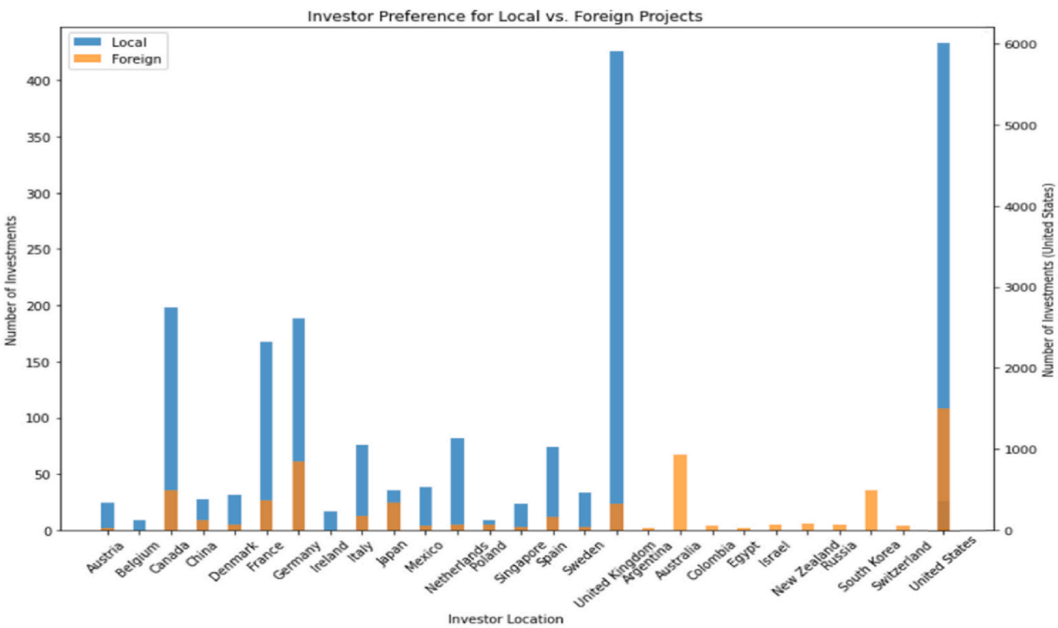


Fig. 1. Investor preference for local and foreign projects.

and family and social ties (Agrawal et al., 2015), which strengthens the positive relationship between domestic investors and funding/implementation success.

$$Success_i \Big/ Delivery_i = \beta_0 + \beta_1 Samecountry_i + \beta_2 Facebook_i + \beta_3 Same\ country_i * Facebook_i + \beta_4 Control_i + \beta_5 Year_i + \beta_6 Industry_i + \beta_7 Country_i + \varepsilon_i. \tag{2}$$

For Hypothesis 3, we adopt the regression model in Equation (3). The moderation effects of the platform social networking capability of creators on the positive relationship between domestic investment and crowdfunding performance are tested. The communication among crowdfunding participants and the inner social community formed based on the platform is measured by the number of comments on the campaign webpage. The interaction term of *Samecountry* and *Comment* is included to test the moderation effect. Comments act as channels for transmitting the correct information and mitigate the positive relationship between domestic investors and funding/implementation success.

$$Success_i \Big/ Delivery_i = \beta_0 + \beta_1 Samecountry_i + \beta_2 Comment_i + \beta_3 Same\ country_i * Comment_i + \beta_4 Control_i + \beta_5 Year_i + \beta_6 Industry_i + \beta_7 Country_i + \varepsilon_i. \tag{3}$$

4. Empirical evidence

4.1. Descriptive statistics

We first present some stylized facts for the existence of home bias in our data sample. Fig. 1 plots investor preference for local and foreign projects that have more than 2 crowdfunding backers in the countries with above-median campaign numbers. The blue bars represent projects attracting more domestic investment (Defined as Local) and the orange bars represent projects attracting more foreign investment (Defined as Foreign). The number of the U.S. Campaigns, which is the largest one, is indicated on the right axis, while all the rest countries' numbers are exhibited on the left axis. As exhibited in Fig. 1, most of the countries have a larger proportion of the number of investments in local projects, which shows that the home bias effect exists. A similar pattern is observed for campaigns in the United States.

Table 5
Impact of home bias on the performance of technology crowdfunding.
This table presents logistic regression results with fixed effects from regressing whether the largest group of investors is from the same country as the creator on financing and implementation performance on the Kickstarter crowdfunding platform. Standard errors are clustered at the country level. The *standard errors* are reported in brackets. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively. The *p*-VALUE shows the significance of estimated coefficients.

Variables	*Success*	*Success*	*Success*	*Delivery*	*Success*	*Delivery*
	(1)	(2)	(3)	(4)	(5)	(6)
Samecountry	0.704***			0.371**		
	(0.228)			(0.156)		
Samecountry%		1.517***				0.286**
		(0.341)				(0.130)
FAQ	0.428***	0.422***	0.273***	0.095	0.258***	0.057
	(0.054)	(0.052)	(0.025)	(0.062)	(0.015)	(0.059)
Collaborator	0.536***	0.524***	0.435***	0.131	0.443***	0.138
	(0.138)	(0.139)	(0.096)	(0.080)	(0.062)	(0.085)
Website	0.347***	0.287***	0.232***	0.196**	0.247***	0.165***
	(0.081)	(0.094)	(0.019)	(0.085)	(0.019)	(0.057)
Backed	0.495***	0.478***	0.237***	0.077	0.273***	0.116***
	(0.031)	(0.028)	(0.013)	(0.068)	(0.010)	(0.043)
Created			0.541***		0.501***	
			(0.040)		(0.050)	
athrho			−0.610***		−0.535**	
			(0.218)		(0.239)	
Marginal effect of key variables	0.112***	0.237***		0.059**		0.051***
	(0.035)	(0.050)		(0.026)		(0.019)
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	7945	7945	7352	7352	7352	7352
p-VALUE	0.000	0.000		0.000		0.000
Pseudo R-squared	0.218	0.232				

4.2. Baseline result

Table 5 reports the results on whether the effect of home bias still exists in the reward crowdfunding context. The dependent variable of Models 1 and 2 is *Success*, which takes a value of 1 when the initiator successfully reached the goal during the time established and 0 otherwise. We apply Heckman-probit models to address the selection bias concerns when the dependent variable is *Delivery*, Model 3 to 6 present the results. The coefficient of *athrho* is significant at the 1 % level, which indicate the existence of the selection bias. The key independent variable for Models 1 and 4 is *Samecountry*, a dummy that equals 1 if the largest group of investors comes from the creator's location. For Models 2 and 6, the key independent variable is *Samecountry%,* which is the number of backers from the creator's home country divided by the total number of backers of the campaign. The coefficient estimates in Models 1 and 2 indicate that the largest group of investors coming from the home country is associated with a significant increase in the possibility of funding success of a crowdfunding campaign due to barriers to information asymmetry and monitoring costs. Models 4 and 6 show similar patterns in *Delivery*. We also report the marginal effect of the key explanatory variables in the regression, which shows the odds of success of a crowdfunding campaign. For example, the marginal effect of *SameCountry* in Model 1 is 0.112, which indicates the odds of the success of a "*Samecountry*" campaign is 0.112. When *Samecountry* changes from 0 to 1, indicating that the Kickstarter campaign has the largest group of investors within the country, the probability of fundraising success and successful implementation of the project is significantly higher. All regressions include yearly, industry, and country-fixed effects and are clustered at the country level.

