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When do venture capital and startups team up? Matching matters

Hui Fu [a], Huilan Qi [a], Yunbi An [b,*]

[a] School of Business, Jiangnan University, No. 1800 Lihu Avenue, Wuxi, Jiangsu 214122, China
[b] Odette School of Business, University of Windsor, 401 Sunset Avenue, Windsor, Ontario N9B 3P4, Canada

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ABSTRACT

This paper investigates the timing of venture capital (VC) investment in startups from the perspective of the matching relationship between VC firms and startups. Using data on VC investments in China, we find that matching between VCs and startups with similar quality rankings promotes VC investment in early-stage startups. The promoting effect of balanced matching is particularly pronounced for private VCs and domestic VCs. In addition, exit market liquidity strengthens this positive association, as evidenced by the finding that the effect of matching is more pronounced when the IPO market is open than when it is closed. We further show that balanced matching between the two parties helps increase the risk-taking by VCs, thereby enhancing their propensity to invest in early-stage startups.

1. Introduction

The involvement of venture capital institutions (VCs) in the development of startups is crucial for the growth and success of startups. In addition to providing critical financial support to their investee startups, VCs actively play a professional role in helping these companies establish closer ties with various parties including upstream and downstream business partners and consumers (Macmillan et al., 1989; Steier and Greenwood, 1995; Hsu, 2006). VCs also provide a full range of value-adding services to startups, such as business modelling, market development, corporate governance, as well as refinancing and growth strategies (Gorman and Sahlman, 1989; Busenitz et al., 2004; Park and Steensma, 2012; Vanacker et al., 2013). It is very typical in the VC market that some VC investments occur when startups are in an early stage of development, while others happen when startups are in a mid- to late-stage of development. Prior studies examine VCs' investment behavior based on their investment preferences (Gompers, 1995; Cumming et al., 2005; Hallen, 2009; Arvanitis and Stucki, 2014; Chaplinsky and Gupta-Mukherjee, 2016), ignoring the role of their matching partners in this regard. However, VCs' investment in startups is essentially an element of the bilateral matching process between the two parties, as startups likewise endeavor to select their VC partners. This paper attempts to explore why the timing of VC investment varies among startups, from the perspective of matching between VCs and startups.

We assert that the timing of VC investment in startups reflects not only the investment behaviors of VCs, but also the financing behaviors of startups. Thus, to better understand the timing of VC investment in startups, it is important to recognize the cooperative nature of the relationship between VCs and startups in joint ventures. The equilibrium matching structure of VCs and startups under ideal market conditions is well documented in prior literature. For example, the Gale-Shapley algorithm (Gale and Shapley, 1962), also known as the deferred-acceptance algorithm, provides a solution for stable matching between two groups under the condition of both ex-ante and ex-post complete information. Subsequently, many studies explore this issue further, analyzing the existence and

* Corresponding author.
E-mail addresses: hui_fu@hotmail.com (H. Fu), yunbi@uwindsor.ca (Y. An).

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uniqueness of two-sided stable matching (Wolinsky, 1987; Binmore and Herrero, 1988; Satterthwaite and Shneyerov, 2007; Lauermann, 2013), while some investigate the stability of matching and matching strategies, as well as matching relationships and properties (Roth, 1985; Roth and Sotomayor, 1989; Hatfield and Milgrom, 2005; Echenique and Oviedo, 2006). These studies generally assume that ex-ante information is symmetric and complete, following Gale and Shapley (1962).

Fu et al. (2019a) propose a perfect matching model between VCs and entrepreneurial firms under the conditions that there is ex-ante information symmetry between the two parties and there is only ex-post double-sided moral hazard (Casamatta, 2003; Schmidt, 2003; Repullo and Suarez, 2004; Hellmann, 2006; Fairchild, 2011; Fu et al., 2019b), finding that perfect matching follows the principle of positive assortative matching (PAM). More specifically, a perfect match, also referred to as a balanced match, is achieved if the two matching parties occupy the same quality rankings among their respective peers in the competitive market. A deviation from perfect matching lowers the actual efforts that the VC and the startup put in a joint venture, as well as the resultant output and social surplus (Fu et al., 2019a, 2023a). As a result, the matching structure between VCs and startups can significantly impact both parties' investment and financing decisions.

There is a lack of literature that directly examines the timing of VC investment in startups in relation to matching.[1] Prior literature focuses mainly on the economic behaviors of VCs and startups as well as the consequences of their matching structure (Fu et al., 2023a; Ewens et al., 2022; Hong et al., 2020). Due to the presence of ex-ante information asymmetry in VC markets, actual matching outcomes can deviate from those predicted by theoretical models applied to a hypothetical market (Fu et al., 2023b). However, little research is devoted to how the matching relationship between the two parties is related to the timing of VC investment in startups.

Balanced matching is arguably a key factor that drives VCs and startups to collaborate with each other early. Early-stage VC investment in startups can better enhance VCs' value-adding effects and increase the chance of startups' success (Fitza et al., 2009; Dai et al., 2022). Thus, VCs may choose to invest in early-stage startups to maximize their exit performance, while startups may also bring in VCs in an early stage of development to better take advantage of the value-adding services provided by VCs. However, the efforts of VCs and startups are unobservable and unverifiable in practice, so both parties may exhibit opportunistic behaviors (Casamatta, 2003; Schmidt, 2003; Repullo and Suarez, 2004; Hellmann, 2006; Fairchild, 2011). Theoretical matching models suggest that matching between similarly ranked partners according to their capabilities would motivate both to strive for mutual benefits (Fu et al., 2019a, 2019b), thereby reducing the negative effects of opportunism. Fu et al. (2023a) confirm that matching between similarly ranked VCs and startups motivates both parties to exert more efforts and improves their value-adding functions, which enhances venture performance. Since balanced matching can help deliver the greatest synergistic thrust to the success of ventures beyond the contribution made by the individual quality of both business partners, we contend that it motivates VCs to invest in early-stage startups and startups to bring in VCs in an early stage of development.

Following Fu et al. (2019a, 2023a, 2023b), we measure the degree of matching, based on the degree to which a VC's quality ranking and a startup's quality ranking in their respective markets are close to each other. If the two matching parties have similar quality rankings among their respective peers, then the degree of matching is high. To this end, we use the investment experience of a VC firm to measure its quality, as well as the number of funding rounds and the number of VC firms in each round for a startup to measure its development potential. Then, based on the quality rankings of the two parties in a market, we construct and calculate various matching degree measures for our analysis. In robustness tests, we also consider alternative measures for the quality of VCs and startups.

Using data from the Chinese VC market, we first explore whether the degree of matching between VCs and startups affects the timing of VC financing in startups. Second, we examine whether such effects vary across VCs with different backgrounds. Third, we investigate the way in which repetitive IPO suspensions in China moderate the relationship between matching and investment timing, and finally, we are interested in understanding the mechanisms through which the degree of matching between the two parties impacts the timing of VC investment in startups.

China's VC market has grown rapidly since it began to develop around 2000. In terms of total capital invested, the Chinese VC market is now the second largest VC market in the world, with the US market being the largest. In the early years, the Chinese VC market was led by foreign VCs, while local VCs grew slowly by learning from their foreign counterparts, as evidenced by the fact that many local VC managers have experience studying and working overseas. Nowadays, the market consists of government-backed VCs, private VCs, and foreign VCs. Given the increasing degree of professionalism of investment institutions in the market and increasing degree of marketization, the Chinese market provides a context for this study that is rich in institutional and market conditions.

We find that the better the match between a VC and a startup, the more likely it is for the startup to secure its first round of funding from the VC at an early stage. The effects of the degree of matching on the timing of VC investment are particularly pronounced when VCs do not have either a foreign capital or a government background. Importantly, the effects of matching on VC investment timing are stronger when there is an active IPO market than when IPOs are suspended, suggesting that the effects of matching are strengthened by exit market liquidity. Finally, we show that the underlying mechanism for the effects is that the market-level matching degree affects the overall risk-taking of VCs in the entire market.