The results indicate consistent effects across both dependent variables. Specifically, the coefficient for *Samecountry* is statistically significant at the 1 % level. Therefore, Hypothesis 1 is proven based on the results of Model 1 to Model 6 in Table 5. The home bias effect is confirmed to persist in reward crowdfunding platforms. The empirical evidence supports the underlying costs of investing in foreign countries, including culture clash, which increases the time required to learn about the firm and reduces the likelihood of deal completion (Alexandridis et al., 2022).

4.3. Moderation effects of two types of social capital

Table 6 presents the regression results based on Equation (2) for Hypothesis 2, which states that preexisting social relationships help to strengthen the positive impact of home bias on project performance. The dependent variable of Models 1 and 2 is *Success,* which takes a value of 1 when the initiator successfully reached its goal during the time duration and 0 otherwise. For Models 4 and 6, the dependent variable is *Delivery,* which takes a value of 1 when the product and service are successfully delivered and 0 otherwise. The key independent variable is *Samecountry*. *Facebook* is the moderation variable, valued by the natural logarithm of the number of

Table 6
The moderation effect of *Facebook* on the link between home bias and crowdfunding performance.
This table presents logistic regression results from regressing whether the largest group of investors is from the same country as the creator on financing and implementation performance on the Kickstarter crowdfunding platform, which could be moderated by the pre-existing social network of the campaign. Standard errors are clustered at the country level. The *standard errors* are reported in brackets. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively. The *p*-VALUE shows the significance of estimated coefficients.

Variables	*Success*	*Success*	*Success*	*Delivery*	*Success*	*Delivery*
	(1)	(2)	(3)	(4)	(5)	(6)
Samecountry	0.704***	0.576***		0.465***		0.369*
	(0.228)	(0.205)		(0.173)		(0.210)
Facebook	−0.002	−0.041*	0.016***	0.018		−0.013
	(0.007)	(0.023)	(0.003)	(0.011)		(0.024)
*Samecountry * Facebook*		0.062***				0.049**
		(0.022)				(0.024)
FAQ	0.428***	0.430***	0.278***	0.137***	0.277***	0.147***
	(0.054)	(0.054)	(0.024)	(0.048)	(0.024)	(0.052)
Collaborator	0.536***	0.531***	0.438***	0.217**	0.438***	0.232**
	(0.138)	(0.134)	(0.096)	(0.093)	(0.095)	(0.095)
Website	0.348***	0.349***	0.250***	0.217**	0.256***	0.236**
	(0.080)	(0.079)	(0.024)	(0.104)	(0.023)	(0.099)
Backed	0.496***	0.492***	0.253***	0.090	0.260***	0.104*
	(0.031)	(0.031)	(0.017)	(0.064)	(0.017)	(0.061)
Created			0.521***		0.528***	
			(0.041)		(0.043)	
athrho			−0.514***		−0.488***	
			(0.147)		(0.176)	
Marginal effect of key variables	0.112***	0.010***		0.084***		0.008**
	(0.035)	(0.003)		(0.030)		(0.004)
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	7945	7945	7067	7067	7067	7067
p-VALUE	0.000	0.000				
Pseudo R-squared	0.218	0.219				

Facebook friends of the creator shown on the campaign page. All regressions include yearly, industry, and country-fixed effects and are clustered at the country level.

Following Buis (2010) and Ai and Norton (2003), we use the marginal effect at representative values (MER) of the interaction term to interpret our results. In our paper, we first report the marginal effect of the interaction term at means in Table 6. Then, we calculate MER for home bias when *Facebook* takes different values and plot the results in Fig. 2. As shown in Fig. 2, as *Facebook* increases from 0 to 8, the probability of successful fundraising and project implementation with *Samecountry* equalling 1 remains positive. Results indicate that if project creators own a higher level of pre-existing social networks, home dependence is more prominent in determining entrepreneurs' success and project delivery. Therefore, Hypothesis 2 is confirmed.

We also propose that newly created social capital based on platform social networking helps effectively reduce information costs and, thus, helps to weaken the positive home bias impact on crowdfunding success in Hypothesis 3. Table 7 shows the empirical results of the moderation effects of *Comment* to the influence of *Samecountry* on successful fundraising and project implementation to test Hypotheses 3. We report the marginal effect of the interaction term in Table 7. In Fig. 3, we plot the marginal effect at representative values for the interaction term in this regression model.

As shown in Table 7 and Fig. 3, the marginal effect first shows an increasing trend and then decreases when the variable "Comments" exceeds a threshold value of 55 (e4 = 55), confirming Hypothesis 3. All regressions include yearly, industry, and country-fixed effects clustered at the country level.

5. Cross-sectional heterogeneity

5.1. Financial inclusion

Financial development is highly relevant to economic activities (An et al., 2022; An & Rau, 2021; Bollaert et al., 2021). Financial inclusion refers to a wide range of financial products and services that are made accessible to both businesses and individuals in a manner that is responsible and enduring, which helps to promote financial development. Bollaert et al. (2021) indicate that in areas with low financial inclusion, entrepreneurs have limited access to traditional financial channels in their home countries, while domestic investors have relatively fewer choices for investment projects. Crowdfunding, thus, provides a new platform for entrepreneurs to attract domestic investors to back their projects. In sharp contrast, investors have more access to various investment opportunities in areas with high financial inclusion levels, so they become pickier on domestic investments. Thus, home bias's importance on crowdfunding success is less dominant. Therefore, we expect the home bias effect on crowdfunding performance to be significantly positive in the areas with low levels of financial inclusion.

Table 8 reports the results of regressing the heterogenous effects of home bias in technology reward crowdfunding concerning financial inclusion. The dependent variable in Model 1 and Model 4 is *Success*, and the dependent variable for Model 3 and Model 6 is Delivery. The coefficient of *Samecountry* in Model 1 is positive and statistically significant for the low financial inclusion sample but is insignificant in the high financial inclusion sample in Model 4. There are similar patterns in Model 3 and Model 6, where the significance level of the coefficient for the effect of the *Samecountry* decreased to 10 % for the high financial inclusion sample in Model 6 but was statistically significant at 1 % for the low financial inclusion sample in Model 3. The results indicate that the effects of home bias are stronger in countries characterised by a low level of financial inclusion, which is consistent with our conjecture.

5.2. Investor protection

We then examine heterogeneous responses based on investor protection. John et al. (2008) find that investor protection is related to the level of risk-taking. Investors from low investor protection cities could undertake lower risk. They are more willing to invest in their

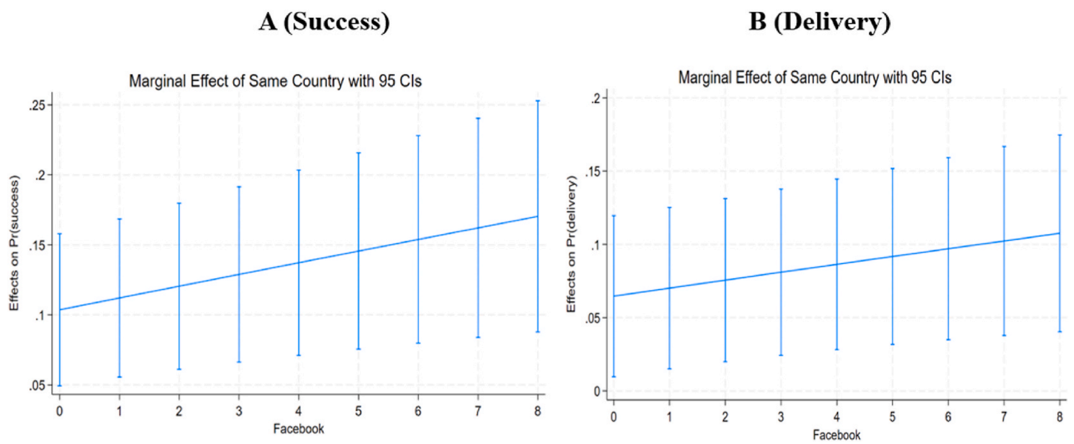


Fig. 2. The marginal effects of *Samecountry* on *Facebook*.

Table 7
The moderation effect of *Comment* on the link between home bias and crowdfunding performance.
This table presents logistic regression results on whether the largest group of investors is from the same country as the creator on financing and implementation performance on the Kickstarter crowdfunding platform, which the platform social networking of the campaign could moderate. Standard errors are clustered at the country level. The *standard errors* are reported in brackets. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively. The *p*-VALUE shows the significance of estimated coefficients.

Variables	*Success*	*Success*	*Success*	*Delivery*	*Success*	*Delivery*
	(1)	(2)	(3)	(4)	(5)	(6)
Samecountry	1.007***	2.034***		0.445***		0.634***
	(0.130)	(0.260)		(0.140)		(0.214)
Comment	1.155***	1.556***	0.635***	0.048		0.179***
	(0.018)	(0.096)	(0.015)	(0.075)		(0.032)
Samecountry		−0.629***				−0.092**
* *Comment*		(0.084)				(0.047)
FAQ	−0.072*	−0.094***	0.003	0.141**	0.273***	0.046
	(0.040)	(0.034)	(0.020)	(0.057)	(0.025)	(0.046)
Collaborator	0.049	0.060	0.184*	0.203**	0.434***	0.090
	(0.118)	(0.113)	(0.101)	(0.087)	(0.097)	(0.071)
Website	0.245***	0.192***	0.178***	0.260***	0.233***	0.182**
	(0.062)	(0.065)	(0.023)	(0.080)	(0.019)	(0.087)
Backed	0.250***	0.241***	0.134***	0.146**	0.238***	0.049
	(0.027)	(0.026)	(0.017)	(0.069)	(0.013)	(0.085)
Created			0.302***		0.538***	
			(0.028)		(0.037)	
athrho			−0.207		−0.659**	
			(0.210)		(0.259)	
Marginal effect of key variables	0.114***	−0.071***		0.091***		−0.015*
	(0.015)	(0.008)		(0.034)		(0.008)
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	7945	7945	7352	7352	7352	7352
p-VALUE	0.000	0.000				
Pseudo R-squared	0.414	0.427				

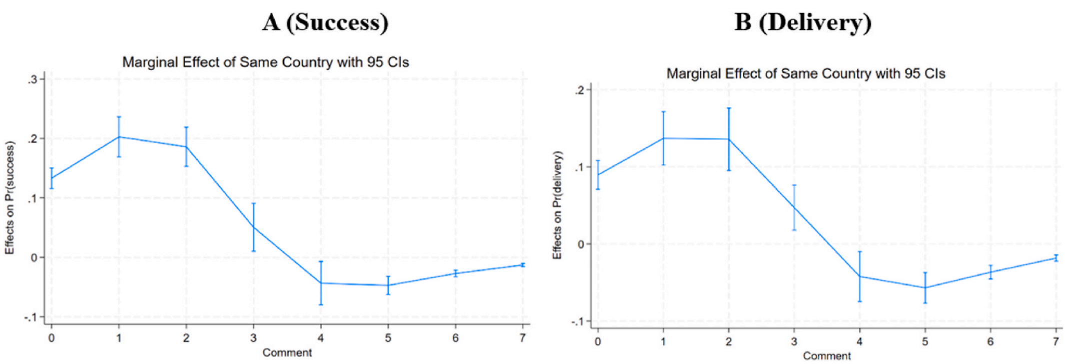


Fig. 3. The marginal effects of *Samecountry* on *Comment*.

own country's project to avoid the potential risk. In addition, high investor protection has higher costs for investors than the benefits it could bring (Xu, 2023). This would be a barrier to the successful implementation of a crowdfunding campaign. Armitage et al. (2021) also point out that poor investor protection can lead to less efficient resource allocation. In areas with low resource allocation efficiency, information asymmetry is more severe. Therefore, we expect the home bias effect on crowdfunding performance to be significantly positive in areas with low investor protection.

Table 9 reports our findings of heterogenous effects of home bias in technology reward crowdfunding based on investor protections. Similar to other cross-sectional tests, we split the sample based on the median of investor protection. As indicated, Model 1 and Model 3 include campaigns with below-median data, and Model 4 and Model 6 include campaigns with above-median investor protection. The coefficient for the effect of *Samecountry* in Model 1 is 0.416 at the 5 % significance level for the low investor protection sample. There are similar patterns in Model 3 and Model 6, where the coefficients for the effect of *Samecountry* are statistically insignificant for the high investor protection sample in Model 6 but statistically significant for the low investor protection sample in Model 3. The evidence indicates that the effects of home bias are stronger in countries characterised by the weaker protection of investors.

Table 8
Heterogenous impact of home bias on crowdfunding performance across financial inclusion.
This table uses logit regressions to examine the differential effects of home bias on technology reward crowdfunding based on financial inclusion. Standard errors are clustered at the country level. The *standard errors* are reported in brackets. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % level, respectively. The *p*-VALUE shows the significance of estimated coefficients.

Financial inclusion						
	Low Financial inclusion			High Financial inclusion		
Variables	*Success*	*Success*	*Delivery*	*Success*	*Success*	*Delivery*
	(1)	(2)	(3)	(4)	(5)	(6)
Samecountry	1.590***		0.376***	−0.004		0.318*
	(0.546)		(0.109)	(0.157)		(0.179)
FAQ	0.574***	0.309***	0.086***	0.278***	0.178***	0.106
	(0.057)	(0.030)	(0.022)	(0.044)	(0.020)	(0.072)
Collaborator	0.333***	0.467***	−0.516***	0.608***	0.450***	0.352**
	(0.097)	(0.135)	(0.049)	(0.185)	(0.111)	(0.178)
Website	0.496***	0.341***	0.098	0.134	0.046*	0.324**
	(0.103)	(0.019)	(0.082)	(0.092)	(0.024)	(0.130)
Backed	0.473***	0.409***	−0.137***	0.398***	0.127***	0.096
	(0.068)	(0.018)	(0.010)	(0.035)	(0.026)	(0.089)
Created		0.027			0.633***	
		(0.045)			(0.032)	
athrho		−1.438***			−0.727**	
		(0.141)			(0.315)	
Marginal effect of key variables	0.168***		0.035**	−0.001		0.342
	(0.056)		(0.014)	(0.032)		(0.023)
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4127	3761	3761	3804	3649	3649
Pseudo R-squared	0.319			0.139		

Table 9
Heterogenous impact of home bias on crowdfunding performance across investor protection.
This table uses logit regressions to examine the differential effects of home bias on technology reward crowdfunding based on financial inclusion. Standard errors are clustered at the country level. The *standard errors* are reported in brackets. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % level, respectively. The *p*-VALUE shows the significance of estimated coefficients.