Note that our analysis might be subject to survivorship bias, as the sample is limited to the dataset of successful team-ups. Focusing on successful team-ups, we are able to directly measure the matching degree between VCs and startups, as well as the timing of team-up events. However, this analysis ignores unsuccessful team-ups, which may include successful startups with no VC funding and failed

[1] Fairchild (2011) explores startups' preferences and choices regarding angel and VC investments. This paper does not consider the case in which startups may receive angel investments. In general, compared to angel investments, VC is often the primary and more significant source of funding for startups. Angel investments are primarily targeted toward seed-stage startups, while VC targets startups that can be in various stages including the early, expansion, and mature stages. Thus, future research could investigate whether angel investments impact a startup's subsequent decisions of accepting VC funding.

startups during their development. The results could be biased, as unsuccessful team-ups are excluded from the sample. On the other hand, unsuccessful team-ups often result from startups failing to find well-matching VCs, which is in line with the logic that matching affects the timing of successful team-ups. This implies that while there might be survivorship bias in the analysis, it is less of a concern especially when the impact of matching is investigated. Future research could further explore this issue. Moreover, to ensure the robustness of our findings, we address selection bias through a two-stage Sørensen-Heckman regression with bilateral selection effects.

The contributions of this paper are as follows. This research extends prior research on the timing of VC investment by shifting its focus from the unilateral selection and investment of VCs to the bilateral selection and joint efforts of both VCs and startups. Prior research examines VCs' investment behavior from the perspective of their investment preferences, such as their syndicated investment and phased investment preferences, focusing mainly on the motives and economic consequences of early VC investment in startups (Gompers, 1995; Cumming et al., 2005; Hallen, 2009; Arvanitis and Stucki, 2014; Chaplinsky and Gupta-Mukherjee, 2016). These studies focus mainly on VCs, assuming that VCs' investment preference is independent of the quality of their partnership with startups. Uniquely, we assert that the matching relationship between VCs and startups is also critical for their investment and financing decisions in joint ventures. Our findings provide new insight into the timing of investment and financing of both VCs and startups from a unique perspective, which can help us better understand how to facilitate VC funds to flow to early-stage projects.

This research also extends and enriches prior literature on matching by relating matching to the timing of VC financing. Prior literature in this area focuses primarily on the matching structure between VCs and startups at the time when matching occurs, stability and efficiency of matching, and the economic consequences of matching (Bengtsson and Hsu, 2015; Fu et al., 2019a; Ewens and Townsend, 2020; Hong et al., 2020; Fu et al., 2023a, 2023b), but no studies investigate the consequences of matching in relation to the timing of VC investment in startups. Our research reveals that the timing of VC investment in startups represents an important aspect of matching, which is also applicable to the study of matching problems in other fields, especially those with double-sided moral hazard. Deviations from the perfect matching structure derived from theoretical models (Fu et al., 2019a) imply not only mismatches but also delays in matches in the real-life markets. The research furthers our understanding of why the investment and financing behaviors as well as risk preferences of VCs and startups vary, depending on the efficiency of matching.

The remainder of the paper proceeds as follows. Section 2 provides a literature review and develops research hypotheses. Section 3 introduces the research design, including the data, variables, and empirical models. Section 4 presents the empirical results and analyses. Section 5 concludes the paper.

2. Literature review and hypotheses development

2.1. Literature review

2.1.1. Matching between VCs and startups

Matching between VCs and startups in the VC market is extensively examined in prior literature. Some studies focus only on VCs' selection behavior in the matching process (Sørensen, 2007; Bottazzi et al., 2008). For example, Bengtsson and Hsu (2015) show that shared ethnicity increases the probability of a startup being selected by a VC, and also helps the startup obtain financing earlier and also acquire more investment funds. Ewens and Townsend (2020) find that VCs exhibit gender discrimination in selecting their startup counterpart in the sense that male investors tend to favor male-founded firms while female investors favor female-founded ones. These studies investigate the matching structure between VCs and startups from the perspective of VCs, without considering startups' selection behavior.[2]

In fact, startups also have the motivation and ability to choose their matching partners in the VC market. When bringing in VC investment, startups evaluate and select VCs based on VCs' professional qualifications and their value-adding capabilities, as well as the financial covenants in VC contracts. This means that both VCs and startups have bargaining power for the timing of financing and contract terms. In a classic paper, Gale and Shapley (1962) resolve the stable matching problem under complete information in the context of marriage and college admissions, confirming the existence of market equilibrium of perfect matching. Fu et al. (2019a) introduce the bargaining game process to the matching problem between VCs and startups under a double-sided moral hazard scenario. They find that stable and efficient matching between VCs and entrepreneurial firms follows the principle of positive assortative matching, which means that high−/low-quality VCs match with high−/low-quality entrepreneurial firms. Hong et al. (2020) investigate the impacts of VC market competition on the exit performance of VCs, using a matching model with double-sided moral hazard, and confirm that the matching structure in market equilibrium is a positive assortative matching structure. Ewens et al. (2022) establish a bilateral dynamic matching model between VCs and startups to investigate how contract designs are related to VCs' performance. In these studies, matching is examined from a bilateral perspective, taking into consideration the selection behaviors of both VCs and startups.

One key assumption underlying the bilateral matching models is that there is either complete information or ex-ante information asymmetry between the two parties with only an ex-post double-sided moral hazard (Casamatta, 2003; Schmidt, 2003; Repullo and Suarez, 2004; Hellmann, 2006; Fairchild, 2011; Fu et al., 2019b). With complete information, both VCs and startups are able to accurately assess each other's capabilities and the prospects of the projects when a match is formed. Thus, a VC and a startup are more

[2] Our research is based on the notion that the fundamental driver of VC investment is future returns of invested startups. We understand that VCs may also focus on a specific industry or show enthusiasm for racial or gender similarity, based on trust and resonance. There is little attention paid to this aspect in prior research, and thus it represents a promising avenue for future research.

likely to enter into investment and financing contracts and form a stable and efficient matching relationship when the growth potential of the entrepreneurial firm is commensurate with the VC's expertise. On the other hand, in the presence of double-sided moral hazard, both VCs and entrepreneurial firms can exhibit unobservable ex-post opportunistic behaviors that affect the development and success of entrepreneurial firms. These models focus solely on the matching structure and matching efficiency, but pay little attention to the match timing problem.

2.1.2. Timing of VC investment in startups

The timing of VC investment in startups is important for the development and success of startups and thus the exit performance of VCs. Using data on Chinese listed firms, Dai et al. (2022) examine the impact of the timing of VC investment on the initial innovation activity of startups from both financial and innovation performance perspectives, showing that late-stage VC investment in startups undermines startups' innovation performance, but improve their financial performance. Cheng and Zou (2019) argue that the screening and incubation roles of VCs are the mechanisms through which early VC investment significantly contributes to the innovation performance of startups. The screening role refers to the certification effect created by the selection effect of VCs, which can signal to the market a company's development potential and thus attract the attention of more potential investors (Hsu, 2004). The earlier the VC investment in a startup, the more prominent this selection effect is and the greater the positive economic consequences can be. The incubation role refers to the monitoring and value-adding effects that help startups improve their governance and reduce the opportunistic behavior of individual entrepreneurs (Buchner et al., 2017; Hochberg, 2012; Krishnan et al., 2011). Early VC investment in startups can better promote the development of investee startups, provide more value-adding services to startups, and also reduce the short-term earnings-seeking behavior of VCs (Fitza et al., 2009).

On the other hand, VC investment in early-stage startups entails particularly high risk. The development stage of a startup can be divided into four stages: seed stage, startup stage, expansion stage, and maturity stage. Startups at an early development stage can face great technological risk, management risk, and market risk (Hallen, 2009). Thus, VCs need to trade-off the risk and return when making investment choices. When a VC's major fund contributors consist of pension funds rather than individual investors, the pressure on the VC to preserve and grow the fund value tends to be greater; the VC may adopt a relatively conservative investment strategy and prefer to invest in companies in the middle and late stages of development (Mayer et al., 2005). In addition, factors such as the sophistication of the capital market, the exit liquidity in the IPO market, and macroeconomic conditions may all influence the timing of VC investment. When capital markets are relatively immature and inefficient, the monitoring and agency costs tend to increase with the degree of information asymmetry in the market, making VCs more inclined to invest in expansionary or mature firms (Gompers, 1995). Cumming et al. (2005) argue that the IPO market prospects affect the likelihood of VCs' successful exits, and thus influence their tolerance for technological risk. They show that with a lack of exit liquidity, VCs prefer to invest in startups in the early stage of development, balancing the overall risk and benefits by taking on greater technology risk and delaying exits. Chaplinsky and Gupta-Mukherjee (2016) find that the performance of VCs in the exit market affects their fund allocation to early-stage projects, and when exit markets perform poorly, VCs become more conservative in allocating capital to early-stage projects and thus are less likely to invest in early-stage projects. It is important to note that the timing of VC investment reflects the search and matching decisions of both VCs and startups, and thus is inseparable from the bilateral matching process in the VC market. However, no prior research is devoted to how the timing of VC investment is related to the matching structure between VCs and startups.