Investor protection						
	Low Investor protection			High Investor protection		
Variables	*Success*	*Success*	*Delivery*	*Success*	*Success*	*Delivery*
	(1)	(2)	(3)	(4)	(5)	(6)
Samecountry	0.416**		0.899**	−0.082		0.227
	(0.186)		(0.371)	(0.225)		(0.225)
FAQ	0.458***	0.350***	0.325**	0.629***	0.225***	0.148**
	(0.166)	(0.052)	(0.129)	(0.079)	(0.032)	(0.059)
Collaborator	0.434***	0.347***	0.892***	0.155**	0.484***	0.044
	(0.103)	(0.102)	(0.168)	(0.071)	(0.048)	(0.114)
Website	0.639***	0.114*	0.498***	0.357***	0.196***	0.191**
	(0.085)	(0.059)	(0.137)	(0.018)	(0.025)	(0.089)
Backed	0.483***	0.153**	0.182***	0.321***	0.213***	0.132
	(0.079)	(0.061)	(0.055)	(0.061)	(0.012)	(0.082)
Created		0.647***			0.616***	
		(0.074)			(0.024)	
athrho		1.160*			−0.597*	
		(0.621)			(0.331)	
Marginal effects of key variables	0.044**		0.121**	−0.017		0.030
	(0.018)		(0.053)	(0.047)		(0.038)
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4250	4007	2420	3680	4007	4007
Pseudo R-squared	0.362			0.107		

Table 10
Robustness tests.
The following table shows the regression results. Standard errors are clustered at the country level. *Standard errors* are reported below the coefficients. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % level, respectively. The *p*-VALUE shows the significance of estimated coefficients.

Variables	Panel A: Alternative measure of crowdfunding success			Panel B: Excluding U.S. campaigns			Panel C: Excluding countries less attractive		
	Success rate	*Success rate*	*Success rate*	*Success*	*Success*	*Success*	*Success*	*Success*	*Success*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Samecountry	1.802***	0.222	0.216**	0.377***	0.598***	1.794***	0.712***	0.585***	2.031***
	(0.631)	(0.317)	(0.104)	(0.124)	(0.132)	(0.204)	(0.228)	(0.204)	(0.264)
Facebook		−0.035			−0.014			−0.041*	
		(0.062)			(0.021)			(0.023)	
Comment			1.111***			1.344***			1.553***
			(0.096)			(0.048)			(0.097)
*Samecountry *Facebook*		0.727***			0.077**			0.062***	
		(0.151)			(0.036)			(0.022)	
*Samecountry *Comment*			−1.175**			−0.452***			−0.623***
			(0.088)			(0.092)			(0.087)
FAQ	0.596***	0.621***	0.008	0.353***	0.710***	−0.091	0.428***	0.429***	−0.092***
	(0.128)	(0.120)	(0.030)	(0.067)	(0.055)	(0.071)	(0.055)	(0.055)	(0.035)
Collaborator	−0.576	−0.572	0.465***	0.342***	0.603***	−0.200*	0.540***	0.536***	0.064
	(0.821)	(0.833)	(0.071)	(0.127)	(0.107)	(0.106)	(0.138)	(0.134)	(0.112)
Website	4.025***	3.872***	0.021	0.488***	0.900***	0.277	0.351***	0.353***	0.194***
	(1.422)	(1.391)	(0.062)	(0.146)	(0.095)	(0.173)	(0.083)	(0.082)	(0.067)
Backed	0.837***	0.564***	0.140	0.530***	0.497***	0.287***	0.492***	0.488***	0.237***
	(0.084)	(0.126)	(0.122)	(0.054)	(0.065)	(0.059)	(0.031)	(0.031)	(0.026)
Marginal effect				0.059***	0.009***	−0.048***	0.113***	0.010***	−0.070***
				(0.020)	(0.003)	(0.010)	(0.034)	(0.003)	(0.009)
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,055	12,055	12,055	4036	4036	4036	7921	7921	7921
p-VALUE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R-squared	0.0002	0.0002	0.083	0.259	0.423	0.472	0.218	0.219	0.427

6. Robustness check

In this section, we provide several robustness checks to examine the robustness of our results by using an alternative dependent variable and subsamples. Table 10 reports our results. Firstly, we use an alternative measure of crowdfunding success and summarise the results in Table 10. The dependent variable for Models 1 to 3 in Table 10 is the Success rate, which is defined as the total money pledged divided by the goal amount. The result is still robust. The coefficient is 1.802 in Model 1, which is statistically significant at the 1 % level. Secondly, we examine the dominant role of the U.S. campaigns in the sample. We repeated the panel regression tests without U.S. campaigns to gauge how sensitive our conclusions are to the U.S. (Karolyi, 2016). As shown in Model 4 to Model 6, the result is consistent with our findings. Thirdly, some countries with a small number of campaigns may not be attractive at all for some foreign investors. So, we exclude countries with less than the median sample value of campaigns in Models 7 to 9. The result is consistent with our findings.

Our results could suffer from endogeneity problems such as omitted-variable bias, which means there could be unobservable factors that influence our key independent variable (*Samecountry*) and dependent variables (*Success/Delivery*) simultaneously. We thus exploit an instrumental variable (IV) strategy to address such concerns. Specifically, we define *Backer openness* as our instrumental variable, constructed as the natural logarithm of a weighted average of trade openness divided by 100. Trade openness is the average of the exports and imports of goods and services as a share of GDP from 2009 to 2016. This variable is weighted by the percentage of backers of each country.

Since investors from countries with a higher level of *Backer openness* undertake fiercer competition in domestic markets (Ang & Kumar, 2014; Damoah, 2021), our instrumental variable should be negatively correlated with the key independent variable. Furthermore, the *Success* or *Delivery* of a crowdfunding project is an individual behaviour; there is no current evidence showing that the country's openness will directly influence the success of a crowdfunding project. The empirical results of the IV strategy are presented in the first two columns of Table 11.

Second, we add a new instrumental variable, *backer terrorism*, to address the endogeneity problem. Wang and Young (2020) state that terrorist activity increases investor risk aversion. When there are more terrorist activities, investors would be more conservative and avoid potential risks. Therefore, these investors will be more hesitant to invest in a foreign country. We also use Cragg-Donald F-statistic and Stock-Yogo tests to check the validity and relevance of the instrument. The result also shows no weak instrumental variable in our test. The empirical results of the IV strategy are presented in the last two columns of Table 11.

The results of the Wald test show that the *p*-value is equal to 0.000, and the original exogenous hypothesis can be rejected at the

Table 11
Results of the robustness tests based on the IV method.
The following table shows the regression results. Standard errors are clustered at the country level. The estimation results show that after considering the endogenous problem, the relationship between the home bias and the performance of the crowdfunding projects is still significant. The *standard errors* are reported in brackets. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Variables	First step regression	Second step regression	First step regression	Second step regression
	Samecountry	Success	Samecountry	Success
	(1)	(2)	(3)	(4)
Backer openness	−0.606***			
	(0.064)			
Backer terrorism			0.116**	
			(0.052)	
Samecountry		0.140**		0.401***
		(0.006)		(0.126)
FAQ	−0.009	0.064***	−0.012	0.068***
	(0.007)	(0.006)	(0.008)	(0.007)
Collaborator	0.033**	0.114***	0.010	0.122***
	(0.016)	(0.022)	(0.020)	(0.024)
Reward	−0.007	0.022***	0.122***	−0.003
	(0.009)	(0.007)	(0.020)	(0.020)
Website	0.007	0.023**	0.040***	0.010
	(0.011)	(0.011)	(0.011)	(0.009)
Backed	0.020*	0.065***	0.044***	0.052***
	(0.011)	(0.005)	(0.010)	(0.010)
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
First stage R^2	0.150		0.185	
Cragg-Donald F-statistics	2214.293		1590.294	
N	9279	9279	12,055	12,055

confidence level of 1 %; that is, there are instrumental variables. In the first stage, the estimation coefficient of instrumental variables is statistically significantly different from 0. The two-step method is used to estimate the equation. The F values of the equation in the first stage are 121.05. Furthermore, the Cragg-Donald Wald F statistic is 2214.293 and 1590.294, respectively, which is greater than 16.38, which is the critical value of the 10 % maximal IV size of Stock-Yogo weak ID test, so there is no weak instrumental variable. The estimation results show that after considering the endogeneity problem, the relationship between home bias and the performance of crowdfunding projects is still significant and confirmed.

We also differentiate the sample, including only the initial campaigns, from the sample containing both initial and follow-up campaigns. The results are reported in Appendix D. We find the results are persistent even though we treat follow-up campaigns differently. Besides, we have done a robustness check based on the key independent variable *Samecountry%*, which is the number of backers from the creator's home country divided by the total number of campaign backers. Hypothesis 1 has been confirmed based on this alternative measure, and the results remain consistent and solid. Please see the additional mechanism tests in Appendix E and F.

7. Conclusions

We explore what type of social capital reduces home bias in the fintech era. Home dependence still exists in technology reward crowdfunding due to high information asymmetry and unfamiliarity levels. We then explore the moderation impact of different social capital. We first connect the "old" social capital with the investment preference of pre-existing social capital from the behaviour bias perspective and tie the "new" social capital with excessive communication efforts of entrepreneurs to potential investors, which results in less information asymmetry and higher trust. Cross-sectional heterogeneity analysis implies that entrepreneurs' home countries with high levels of financial inclusion and investor protection are less affected by home bias, highlighting the intricate relationship between individual investor behaviour and overarching systemic elements.

Our paper is the first to differentiate the preference-based and information-based influencing channels of social capital through which home bias affects crowdfunding performance. Besides, we construct a dictionary enriched with terms of successful project execution and determine the delivery status using the Word2Vec model (Mikolov et al., 2013). We pioneer the application of textual analysis in assessing campaign delivery status, offering a more precise measurement than traditional methods by capturing linguistic cues that reflect the campaign's true process and effectiveness.

Our research findings have significant practical implications for policy formulation, highlighting the necessity for a more integrated strategy to enhance the success of crowdfunding initiatives. They prompt crowdfunding professionals and regulatory bodies to recognise the critical role of fostering new social capital within fintech platforms. This is essential for reducing home bias, especially in developing nations with comparatively low financial inclusion and investor protection.

Declarations of interest

None.

Acknowledgements

This paper was supported by the Major Program for Philosophy and Social Science at Ministry of Education of China (Project No. 2023J2DZ017), the Key Program for Philosophy and Social Science at Ministry of Education of China (Project No. 23JZD011), Ningbo Science and Technology Bureau for Key Plan Program (Project No. 2022Z243, 2022Z173), and Ningbo Science and Technology Bureau for Soft Science Program (Project No. 2024R034). All errors remain the responsibility of the authors.

Appendix A. Country distribution of technology crowdfunding campaigns and backers on Kickstarter

Panel A: Country distribution of technology crowdfunding campaigns

Country and home bias	No. of Obs.	Country and home bias	No. of Obs.
Austria	60	Latvia	4
Belgium	28	Lithuania	2
Bulgaria	3	Luxembourg	1
Cambodia	3	Malaysia	3
Canada	719	Malta	1
China	336	Mexico	77
Croatia	6	Netherlands	212
Czech Republic	7	Philippines	3
Denmark	89	Poland	23
Estonia	3	Portugal	2
Finland	3	Romania	2
France	301	Singapore	64
Germany	384	Slovak Republic	1
Greece	2	Slovenia	12
Hungary	3	Spain	204
India	11	Sweden	97
Indonesia	5	Thailand	6
Ireland	50	United Kingdom	1062
Italy	252	United States	7927
Japan	85	Viet Nam	2
Total			12055

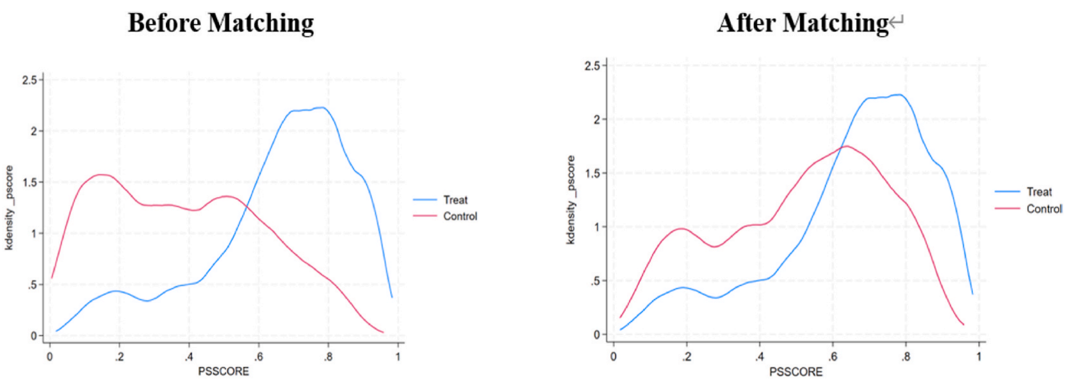
Panel B: Country distribution of technology crowdfunding backers

Country	Count	Country	Count	Country	Count
United States	739561	New Zealand	300	Malaysia	40
United Kingdom	20772	Croatia	244	Romania	34
France	11793	India	201	Brazil	24
Germany	11508	Thailand	194	South Africa	24
Japan	9345	Slovenia	192	Turkey	19
Canada	7530	Russia	173	Argentina	18
Australia	3583	Slovak Republic	166	Belarus	16
Netherlands	3293	Colombia	136	Ecuador	16
Italy	2208	Bulgaria	121	Guatemala	13
South Korea	2162	Lebanon	121	Moldova	13
Denmark	1577	Hungary	100	Greece	9
China	1528	Ukraine	80	Hong Kong (China)	9
Sweden	1323	Latvia	76	Serbia	8
Mexico	1132	Czech Republic	75	Bolivia	4
Singapore	1102	Philippines	68	Nigeria	4
Austria	1035	Switzerland	63	United Arab Emirates	4
Ireland	579	Egypt	57	Indonesia	3
Belgium	370	Finland	49	Qatar	3
Poland	360	Portugal	47	Bahrain	2
Israel	307	Pakistan	44	Total	823838