2.2. Hypotheses development

2.2.1. Matching and the timing of VC investment in startups

A common assumption in the matching models with complete information (Gale and Shapley, 1962) and in the models with ex-post double-sided moral hazard (Fu et al., 2019a; Hong et al., 2020; Ewens et al., 2022) is that ex-ante information is symmetric. This means that the ex-ante information of VCs and startups is a common knowledge in the VC market. As such, the matching model is static, in which both parties can achieve a stable and efficient matching relationship at a given point in time (Fu et al., 2019a). Therefore, in the context of Fu et al.'s (2019a) perfect matching model, the timing of VC investment in startups is irrelevant.

However, in the real world, the ex-ante information is prone to be asymmetric for both VCs and startups. At early stages of development, a startup's business model is often not well established, its business operations are highly risky and uncertain, and VCs' understanding of the startup' prospects is limited and may be biased (Howell, 2020). On the other hand, the professional qualifications, expertise, and risk appetite of VCs may not be fully understood by the market. This simply means that there is severe ex-ante information asymmetry between the two parties in the real-life VC market, which can lead to potentially imperfect matching relationships (Fu et al., 2023b).

Mismatching can adversely impact the effectiveness of both parties' cooperative efforts and the output of joint projects, which in turn can affect the time when both parties are willing to team up. Fu et al. (2023a) show that the matching structure between the two parties can influence the chance of startups' success and VCs' exit performance. They confirm that the matching degree affects the optimal levels of effort of both parties, leading to dynamic heterogeneity in the value-adding functions of both parties. This also suggests that a high degree of matching can effectively mitigate the negative impact of ex-post double-sided moral hazard on the post-matching partnership, thereby promoting the efficiency of cooperation. As a result, mismatching between the two parties can reduce their cooperative performance, delaying VCs' investment in startups.

Mismatching also reduces the willingness and motivation of both parties to match and cooperate. As revealed by the theory of stable matching (Gale and Shapley, 1962; Fu et al., 2019a), the equilibrium outcome of stable matching can be achieved only when the premises of the matching stability and economic efficiency are simultaneously satisfied. Otherwise, a matching relationship will be difficult to form; even if a matching relationship is formed, it will be unstable and detrimental to the synergistic cooperation and the ultimate utilities of both parties.

Therefore, if the matching degree between a VC and a startup is low, it may result in reluctance on the part of the startup to work with the VC, and the VC may also be less willing to invest in the project, delaying the timing of VC investment in the startup. Therefore, we propose the following hypothesis.

Hypothesis 1. The matching degree between VCs and startups affects the timing of VC investment in startups, and a high matching degree increases the likelihood of VC investment in early-stage startups.

VCs are different from one another in capital size, investment expertise, investment preference, resource advantage, and investment objective. Therefore, different types of VCs may have different abilities to assess their investment targets and their own qualification levels, as well as to make investment decisions according to a stable and economically efficient matching model. We contend that the effect of matching between VCs and startups on the timing of VC investment in startups varies, depending on VCs' backgrounds and types.

VCs can be classified as foreign VCs or domestic VCs, based on whether they have a foreign capital background. Compared with local VCs, foreign VCs are significantly more international in nature, with the advantage of strong financial backing and rich investment experience (Cumming et al., 2016), which gives them strong bargaining power[3] and allows them to better provide value-adding services for the subsequent development of the startups in which they invest. This may help mitigate the effect of matching efficiency on startups' decisions on when to bring in VCs. Thus, the investment timing decision may be subject to a weaker influence of the matching degree for foreign VCs than for local VCs.

On the other hand, foreign VCs lack contacts and information resources in the host country, and these outsider disadvantages exacerbate information asymmetry between foreign VCs and startups. Like multinational companies, foreign VCs are also exposed to political and socio-cultural risks in the host country, which will lead to higher investment risks, management risks, and exit risks. To mitigate the adverse effects of outsider disadvantages, foreign capital-backed VCs usually adopt a more prudent investment strategy, such as strict screening of startups or forming a syndicate with local VCs (Dai et al., 2012). As a result, in the decision-making process, foreign capital-backed VCs pay less attention to their matching relationship with startups, and thus their propensity to invest in early-stage startups is less dependent on matching than domestic VCs. Accordingly, we propose the following hypothesis.

Hypothesis 2-1. The positive effect of the matching degree on the timing of VC investment in startups is more pronounced when VCs have no foreign capital background than when VCs have a foreign capital background.

VCs can also be classified as state-owned VCs or non-state-owned VCs, according to whether they are controlled by the state. Since its inception, China's VC market has been mainly led by the government. State-owned VCs are expected to play an important role in correcting market failures, and serve as a role model in guiding more social capital toward highly risky cutting-edge innovation projects. Thus, the aim of state-owned VC investments is to support and promote the innovation and growth of startups. However, in reality, state-owned VCs can deviate from the public function set by the government, mainly because they are less professional than are private VCs (Luukkonen et al., 2013; Alperovych et al., 2015). They are very conservative, due to pressure to preserve and enhance state-owned capital, leading to a low degree of risk preference (Cumming et al., 2017) and thus low investment in risky early-stage projects. In China, senior managers of state-owned VCs are essentially government officials (Zhang and Mayes, 2018), creating a close and direct connection between these VCs and the government. Such political connections apparently bring state-owned VCs more social resources, tax incentives, and policy resources (Colombo et al., 2016). Given state-owned VCs' dual characteristics of low expertise and high conservatism, they may be overly conservative in their choice of investment timing, or may be motivated by unique political requirements or industrial policy needs. As a result, their investment timing decision is less likely to be affected by their matching relationship with the startups in which they invest. Second, given the strong political connection of state-owned VCs, startups may be interested more in what resources these VCs can bring to the table than in whether VCs' professional qualifications well match their own development potential.

Overall, in the VC market, state-owned VCs' major advantages lie in their capabilities of obtaining resources from the government, rather than their superior selection and value-adding functions, indicating that for state-owned VCs, their matching relationship with startups plays a relatively weak role in their investment timing decisions. Therefore, the timing of VC investment in startups may be influenced less significantly by the degree of matching between the two parties when VCs are state owned than when VCs are privately owned. Accordingly, we propose the following research hypothesis.

Hypothesis 2-2. The positive effect of the matching degree on the timing of VC investment in startups is more pronounced when VCs are non-state owned than when VCs are state owned.

Cumming et al. (2005) argue that the IPO market outlook affects the liquidity risk of VC exits and thus the degree to which VCs tolerate the technology risk of startups. They find that when exit liquidity is insufficient, VCs prefer to invest in early-stage startups, balancing overall risk by taking greater technology risks and delaying exits. Chaplinsky and Gupta-Mukherjee (2016) find that VCs'

[3] In general, VCs and startups can have unequal bargaining power. In fact, in Sørensen's (2007) model, it is assumed that VCs have complete bargaining power, and startups are selected by VCs. In contrast, in Fu et al.'s (2019a) model, both VCs and startups are assumed to have certain bargaining power, and both the bargaining power and matching are simultaneously endogenized. They show that the bargaining power of the two parties is independent of stable matching. This means that the bargaining power of both parties does not affect the optimal matching relationship. This paper follows the same line of thought and pays little attention to bargaining power.

returns in the exit market affect their allocation of capital to early-stage projects, and that when the exit market performs poorly, VCs become more conservative in investing in early-stage projects. In China, companies must gain approval for IPO from the China Securities Regulatory Commission (CSRC), and IPOs might be suspended from time to time by the CSRC. When IPOs are temporarily suspended, the liquidity risk of exits is extremely high for VCs, and thus IPO suspensions are arguably an important factor that impacts VCs' investment timing, which means that role of matching in VCs' investment timing decisions is less pronounced. On the other hand, IPO suspensions can impose an adverse effect on startups' innovation capabilities (Cong and Howell, 2021), corporate social responsibility (Li et al., 2022), and corporate equity financing constraints (Cui and Yang, 2018). As a result, IPO suspensions pose a great challenge to startups in obtaining financing. Under such market conditions, startups become particularly eager to secure VC financing at an early time, irrespective of their matching relationship with VCs. Thus, during the period of IPO suspensions, the timing of VC investment in startups is less likely to be influenced by the degree of matching between the two parties. Accordingly, we propose the following hypothesis.