Appendix B. Variable definitions

Variable	Definition
Dependent variable: Measure of project success	
Success	Campaign survival dummy. It takes a value of one when the initiator successfully reaches its goal during the time duration; otherwise, it takes zero.
Delivery	Campaign implementation dummy. It takes a value of one when the initiator successfully implements its project and delivers the product and service as promised, zero otherwise.
Success rate	The ratio of funding goal reached during the time duration, calculated as the goal amount divided by total money pledged.
Key explanatory variables: Measures of domestic investors	
Samecountry	A dummy variable which is 1 when the largest group of funders for the crowdfunding campaign is from the creator's home country, and 0 otherwise.
Samecountry%	The number of backers from the creator's home country divided by the total number of backers of the campaign.
Moderating variables	
Comment	The natural logarithm of the number of comments posted by the creator on the campaign page before the funding period ends.
Facebook	The natural logarithm of the number of Facebook friends of the creator shown on the campaign page.
Control variables	
FAQ	The natural logarithm of the number of frequently asked questions on the campaign page.
Website	The natural logarithm of the number of website links the creator has provided.
Loved	A dummy variable that takes a value of one when the campaign is favoured by Kickstarter and tagged with "Project We Love", zero otherwise.
Backed	The natural logarithm of the number of campaigns that the creator has backed before.
Created	The number of campaigns that the initiator had created before.
Collaborator	The natural logarithm of the number of collaborators in the team who have been introduced on the webpage.
Video	A dummy variable takes a value of one when there is a video presented on the platform, and zero otherwise.
Backer openness	The natural logarithm of a weighted average of trade openness divided by 100, weighted by the percentage of backers of each country. Trade openness is the average of the exports and imports of goods and services as a share of GDP from 2009 to 2016.
Financial inclusion	The financial inclusion indexes of the country of the campaign. The index is constructed using PCA from the IMF Financial Access Database.
Investor protection	The investor protection indexes of the country of the campaign. The index is obtained from the World Bank Doing Business database.

Appendix C. PSM density plot



Appendix D

The table below uses information in the variable of *Created,* namely the number of campaigns created by creators, and divides our sample into two subgroups, one with initial campaigns only *(Created* = 1) and the other with both initial and follow-up campaigns (*Created*>1) in the empirical analysis. As shown in the table below, all of the regressions show that there is a statistically significant and positive relationship between *Samecountry* and our dependent variables. It turns out that there is no difference between the initial campaigns or follow-up campaigns and shows our results are consistently robust. The *p*-VALUE shows the significance of estimated coefficients.

Panel A

	Created = 1			*Created>1*		
Variables	*Success*	*Success*	*Success*	*Success*	*Success*	*Success*
	(1)	(2)	(3)	(4)	(5)	(6)
Samecountry	0.895***	0.722***	2.286***	0.643***	0.544**	1.739***
	(0.199)	(0.183)	(0.204)	(0.231)	(0.218)	(0.289)
Facebook		−0.073***			0.013	
		(0.021)			(0.025)	
Comment			1.576***			1.509***
			(0.078)			(0.105)
*Samecountry *Facebook*		0.090***			0.036***	
		(0.020)			(0.012)	
*Samecountry *Comment*			−0.637***			−0.624***
			(0.071)			(0.104)
FAQ	0.526***	0.531***	−0.019	0.270***	0.267***	−0.201***
	(0.051)	(0.050)	(0.035)	(0.057)	(0.056)	(0.063)
Collaborator	0.663***	0.655***	0.147	0.604***	0.597***	−0.115
	(0.147)	(0.141)	(0.134)	(0.199)	(0.197)	(0.184)
Website	0.358***	0.365***	0.196***	0.157	0.151	0.140
	(0.068)	(0.067)	(0.065)	(0.120)	(0.122)	(0.132)
Backed	0.450***	0.451***	0.230***	0.398***	0.390***	0.173***
	(0.032)	(0.030)	(0.027)	(0.034)	(0.036)	(0.034)
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	6103	6103	6103	1830	1830	1830
p-VALUE	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R-squared	0.209	0.211	0.411	0.231	0.232	0.441

Panel B

	Created = 1			*Created>1*		
Variables	*Delivery*	*Delivery*	*Delivery*	*Delivery*	*Delivery*	*Delivery*
	(1)	(2)	(3)	(4)	(5)	(6)
Samecountry	0.412***	0.328***	1.051***	0.275**	0.279**	0.527***
	(0.102)	(0.103)	(0.074)	(0.133)	(0.130)	(0.184)
Facebook		−0.035***			0.003	
		(0.012)			(0.011)	
Comment			0.788***			0.720***
			(0.023)			(0.042)
*Samecountry *Facebook*		0.044***			0.003***	
		(0.014)			(0.001)	
*Samecountry *Comment*			−0.295***			−0.134**
			(0.023)			(0.054)
FAQ	0.290***	0.291***	0.025	0.175***	0.175***	−0.109***
	(0.020)	(0.021)	(0.027)	(0.028)	(0.027)	(0.033)
Collaborator	0.386***	0.384***	0.113	0.456***	0.456***	0.086
	(0.109)	(0.106)	(0.114)	(0.105)	(0.104)	(0.088)
Reward	0.215***	0.219***	0.127***	0.197***	0.196***	0.223***
	(0.031)	(0.031)	(0.034)	(0.054)	(0.056)	(0.065)
Website	0.278***	0.277***	0.160***	0.230***	0.229***	0.103***
	(0.012)	(0.011)	(0.019)	(0.029)	(0.029)	(0.036)
Backed	0.290***	0.291***	0.025	0.175***	0.175***	−0.109***
	(0.020)	(0.021)	(0.027)	(0.028)	(0.027)	(0.033)
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	6073	6073	6073	1894	1894	1894
p-VALUE	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R-squared	0.243	0.244	0.419	0.275	0.275	0.470

Appendix E

The moderation effect of *Facebook* on the link between home bias percentage and crowdfunding performance. Standard errors are clustered at the country level. The *standard errors* are reported in brackets. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively. The *p*-VALUE shows the significance of estimated coefficients.

Variables	*Success*	*Success*	*Delivery*	*Delivery*
	(1)	(2)	(3)	(4)
	1.766***	1.616***	0.795***	0.709***
	(0.338)	(0.307)	(0.207)	(0.204)
Samecountry%	0.026***	−0.013	0.014***	−0.008
	(0.007)	(0.029)	(0.004)	(0.014)
Samecountry%		0.064**		0.037**
* *Facebook*		(0.032)		(0.017)
FAQ	0.413***	0.413***	0.254***	0.254***
	(0.031)	(0.031)	(0.018)	(0.019)
Collaborator	0.578***	0.576***	0.345***	0.344***
	(0.165)	(0.163)	(0.091)	(0.090)
Website	0.353***	0.355***	0.260***	0.260***
	(0.080)	(0.078)	(0.040)	(0.040)
Loved	0.413***	0.406***	0.298***	0.294***
	(0.114)	(0.115)	(0.069)	(0.070)
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	7895	7895	7979	7979
p-VALUE	0.000	0.000	0.000	0.000
Pseudo R-squared	0.209	0.209	0.241	0.241

Appendix F

The moderation effect of *Comment* on the link between home bias percentage and crowdfunding performance. The *standard errors* are reported in brackets. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively. The *p*-VALUE shows the significance of estimated coefficients.