Hypothesis 2-3. The positive effect of the matching degree on the timing of VC investment in startups is more pronounced when the IPO market is open than when the market is closed.

2.2.2. Matching and VCs' risk-taking

The risk-taking of a VC reflects its risk tolerance when investing in a project. VCs with a higher risk-taking level are more inclined to invest in high-risk startups. Startups tend to be riskier when they are in an early stage of development than when they are in a late stage of development. Therefore, the timing of VC investment in startups is essentially a manifestation of VCs' risk tolerance.

According to the portfolio theory, investors trade off the risk and return of an investment, and in equilibrium, VCs allocate an optimal proportion of their capital to high-risk startups and the remaining capital to low-risk mature companies (Buchner et al., 2017). A VC's investment timing preference and the size of its investment in a startup are highly influenced by the VC's risk-taking level. The level of VCs' risk-taking increases if the expected return on an investment is high enough to compensate for the high risk. Larger fund size, more investment experience, and better exit market conditions all contribute to higher levels of risk-taking by VCs, as evidenced by their increased willingness to invest in early-stage new ventures (Chaplinsky and Gupta-Mukherjee, 2016; Del-Palacio et al., 2012).

Since the social welfare of the market as a whole is maximized when all VCs and startups in the market are perfectly matched (Fu et al., 2019a), the matching structure between VCs and startups in the market is closely related to the value-adding effect of VC investment in startups. As the matching degree increases, the total returns to both VCs and startups tend to increase. There is empirical evidence that the matching degree helps improve the chance of startups' success as well as the exit performance of VCs (Fu et al., 2023a). In this case, the total returns obtained by VCs in the market can better compensate for the high risks associated with investments in early-stage startups, which in turn can potentially increase the overall risk-taking level of VCs in the entire market.

Moreover, investors' risk-taking often depends on the degree of market uncertainty and information asymmetry (Janney and Dess, 2006; Mollah et al., 2021). For a given level of market uncertainty, a reduction in the degree of information asymmetry tends to cause investors to be more risk tolerant. Fu et al. (2023b) confirm that ex-ante information asymmetry leads to mismatching in VC markets. This suggests that a high degree of matching is often associated with a relatively low degree of information asymmetry between the two parties. Fu et al. (2023a) show that a high degree of matching between VCs and startups can help mitigate the ex-post moral hazard problem between the two parties and motivate them to make greater efforts so as to achieve the best possible project output. In general, a high degree of matching between the two parties helps mitigate the negative impacts of ex-post information asymmetry, and also helps VCs and startups to better understand and evaluate the quality of their counterparties as well as the prospects of the joint project, thus improving the risk-taking level of VCs. Accordingly, we propose the following hypothesis.

Hypothesis 3-1. A higher matching degree between VCs and startups increases the risk-taking level of VCs, thereby boosting the likelihood of VC investment in early-stage startups.

Syndicated investment is one of the most common strategies adopted by VCs to share the risk of a particular investment, as well as to better diversify their project portfolio and reduce the overall risk of their investment funds (Manigart et al., 2006; Dimov and Milanov, 2010). First, while a single VC investor must cover the entire financing needs for a startup and bear all risk in a stand-alone investment, syndicated investment can spread the risk by bringing in other investment partners (Lockett and Wright, 2001). Second, syndicated investment combines the experience, knowledge, and resources of multiple VCs and can provide additional financial, technical, and strategic support to investee startups. This helps promote the development and growth of startups, leading to a higher likelihood of successful exits and better exit performance for VCs (Hochberg et al., 2007; Tian, 2012).

As syndication helps share investment risk among syndicated VCs, a VC has to bear higher risk when investing alone than when investing jointly with other VCs. Other things being equal, VCs could exhibit a strong propensity for early-stage startups with syndicated investment compared with the case of stand-alone investment. As a result, a higher matching degree can better alleviate the risk concern arising from early-stage investment in startups when VCs invest alone than when they invest jointly. Since one channel through which matching affects the investment timing of VCs is that matching changes the risk-taking level of VCs, we expect that a higher matching degree can better motivate VCs to invest in early-stage projects when they invest alone. Accordingly, we propose the following hypothesis.

Hypothesis 3-2. The effect of matching between VCs and startups on the level of risk-taking of VCs is more pronounced for stand-alone investment than for syndicated investment.

3. Research design

3.1. Sample and data

Our initial sample contains VC investment events that occurred from January 1, 2002 to December 31, 2020 in China, and the data is obtained from the Zero2IPO database (https://www.pedata.cn). Our final sample is selected according to the following criteria. First, the sample is limited to startups registered in Beijing, Shanghai, or Shenzhen. According to the Zero2IPO database, these cities are the three major cities in Mainland China with the most active entrepreneurial markets.[4] Second, in the case of syndicated investment, only the lead VC is considered. The lead VC is the one with the largest amount invested, and if the investment sums of VCs are the same, then the lead VC is the one with the most experience in the entire sample period. Third, the information about the characteristics of VCs is obtained from the institutional sub-database of Zero2IPO. We check all this information and add it to the dataset of our investment sample. We keep the data samples of investment events associated with only two types of institutions: PE (private equity) and VC, and then calculate the variables of the characteristics related to VCs and entrepreneurial enterprises. Finally, we remove the data samples with missing values in key variables. Our final sample includes Series A investments of 2021 VCs in 7070 startups. [5]

3.2. Variables

3.2.1. Measuring the degree of matching

As noted, the matching structure between VCs and startups can be positive assortative matching or negative assortative matching. The matching degree reflects the degree to which a VC and a startup occupy a similar standing in their respective peer groups. To construct the variables of the degree of matching, we first measure the quality of VCs and the development potential of startups. Following Fu et al. (2019a), we use two variables to measure the quality of a VC: *VC_exp* and *VC_total_exp*. The former denotes the cumulative number of investments made by the VC from the beginning of the sample period to the year of a particular observation, while the latter calculates the total number of investments over the entire sample period. We use two variables to indicate the development potential of a startup: *EN_number* and *EN_round*. *EN_number* denotes the total number of VC investments received by a startup during the sample period, and *EN_round* denotes the total number of rounds of VC investments received by a startup during the sample period. These metrics are based on the number of investments and financing experiences of a VC or a startup, capturing how each party is perceived by the other in the VC market. On the one hand, the number of funding rounds received by a startup reflects its attractiveness to VCs and conveys information about its development potential from the perspective of VCs. On the other hand, the number of investments made by a VC not only measures the VC's capability of identifying investment opportunities but also reflects its experience in the market.

We then calculate the matching degree between a VC and a startup, based on the closeness of the ranking of the quality of the VC and the ranking of the development potential of the startup in their respective markets. For this purpose, following Sørensen (2007) and Fu et al. (2019a), we divide the market into various sub-markets, based on the geographic location of a startup and the time of a VC investment event. In our sample, the location dimension comprises three cities of Beijing, Shanghai, and Shenzhen, and the time dimension includes the 19 years in our sample period from 2002 to 2020. Thus, there are 57 VC markets. In each of these markets, VCs and startups are ranked according to their quality variables to obtain their ranking indicators denoted as *EN_number_rank* and *EN_round_rank* for startups, as well as *VC_exp_rank* and *VC_total_exp_rank* for VCs, and then the degree of matching is calculated for each pair. The degree of matching variable *mdgree* is defined as follows if *EN_number_rank* and *VC_total_exp_rank* are used in the calculation:

$$mdgree = 1 - \frac{|VC\_total\_exp\_rank - EN\_number\_rank|}{totalrank}, \tag{1}$$

where *totalrank* is the total number of entrepreneurial firms that secure VC investment in a particular market. The variable *mdgree* has a value between 0 and 1. If the rankings of a VC and a startup are close to each other, the value of this variable is close to one; if their rankings are far apart, the value is close to zero. Similarly, we can calculate three alternative variables for the degree of matching using alternative measures of quality: *mdgree11* based on *VC_total_exp_rank* and *EN_number_rank*, *mdgree22* based on *VC_exp_rank* and *EN_round_rank*, *mdgree12* based on *VC_total_exp_rank* and *EN_round_rank*, and *mdgree21* based on *VC_exp_rank* and *EN_number_rank*.

The degree of matching *mdgree* defined as per Eq. (1) cannot reflect the directional difference in mismatching. For example, the greatest mismatch can be either the result of a match between the highest ranked VC and the lowest ranked startup in a market, or the

[4] This study examines this sample for the following reasons. In 2002, the Chinese government started to provide policy support for VC in a bid to alleviate the financing difficulties of small and medium-sized enterprises. After 2002, the VC market in China entered a period of rapid growth. In addition, according to statistics from the Zero2IPO database, more than half of the startups that received VC financing are registered in Beijing, Shanghai, or Shenzhen. As a robustness test, we also considered the three most economically developed regions in China: the Beijing-Tianjin-Hebei region (including Beijing, Tianjin, and Hebei province), the Yangtze River Delta region (including Shanghai, Jiangsu province, and Zhejiang province), and the Pearl River Delta region (including Guangdong province and Hong Kong). This expanded dataset contains 77.21% of VC investment events in China, and the results remain qualitatively the same.

[5] In some of the investment events, the amount of investment by VCs was not disclosed, but these samples are retained, given that this information is not needed in the baseline test. However, when testing Hypothesis 3, the amount of investment by VCs is needed to calculate the level of risk-taking at both the individual deal level and the market level. As a result, in the tests for Hypothesis 3, the samples with missing investment data are excluded, with total observations of 5572. The sample selection criteria are the same as those in Fu et al. (2019a).

result of a match between the lowest ranked VC and the highest ranked startup. Therefore, we construct another measure, denoted as *ddgree*, to capture the difference in ranking between a VC and a startup as well as their direction of mismatching. The matching difference variable *ddgree* is calculated as follows:

$$ddgree = \frac{VC\_total\_exp\_rank - EN\_number\_rank}{totalrank}. \tag{2}$$

The value of *ddgree* ranges from -1 to 1. A negative value indicates that a high-ranked VC is matched with a low-ranked startup, while a positive value indicates the other way around. The closer the value of *ddgree* is to -1 or 1, the more imbalanced a match tends to be. The value of *ddgree* is 0 if the match occurs between equally ranked VCs and startups. Similar to *mdgree*, we also have four matching difference variables, depending on what ranking indicators of VCs and startups are used in the calculation: *ddgree*11, *ddgree*22, *ddgree*12, and *ddgree*21.

To examine the overall degree of matching in a market, we further construct variables for the market-level degree of matching. Similar to the formula for the correlation coefficient, for a VC market with a market capacity of *N*, there are actually *N* matching events between VCs and startups, denoted as $(i,j) \in \mu$, where $I = \{i|i = 1, 2, \cdots, N\}, J = \{j|j = 1, 2, \cdots, N\}$. Following Fu et al. (2023b), the market-level degree of matching index $\boldsymbol{mdrankp}(N)$ is calculated as follows:

$$mdrankp(N) = \frac{COV[VC\_rank(I), EN\_rank(J)]}{\sqrt{VAR[VC\_rank(I)] \times VAR[EN\_rank(J)]}}, \tag{3}$$

where $\boldsymbol{VC\_rank}(i)$ denotes the ranking of VC *i* as per its quality in the market, similar to *VC_exp_rank* and *VC_total_exp_rank*. $\boldsymbol{EN\_rank}(j)$ denotes the ranking of startup *j* as per its growth potential in the market, similar to *N_number_rank* and *EN_round_rank*. Since ordinal numbers are used in the calculation, $\boldsymbol{mdrankp}(N)$ follows the calculation method of Spearman's correlation coefficient. In the robustness tests, we also adopt Kendall's rank correlation coefficient method to calculate *mdrankk* as an alternative measure of the market-level matching degree. Clearly, when VC *i* and startup *j* match with each other following positive assortative matching, the deal-level matching degree *mdgree* $= 1$, and the market-level matching degree $\boldsymbol{mdrankp}(N) = 1$; when both parties match according to negative assortative matching, the deal-level matching degree is close to 0, and the market-level degree of matching is close to -1; when these two parties match with each other randomly, the market-level degree of matching index converges in probability to 0 with increasing market capacity, i.e. $\boldsymbol{mdrankp}(N) \xrightarrow{P} 0$. Similarly, by using different measures for the quality of VCs and the growth potential of startups, we can obtain four different measures of the market-level degree of matching: *mdrankp*11, *mdrankp*22, *mdrankp*12, and *mdrankp*21. We calculate all these market-level measures in the 57 sub-markets in our sample.

3.2.2. Measuring timing of VC investment in startups

We use the development stage of a startup at which it secures Series A financing to measure the timing of VC investment in the startup. To determine the life cycle of a startup, we adopt the following three indicators and methods: the age of the startup in years, financial indicators such as dividend payout ratios, capital expenditure ratios, and cash flow methods (Anthony and Ramesh, 1992; Dickinson, 2011). Since startups are not yet listed on exchanges, their financial data are not publicly available. The Zero2IPO database divides startups into the seed, startup, expansion, and mature stages according to their product life cycle, with seed-stage startups generally being less than one year old, startup-stage startups generally being one to three years old, and expansion-stage startups generally being three to 10 years old. On average, mature-stage startups are >10 years old. In this paper, we use the classification method of the Zero2IPO database to determine the development stage of a startup at which it secures Series A financing.

Following prior literature, this paper adopts two approaches to measuring the timing of VC investment in a startup at the deal level: (1) A dummy variable *stagesetup* indicating whether a startup is at the seed or startup stage when it secures its Series A funding. In this case, the seed and startup stages are considered the early development stage of the startup. *stagesetup* is equal to 1 if VC investment occurs at the early development stage, and 0 otherwise. (2) A discrete variable *stage* indicating the stage at which a startup secures Series A financing, with values 1 to 4 being assigned to seed, startup, expansion, and mature stages, respectively. Thus, a larger value of the variable *stage* corresponds to a later stage at which the startup receives its Series A funding. Fig. 1 shows the number of startups receiving their Series A financing at various stages for each of the sample years. It can be seen that for most years, a higher proportion of startups receive their Series A financing at a relatively early stage, but for some years, the proportion of startups receiving Series A financing at a late stage is higher than that at an early stage.

3.2.3. Measuring VCs' risk-taking

The level of risk-taking by a VC (the variable *risktaking_individual*) in a single investment project is measured by the ratio of the sum of investment made by the VC in that particular project to its total investment during the same year, which corresponds to the ratios of the VC's capital allocation to a startup in that year. At the market level, following Chaplinsky and Gupta-Mukherjee (2016), the ratio of the total size of financing received by early-stage startups (seed or startup stages) to the total size of financing received by startups in the market is used to measure the aggregate level of risk-taking of VCs in the market (the variable *risktaking_market*). This is essentially the ratio of VC funding allocated to early-stage projects in the entire market. The market-level VCs' risk-taking is calculated for each of the 57 sub-markets.

3.2.4. Control variables

We include the following control variables in our regressions to control for the characteristics of VCs and startups and the external

Table 1
Definitions of variables.