Variable	*Success*	*Success*	*Delivery*	*Delivery*
	(1)	(2)	(3)	(4)
Samecountry%	2.383***	3.424***	1.043***	1.452***
	(0.262)	(0.300)	(0.113)	(0.152)
Comment	1.183***	1.665***	0.647***	0.838***
	(0.070)	(0.125)	(0.037)	(0.052)
Samecountry%		−0.835***		−0.342***
* *Comment*		(0.119)		(0.063)
FAQ	−0.066	−0.073	−0.014	−0.017
	(0.072)	(0.071)	(0.036)	(0.037)
Collaborator	0.127	0.135	0.080	0.081
	(0.106)	(0.112)	(0.060)	(0.064)
Website	0.212***	0.186***	0.183***	0.174***
	(0.071)	(0.070)	(0.057)	(0.057)
Backed	−0.453**	−0.463***	−0.169*	−0.178*
	(0.177)	(0.170)	(0.092)	(0.092)
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	7895	7895	7979	7979
p-VALUE	0.000	0.000	0.000	0.000
Pseudo R-squared	0.403	0.428	0.433	0.444

Data availability

Data will be made available on request.

References

Agrawal, A., Catalini, C., & Goldfarb, A. (2015). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics and Management Strategy, 24*(2), 253–274.
Ahlers, G., Cumming, D., Günther, C., & Schweizer, D. (2015). Signalling in equity crowdfunding. *Entrepreneurship Theory and Practice, 39*(4), 955–980.
Ai, C., & Norton, E. (2003). Interaction terms in logit and probit models. *Economics Letters, 80*(1), 123–129.
Alexandridis, G., Hoepner, A., Huang, Z., & Oikonomou, I. (2022). Corporate social responsibility culture and international M&As. *The British Accounting Review, 54*(1), 1–31.
An, J., Hou, W., & Lin, C. (2022). Epidemic disease and financial development. *Journal of Financial Economics, 143*(1), 332–358.
An, J., & Rau, R. (2021). Finance, technology and disruption. *The European Journal of Finance, 27*(4–5), 334–345.
Ang, J., & Kumar, S. (2014). Financial development and barriers to the cross-border diffusion of financial innovation. *Journal of Banking & Finance, 39*(1), 43–56.
Armitage, S., Hou, W., Liu, X., & Wang, C. (2021). Law, endowment and inequality in access to finance. *Finance Research Letters, 39*, Article 101540.
Bailey, M., Cao, R., Kuchler, T., Stroebel, J., & Wong, A. (2018). Social connectedness: Measurement, determinants, and effects. *The Journal of Economic Perspectives, 32*(3), 259–280.
Bartlett, R., Morse, A., Stanton, R., & Wallace, N. (2022). Consumer-lending discrimination in the FinTech era. *Journal of Financial Economics, 143*(1), 30–56.
Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of Business Venturing, 29*(5), 585–609.
Bertoni, F., Bonini, S., Capizzi, V., Colombo, M. G., & Manigart, S. (2022). Digitization in the market for entrepreneurial finance: Innovative business models and new financing channels. *Entrepreneurship Theory and Practice, 46*(5), 1120–1135.
Bollaert, H., Lopez-de-Silanes, F., & Schwienbacher, A. (2021). Fintech and access to finance. *Journal of Corporate Finance, 68*, Article 101941.
Brav, A., Cain, M., & Zytnick, J. (2022). Retail shareholder participation in the proxy process: Monitoring, engagement, and voting. *Journal of Financial Economics, 144*(2), 492–522.
Buis, M. (2010). Stata tip 87: Interpretation of interactions in nonlinear models. *STATA Journal, 10*(2), 305–308.
Burtch, G., Ghose, A., & Wattal, S. (2014). Cultural differences and geography as determinants of online prosocial lending. *MIS Quarterly, 38*(3), 773–794.
Cai, W., Polzin, F., & Stam, E. (2021). Crowdfunding and social capital: A systematic review using a dynamic perspective. *Technological Forecasting and Social Change, 162*, Article 120412.
Carpio, R., Guo, M., Liu, Y., & Pyun, J. (2021). Wealth heterogeneity, information acquisition and equity home bias: Evidence from U.S. household surveys of consumer finance. *Journal of Banking & Finance, 126*, Article 106100.
Chan, K., Covrig, V., & Ng, L. (2005). What determines the domestic bias and foreign bias? Evidence from mutual fund equity allocations worldwide. *The Journal of Finance, 60*(3), 1495–1534.
Chen, R., El Ghoul, S., Guedhami, O., & Wang, H. (2017). Do state and foreign ownership affect investment efficiency? Evidence from privatizations. *Journal of Corporate Finance, 42*, 408–421.
Cohen, L. (2009). Loyalty-based portfolio choice. *Review of Financial Studies, 22*(3), 1213–1245.
Cooper, I., & Kaplanis, E. (1994). Home bias in equity portfolios, inflation hedging, and international capital market equilibrium. *Review of Financial Studies, 7*(1), 45–60.
Cornaggia, J., Cornaggia, K., & Israelsen, R. (2020). Where the heart is: Information production and the home bias. *Management Science, 66*(12), 5532–5557.
Cornelius, P., & Gokpinar, B. (2020). The role of customer investor involvement in crowdfunding success. *Management Science, 66*(1), 452–472.
Courtney, C., Dutta, S., & Li, Y. (2017). Resolving information asymmetry: Signalling, endorsement, and crowdfunding success. *Entrepreneurship Theory and Practice, 41*(2), 265–290.
Coval, J., & Moskowitz, T. (1999). Home bias at home: Local equity preference in domestic portfolios. *The Journal of Finance, 54*(6), 2045–2073.
Coval, J., & Moskowitz, T. (2001). The geography of investment: Informed trading and asset prices. *Journal of Political Economy, 109*(4), 811–841.
Covrig, V. M., Defond, M. L., & Hung, M. (2007). Home bias, foreign mutual fund holdings, and the voluntary adoption of international accounting standards. *Journal of Accounting Research, 45*(1), 41–70.
Dahl, M. S., & Sorenson, O. (2012). Home sweet home: Entrepreneurs' location choices and the performance of their ventures. *Management Science, 58*(6), 1059–1071.
Damoah, K. (2021). Markups, market imperfections, and trade openness: Evidence from Ghana. *The World Bank Economic Review, 35*(1), 92–116.
Dougal, C., & Rettl, D. (2021). Firm listing status and the investment home bias. *Journal of Corporate Finance, 71*, Article 102095.
Duan, Y., Hsieh, T., Wang, R., & Wang, Z. (2020). Entrepreneurs' facial trustworthiness, gender, and crowdfunding success. *Journal of Corporate Finance, 64*, Article 101693.
Ferris, S., Javakhadze, D., & Rajkovic, T. (2019). An international analysis of CEO social capital and corporate risk-taking. *European Financial Management, 25*(1), 3–37.
Florentsen, B., Nielsson, U., Raahauge, P., & Rangvid, J. (2020). Turning local: Home-bias dynamics of relocating foreigners. *Journal of Empirical Finance, 58*, 436–452.
French, K., & Poterba, J. (1991). Investor diversification and international equity markets. *The American Economic Review, 81*(2), 222–226.
Gedajlovic, E., Honig, B., Moore, C., Payne, G., & Wright, M. (2013). Social capital and entrepreneurship: A schema and research agenda. *Entrepreneurship Theory and Practice, 37*(3), 455–478.
Giudici, G., Guerini, M., & Rossi-Lamastra, C. (2018). Reward-based crowdfunding of entrepreneurial projects: The effect of local altruism and localized social capital on proponents' success. *Small Business Economics, 50*, 307–324.
Goldstein, I., Jiang, W., & Karolyi, G. (2019). To FinTech and beyond. *Review of Financial Studies, 32*(5), 1647–1661.
Gomber, P., Kauffman, R., Parker, C., & Weber, B. (2018). On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems, 35*(1), 220–265.
Grinblatt, M., & Keloharju, M. (2001). How distance, language, and culture influence stockholdings and trades. *The Journal of Finance, 56*(3), 1053–1073.
Haddad, C., & Hornuf, L. (2019). The emergence of the global fintech market: Economic and technological determinants. *Small Business Economics, 53*(1), 81–105.
Hortaçsu, A., Martínez-Jerez, F. A., & Douglas, J. (2009). The geography of trade in online transactions: Evidence from eBay and mercadolibre. *American Economic Journal: Microeconomics, 1*(1), 53–74.
Huberman, G. (2001). Familiarity breeds investment. *Review of Financial Studies, 14*(3), 659–680.
Javakhadze, D., Ferris, S., & French, D. (2016). Social capital, investments, and external financing. *Journal of Corporate Finance, 37*, 38–55.
Jiang, C., Zhou, L., Xu, Q., & Liu, Y. (2022). Home bias in reward-based crowdfunding and its impact on financing performance: Evidence from China. *Pacific-Basin Finance Journal, 76*, Article 101858.
John, K., Litov, L., & Yeung, B. (2008). Corporate governance and risk-taking. *The Journal of Finance, 63*(4), 1679–1728.
Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 363–391.
Karolyi, G. (2016). The gravity of culture for finance. *Journal of Corporate Finance, 41*, 610–625.
Kim, K., & Hann, I. (2019). Crowdfunding and the democratization of access to capital—an illusion? Evidence from housing prices. *Information Systems Research, 30*(1), 276–290.
Kuchler, T., Li, Y., Peng, L., Stroebel, J., & Zhou, D. (2022). Social proximity to capital: Implications for investors and firms. *Review of Financial Studies, 35*(6), 2743–2789.
Lai, S., & Teo, M. (2008). Home-biased analysts in emerging markets. *Journal of Financial and Quantitative Analysis, 43*(3), 685–716.