Variable	Notation	Definition
Degree of matching: deal level	*mdgree*	The degree of matching defined in Eq. (1)
	ddgree	The degree of matching difference defined in Eq. (2)
Degree of matching: market level	*mdrankp*	Market-level degree of matching index
Timing of VC investment in startups at the deal level	*stagesetup*	A dummy variable that equals 1 if a startup secures Series A VC financing at the seed or startup stage of development, and 0 otherwise
	stage	A variable that equals 1, 2, 3, or 4 if a startup secures Series A financing at the seed, startup, expansion, or maturity stages, respectively
Level of risk-taking	*risktaking_individual*	The ratio of the sum of investment made by a VC in a particular project to its total investment during the same year
	risktaking_market	The ratio of the total size of financing received by early-stage startups (seed or startup stages) to the total size of financing received by startups in the market
Quality of VCs	*VC_total_exp*	The number of total investments made by a VC in the sample period
	VC_exp	The cumulative number of investments made by a VC since the start of sample period to the year of a particular investment
Potential of startups	*EN_number*	The total number of VC investments received by a startup during the sample period
	EN_round	The total round of investments received by a startup during the sample period
Location	*market*1	A dummy variable equal to 1 if a startup is located in Beijing, and 0 otherwise
	*market*2	A dummy variable equal to 1 if a startup is located in Shanghai, and 0 otherwise
	*market*3	A dummy variable equal to 1 if a startup is located in Shenzhen, and 0 otherwise
Early-stage investment preference of VCs	*setupprop*	The ratio of the number of investments in early-stage projects to the cumulative total number of investments made by VCs when investing in a particular startup
VC's registration location	*vclocation*	A dummy variable indicating whether a VC is registered in mainland China
VC's foreign background	*foreigndum*	A dummy variable indicating whether a VC (or the lead VC in syndicate investment) has a foreign capital background
Geographical proximity	*distance*	A dummy variable indicating whether the VC and the startup in a joint venture are located in the same city
Economic policy uncertainty	*uncertaintyma*12	The average of the economic policy uncertainty index (Baker et al., 2016), divided by 100, during the 12 months up to the month of VC investment
Industry	*I_telecom*	A dummy variable for telecommunication industries
	I_electron	A dummy variable for semiconductor and electronic equipment industries
	I_machine	A dummy variable for machine building industries
	I_cleantech	A dummy variable for clean tech industries
	I_finance	A dummy variable for finance industries
	I_enterta	A dummy variable for entertainment and media industries
	I_biomedicine	A dummy variable for biotechnology and healthcare industries
	I_computer	A dummy variable for computer industries
	I_intenet	A dummy variable for internet industries
	I_other	A dummy variable for industries other than those listed above

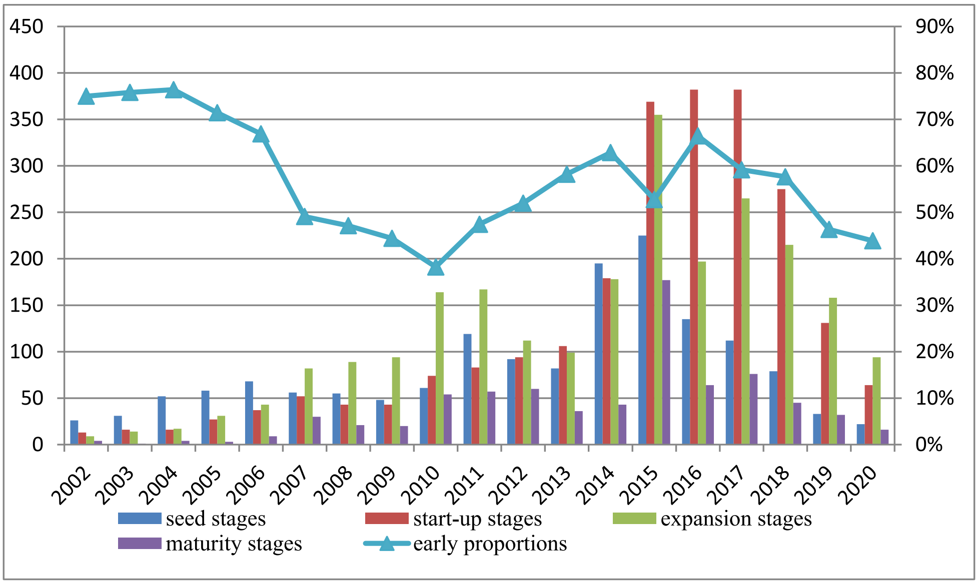


Fig. 1. Distribution of Series A financing stages of sample companies by year.

environment in which they operate.

(1) We include the following variables for the characteristics of startups. Variables that measure the development potential of a startup include the variables *EN_number* and *EN_round*, where *EN_number* is the total number of VC investments received by the startup, and *EN_round* is the total number of rounds of VC investments received during the sample period. Three dummies are adopted to indicate the geographical regions of a startup. *market*1 equals 1 if the startup is located in Beijing, and 0 otherwise; *market*2 equals 1 if it is located in Shanghai, and 0 otherwise; *market*3 equals 1 if it is located in Shenzhen; and 0 otherwise. Dummy variables indicating the industry category to which the firm belongs include *I_telecom* =1 for telecommunications industries, *I_electron*=1 for semiconductor and electronic equipment industries, *I_machine* =1 for machinery manufacturing industries, *I_cleantech* =1 for clean technology industries, *I_finance* =1 for finance industries, *I_enterta* =1 for entertainment and media industries, *I_biomedicine* =1 for biotechnology and healthcare industries, *I_computer* =1 for computer industries, *I_intenet*=1 for internet industries, and *I_other*=1 for all other industries.

(2) We include the following variables to control for the characteristics of VCs: two variables indicating the quality of a VC: *VC_exp* and *VC_total_exp*; a variable measuring the VC's preference for early-stage projects (denoted as *setupprop*), which is calculated as the ratio of the number of early-stage investments of the VC to the total number of cumulative investments from the beginning of the sample period to the time of an investment event; a dummy variable indicating whether the VC is domiciled in China, with *vclocation* = 1 for those domiciled in China; a dummy variable indicating whether the VC has a foreign capital background,[6] with *foreigndum* = 1 for those with a foreign background; and a dummy variable indicating whether the VC and its partner startup are in the same city, with *distance* = 1 indicating that they are in the same city.

(3) To control for the impacts of macroeconomic factors, we use the economic policy uncertainty index developed by Baker et al. (2016) as a measure of economic conditions, and then we incorporate it into the model to capture the influence of macroeconomic conditions. The data is from Baker et al. (2016) at http://www.policyuncertainty.com/. We include a variable to control for the effect of the economic policy uncertainty (the variable *uncertaintyma*12). More specifically, we first divide monthly data on economic policy uncertainty by 100, and then calculate the 12-month moving average as a measure of the impact of the state of economy and macroeconomic shocks.

(4) We finally include year dummy variables *year*2002, *year*2003, ⋯, and *year*2020 to indicate the year in which the investment event occurred. These are also the time dimension variables used to classify the VC markets.

3.2.5. Regression models

To test Hypothesis 1, we run the following regression model:

$$stagesetup\ (stage) = \alpha + \beta_{11} \times mdgree + \gamma \times M + \varepsilon. \tag{4}$$

$$stagesetup\ (stage) = \alpha + \beta_{21} \times ddgree^2 + \beta_{22} \times ddgree + \gamma \times M + \varepsilon. \tag{5}$$

The explained variable in Models (4) and (5) represents the timing of VC investment in a startup. It is either *stagesetup*, which is a dummy variable indicating whether or not the startup is at an early stage of development, or *stage*, which is a discrete variable indicating the development stage of the startup. When the explained variable is *stagesetup*, the regression parameter β_{11} in Model (4) is expected to be positive and significant; when the explained variable is *stage*, the estimated parameter β_{11} is expected to be negative and significant. Similarly, when the explained variable is *stagesetup*, the regression parameter β_{21} in Model (5) is expected to be negative, indicating an inverted U-shaped relationship between *ddgree* and *stagesetup*. When the explanatory variable is *stage*, the estimated parameter β_{21} in Model (5) is expected to be positive, indicating a U-shaped relationship between *ddgree* and *stage*.

To test Hypotheses 2–1, 2–2, and 2–3, we run group regressions using Model (4). The regression parameter β_{11} in Model (4) is expected to be less significant when the VC (or lead VC in the case of syndicated investment) is a foreign VC, a state-owned VC, and when the investment event occurs during the IPO suspension period, but more significant or higher in absolute value when the VC is a domestic VC, a private VC, and when the investment event occurs during the IPO opening period.

To test Hypothesis 3-1, we run the following regression model:

$$risktaking\_individual = \alpha + \beta_{31} \times mdgree + \gamma \times M + \varepsilon, \tag{6}$$

where the explained variable is the level of risk-taking by a VC, which is calculated as the ratio of the amount invested by the VC in a particular project to its total investment in that year. The main explanatory variable is the matching degree (*mdgree*) between the VC and the startup, and *M* is a set of control variables as those in Models (4) and (5). According to Hypothesis 3-1, the regression coefficient in Model (6) β_{31} is expected to be significantly positive.