Lee, S., & Persson, P. (2016). Financing from family and friends. *Review of Financial Studies, 29*(9), 2341–2386.
Levy, H., & Levy, M. (2014). The home bias is here to stay. *Journal of Banking & Finance, 47*(1), 29–40.
Lin, M., Prabhala, N., & Viswanathan, S. (2013). Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science, 59*(1), 17–35.
Lin, T. C., & Pursiainen, V. (2022). Regional social capital and moral hazard in crowdfunding. *Journal of Business Venturing, 37*(4), Article 106224.
Lin, M., & Viswanathan, S. (2016). Home bias in online investments: An empirical study of an online crowdfunding market. *Management Science, 62*(5), 1393–1414.
Maroney, J., McGarry, C., & Ó hÓgartaigh, C. (2008). Familiarity, home bias and investors' reactions to 20-F reconciliation gains and losses and perceptions of the quality of accounting principles. *The British Accounting Review, 40*(2), 103–122.
Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *Advances in Neural Information Processing Systems, 26*.
Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing, 29*(1), 1–16.
Mollick, E. (2015). *Delivery rates on kickstarter. Working paper*. University of Pennsylvania - Wharton School. Available at: SSRN.
Morse, A., & Shive, S. (2011). Patriotism in your portfolio. *Journal of Financial Markets, 14*(2), 411–440.
Parwada, J. (2008). The genesis of home bias? The location and portfolio choices of investment company start-ups. *Journal of Financial and Quantitative Analysis, 43*(1), 245–266.
Petersen, M., & Rajan, R. (2002). Does distance still matter? The information revolution in small business lending. *The Journal of Finance, 57*(6), 2533–2570.
Regner, T., & Crosetto, P. (2021). The long-term effects of self-pledging in reward crowdfunding. *Technological Forecasting and Social Change, 165*, Article 120514.
Rosenbaum, P., & Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.
Santamaría, M., Ventura, J., & Yeşilbayraktar, U. (2023). Exploring European regional trade. *Journal of International Economics, 146*, Article 103747.
Shi, Y., Xu, H., Wang, M., & Conroy, P. (2017). Home bias in domestic art markets: Evidence from China. *Economics Letters, 159*, 201–203.
Sialm, C., Sun, Z., & Zheng, L. (2020). Home bias and local contagion: Evidence from funds of hedge funds. *Review of Financial Studies, 33*(10), 4771–4810.
Strong, N., & Xu, X. (2003). Understanding the equity home bias: Evidence from survey data. *The Review of Economics and Statistics, 85*(2), 307–312.
Thaler, R. H. (2016). Behavioral economics: Past, present and future. *The American Economic Review, 106*(7), 1577–1600.
Van Nieuwerburgh, S., & Veldkamp, L. (2009). Information immobility and the home bias puzzle. *The Journal of Finance, 64*(3), 1187–1215.
Wang, Y., Wang, B., & Yan, Y. (2022). Does network externality affect your project? Evidence from reward-based technology crowdfunding. *Technological Forecasting and Social Change, 180*, Article 121667.
Wang, Y., Wang, B., Yan, Y., & Zhang, J. (2023). The clearer timelines, the better? Evidence from kickstarter. *IEEE Transactions on Engineering Management, 70*(10), 3512–3525.
Wang, A., & Young, M. (2020). Terrorist attacks and investor risk preference: Evidence from mutual fund flows. *Journal of Financial Economics, 137*(2), 491–514.
Wei, C., & Zhang, L. (2020). Trust and local bias. *Journal of Financial and Quantitative Analysis, 55*(7), 2211–2245.
Wessel, M., Thies, F., & Benlian, A. (2016). The emergence and effects of fake social information: Evidence from crowdfunding. *Decision Support Systems, 90*, 75–85.
Xu, J. (2023). Is there a trade-off between protecting investors and promoting entrepreneurial activity? Evidence from angel financing. *Journal of Financial and Quantitative Analysis, 58*(8), 3305–3341.
Yasar, B., Yılmaz, I., Hatipoğlu, N., & Salih, A. (2022). Stretching the success in reward-based crowdfunding. *Journal of Business Research, 152*, 205–220.
Yu, S., Johnson, S., Lai, C., Cricelli, A., & Fleming, L. (2017). Crowdfunding and regional entrepreneurial investment: An application of the CrowdBerkeley database. *Research Policy, 46*(10), 1723–1737.
Zhang, H., & Chen, W. (2019). Crowdfunding technological innovations: Interaction between consumer benefits and rewards. *Technovation, 84–85*, 11–20.
Zhao, X., Hou, W., An, J., Liu, X., & Zhang, Y. (2021). Initial Coin offerings: What rights do investors have? *The European Journal of Finance, 27*(4–5), 305–320.
Zhu, Z., Qi, Z., & Jin, Y. (2023). Familiarity bias and economic decisions: Evidence from a survey experiment. *Economics Letters, 229*, Article 111197.
Zingales, L. (2015). The "cultural revolution" in finance. *Journal of Financial Economics, 117*(1), 1–4.