We consider the following regression model to test Hypothesis 3-1 at the market level:

$$risktaking\_market = \alpha + \beta_{41} \times mdrankp + \gamma \times M + \varepsilon. \tag{7}$$

[6] In this paper, VCs are classified into three categories: VCs with a government background (*VC_governback*), VCs with a foreign capital background (*foreigndum*), and purely domestic private VCs (*domesticNostatedum*). In the second category, 32 VCs also have a government background, which represent the overlapping VCs of the first two categories. In the second category, 36 VCs also have a domestic capital background, of which 28 are joint ventures with domestic private VCs and 8 are joint ventures with domestic government-backed VCs. The above-mentioned 28 VCs are not classified as domestic private VCs. Given the fact that the overlapping parts among these categories are small in number, we do not make further differentiations.

To mitigate the possible estimation biases due to a relatively small sample size in the market-level tests, we run Regression (7) using the market-level variables for the matching degree and risk-taking level together with those control variables measuring characteristics of individual VCs and startups. The regression parameter β_{41} in Model (7) is expected to be significantly positive.

To test Hypothesis 3-2, we use Model (4) for subsamples classified based on whether a VC investment is syndicated investment. The regression parameters β_{11} in Model (4) are expected to be less significant for syndicated investment than for stand-alone VC investment.

4. Empirical results and analysis

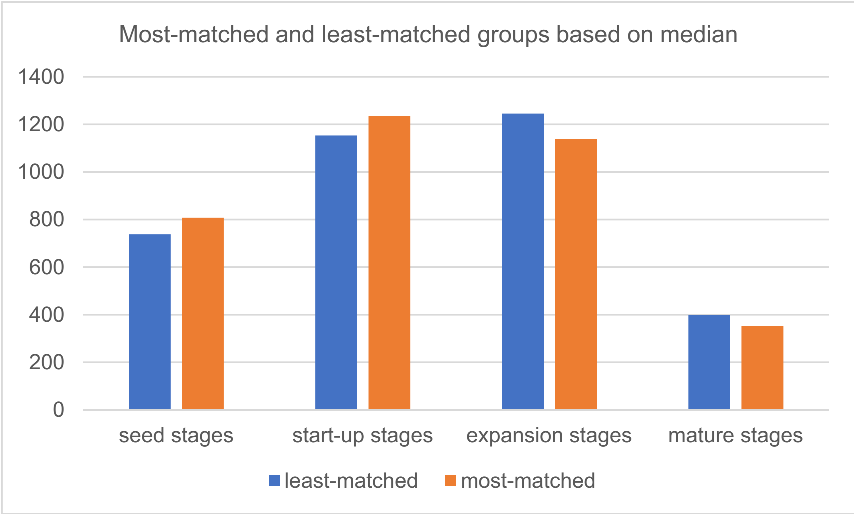
4.1. Descriptive statistics

Table 2 reports the results of the descriptive statistics of all the main variables. There are 7070 companies in the sample; 3931 of these startups were at an early stage of development when they secured Series A financing, accounting for 55.6% of the total sample. In other words, more than one half of the startups were at the seed or startup stage when they secured Series A VC financing. Focusing on the degree of matching, the averaged value of the variable *mdgree* is 0.7, and the average of the matching degree difference variable *ddgree* is 0. The results indicate that the matching structure between VCs and startups is generally a positive assortative structure, with both matching parties having similar rankings in their respective markets. The minimum value of the matching degree variable *mdgree* is close to 0. The maximum value of the matching degree difference *ddgree* is close to 1, while the minimum value is close to −0.9. This indicates that there are mismatches, where high−/low-ranked VCs matched with low−/high-ranked startups. Regarding the market-level matching degree, the overall matching degree between the two parties in most markets is not high. The mean value of the market-level matching degree variable is close to 0.12, the maximum value is close to 0.5, and the minimum value is close to −0.3. The mean value of the risk-taking level of VCs is 0.563, with a maximum value of 1, a minimum value of 0.0006, and a standard deviation of 0.413, indicating that the proportion of capital allocated to individual investment projects by VCs vary greatly among VCs. The mean value of market-level risk-taking variable is 0.52, with a maximum value of 0.91 and a minimum value of 0.052, indicating that there are significant differences in the proportion of capital allocated to early-stage projects by VCs in different markets.

To better understand the effect of matching, we divide the entire sample into two subsamples based on the matching degree variable *mdgree11*. The first subsample (labelled "most-matched group") includes samples with the value of the matching variable higher than the sample median, and the other subsample (labelled "least-matched group") includes samples with the value of the matching variable lower than the sample median. Then, we examine the distribution of VC financing events in four different development stages: seed stage, early stage, expansion stage, and mature stage. The top figure in Fig. 2 illustrates these findings. This preliminary analysis tends to confirm that a higher-matching-degree is more conducive to early-stage VC financing. Moreover, we further divide the entire sample into three equal groups according to the matching degree variable *mdgree11*, and define the most-matched and least-matched groups as those in the top tertile and bottom tertile, respectively. The results are plotted in the bottom

Table 2
Descriptive statistics of variables.

Category	Variables	Obs.	Average	Standard deviation.	Minimum	1/4 quartile	3/4 quartile	Maximum
	stagesetup	7070	0.556	0.497	0	0	1	1
	stage	7070	2.331	0.934	1	2	3	4
	risktaking_individual	5572	0.563	0.413	0.0006	0.126	1	1
	mdgree11	7070	0.698	0.224	0.028	0.547	0.886	1
	mdgree22	7070	0.699	0.221	0.067	0.550	0.884	1
Deal level	*mdgree12*	7070	0.702	0.219	0.033	0.555	0.885	1
	mdgree21	7070	0.695	0.225	0.059	0.538	0.886	1
	ddgree11	7070	0	0.376	−0.909	−0.262	0.256	0.972
	ddgree22	7070	0	0.373	−0.831	−0.260	0.241	0.933
	ddgree12	7070	0	0.370	−0.828	−0.258	0.240	0.967
	ddgree21	7070	0	0.379	−0.889	−0.259	0.257	0.941
	risktaking_market	7070	0.520	0.212	0.052	0.314	0.678	0.910
	mdrankp11	7070	0.138	0.100	−0.282	0.096	0.202	0.589
Market level	mdrankp22	7070	0.114	0.115	−0.439	0.089	0.162	0.436
	mdrankp12	7070	0.134	0.107	−0.337	0.104	0.185	0.469
	mdrankp21	7070	0.121	0.108	−0.422	0.093	0.194	0.669
	VC_total_exp	7070	238.162	343.038	1	11	333	1206
	VC_exp	7070	93.158	172.845	1	4	99	1198
	EN_number	7070	5.199	6.617	1	1	6	188
	EN_round	7070	2.174	1.393	1	1	3	12
	market2	7070	0.306	0.461	0	0	1	1
Control variables	*market3*	7070	0.189	0.392	0	0	0	1
	setupprop	7070	0.512	0.304	0	0.3	0.7	1
	vclocation	7070	0.933	0.251	0	1	1	1
	foreigndum	7070	0.302	0.459	0	0	1	1
	distance	7070	0.472	0.499	0	0	1	1
	uncertaintyma12	7070	2.434	1.760	0.620	1.157	3.162	8.382



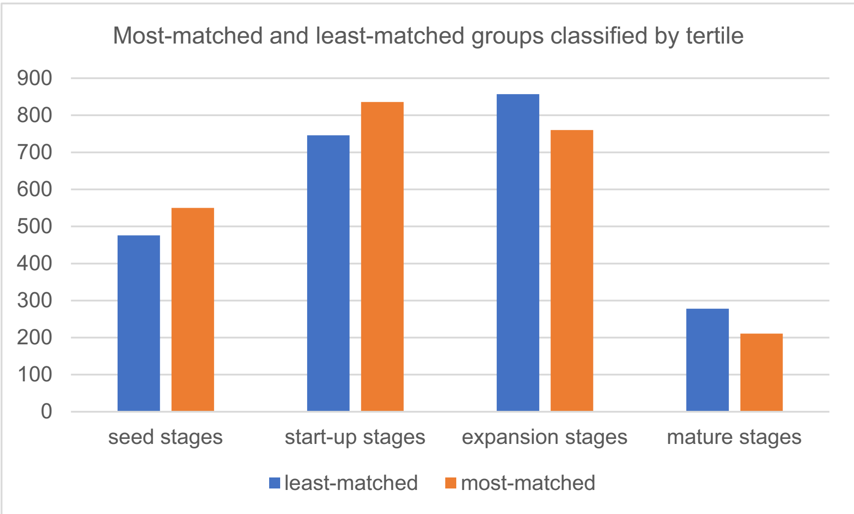


Fig. 2. Distribution of Series A financing in various stages of subsamples classified by the matching degree.

figure in Fig. 2, which clearly shows more pronounced effects.

4.2. *Empirical results*

4.2.1. *Matching and timing of VC investment*

We first examine the effect of the matching degree on the timing of Series A VC financing in entrepreneurial firms. The estimation results are reported in Table 3. The explained variable in columns (1) to (4) is *stagesetup*, and the explained variable in columns (5) to (8) is *stage*. The results show that the degree of matching between a VC and a startup has a significantly positive effect on the timing of Series A VC investment in the startup. When the development potential of the startup is more in line with the level of professional qualification of the VC, the startup is more likely to secure VC financing at an early stage and the VC is more likely to invest in early-stage projects, supporting Hypothesis 1. This suggests that if the degree of matching between a VC and a startup is low, it will be difficult for them to reach an agreement on the investment contract, and the startup will delay VC financing, while the VC will delay its investment in the startup.

As to the control variables, the VC quality variables *VC_total_exp* and *VC_exp*, the startup quality variables *EN_number* and *EN_round*, as well as the variable *setupprop* all have a positive and significant effect on the timing of VC investment in startups. This indicates that with greater development potential, a startup is more likely to secure VC financing at the seed or startup stage, and with higher quality, a VC is more likely to invest in the startup at the early stage of development. In addition, if a VC exhibits a stronger preference for early-stage projects, then it is more likely to invest in the startup at the early stage of development. The estimated

Table 3
Matching and timing of VC investment.

	Explained variables							
	stagesetup *Probit*				*stage* *OLS*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mdgree11	0.285***				−0.166***			
	(0.081)				(0.041)			
mdgree22		0.218***				−0.136***		
		(0.082)				(0.042)		
mdgree12			0.219***				−0.146***	
			(0.083)				(0.042)	
mdgree21				0.281***				−0.150***
				(0.080)				(0.041)
VC_total_exp	0.0002***		0.0002***		−0.0002***		−0.0002***	
	(0.0001)		(0.0001)		(0.00003)		(0.00003)	
VC_exp		0.001***		0.001***		−0.0003***		−0.0003***
		(0.0001)		(0.0001)		(0.0001)		(0.0001)
EN_number	0.009***			0.009***	−0.005***			−0.005***
	(0.003)			(0.003)	(0.001)			(0.001)
EN_round		0.067***	0.068***			−0.037***	−0.037***	
		(0.013)	(0.013)			(0.007)	(0.007)	
market2	0.084**	0.085**	0.085**	0.084**	−0.040*	−0.040*	−0.040*	−0.039*
	(0.040)	(0.040)	(0.040)	(0.040)	(0.021)	(0.021)	(0.021)	(0.021)
market3	0.014	0.021	0.018	0.018	0.023	0.018	0.021	0.019
	(0.049)	(0.049)	(0.049)	(0.049)	(0.025)	(0.025)	(0.025)	(0.025)
setupprop	2.879***	2.887***	2.868***	2.898***	−1.484***	−1.489***	−1.479***	−1.494***
	(0.071)	(0.072)	(0.071)	(0.072)	(0.032)	(0.032)	(0.032)	(0.032)
vclocation	−0.101	−0.093	−0.103	−0.092	0.037	0.022	0.039	0.020
	(0.077)	(0.076)	(0.077)	(0.076)	(0.041)	(0.040)	(0.041)	(0.040)
foreigndum	0.021	0.004	0.013	0.014	−0.101***	−0.103***	−0.096***	−0.110***
	(0.046)	(0.046)	(0.046)	(0.046)	(0.025)	(0.025)	(0.025)	(0.025)
distance	0.051	0.049	0.050	0.050	−0.029	−0.030	−0.029	−0.030
	(0.037)	(0.037)	(0.037)	(0.037)	(0.019)	(0.019)	(0.019)	(0.019)
uncertaintyma12	0.036	0.035	0.039	0.033	0.008	0.009	0.006	0.011
	(0.041)	(0.041)	(0.041)	(0.041)	(0.022)	(0.022)	(0.022)	(0.022)
year&industry	Control	Control	Control	Control	Control	Control	Control	Control
Constant	−2.270***	−2.353***	−2.299***	−2.325***	3.466***	3.513***	3.491***	3.484***
	(0.364)	(0.367)	(0.365)	(0.365)	(0.193)	(0.194)	(0.194)	(0.193)
Observations	7070	7070	7070	7070	7070	7070	7070	7070
Log-likelihood	−3437.421	−3428.205	−3431.588	−3434.217				
AIC	6950.842	6932.411	6939.176	6944.433				
R^2					0.332	0.332	0.333	0.331
Adj_R^2					0.328	0.329	0.329	0.328
Standard errors					0.765	0.765	0.765	0.766
F statistics					94.260***	94.584***	94.707***	94.066***

This table reports the results for the impacts of degree of matching between VCs and startups on the timing of Series A VC financing in entrepreneurial firms. The regressions are estimated by the maximum likelihood method. The standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The detailed definitions of the variables are provided in Table 1.

coefficients on the dummy variable *foreigndum* in columns (5) to (8) are significantly negative at the 1% level, suggesting that VCs with a foreign background are more likely to invest in early-stage startups than are domestic VCs. Domestic VCs are more inclined to choose mature companies with low technology risk rather than highly risky, early-stage startups, while foreign capital-backed VCs focus more on growing startups, and thus are more willing to join the venture at an early stage.

The regression results for the impacts of directional mismatching on the timing of VC investment are reported in Table 4, where the explanatory variables are the same as those in Table 3. Given the way in which the matching difference variable *ddgree* is constructed, we include the quadratic term of the variable in the regression model. The regression results show that the coefficients of the squared matching difference variables are all significant at the 1% level. However, the coefficients in columns (1) to (4) are significantly negative, but the coefficients in columns (5) to (8) are significantly positive, except for columns (5) and (8), where the estimated coefficients on matching difference are insignificant.

The results in Table 4 show that there is an inverted U-shaped relationship between the degree of matching difference and the likelihood of early-stage VC investment, and that there is a U-shaped relationship between the degree of matching difference and the development stage at which startups secure VC financing. The results illustrate that when the matching difference approaches 0, startups tend to get VC financing earlier and VCs are more inclined to invest in projects at their early stages, while when the matching difference approaches −1 or 1, the opposite is true. Thus, the results show that the difference in the direction of mismatching between VCs and startups does not affect the timing of VC investment in startups, which also confirm the results in Table 3 that the degree of

Table 4
Directional mismatching and timing of VC investment.

	Explained variables							
	stagesetup				*stage*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ddgree11^2	−0.412***				0.219***			
	(0.105)				(0.053)			
ddgree22^2		−0.329***				0.179***		
		(0.108)				(0.054)		
ddgree12^2			−0.326***				0.186***	
			(0.109)				(0.055)	
ddgree21^2				−0.416***				0.208***
				(0.104)				(0.052)
ddgree11	0.009				0.011			
	(0.069)				(0.036)			
ddgree22		−0.102				0.071*		
		(0.078)				(0.039)		
ddgree12			−0.145				0.083*	
			(0.091)				(0.046)	
ddgree21				0.008				0.014
				(0.064)				(0.032)
VC_total_exp	0.0002***		0.0001*		−0.0002***		−0.0001***	
	(0.0001)		(0.0001)		(0.00004)		(0.00004)	
VC_exp		0.0004***		0.001***		−0.0002***		−0.0003***
		(0.0001)		(0.0001)		(0.0001)		(0.0001)
EN_number	0.009***			0.009***	−0.006***			−0.006***
	(0.003)			(0.003)	(0.002)			(0.002)
EN_round		0.086***	0.095***			−0.050***	−0.052***	
		(0.019)	(0.021)			(0.010)	(0.010)	
market2	0.084**	0.086**	0.085**	0.084**	−0.040*	−0.040*	−0.040*	−0.039*
	(0.040)	(0.040)	(0.040)	(0.040)	(0.021)	(0.021)	(0.021)	(0.021)
market3	0.013	0.022	0.022	0.018	0.023	0.017	0.019	0.019
	(0.049)	(0.049)	(0.049)	(0.049)	(0.025)	(0.025)	(0.025)	(0.025)
setupprop	2.875***	2.884***	2.864***	2.896***	−1.482***	−1.487***	−1.476***	−1.493***
	(0.071)	(0.072)	(0.071)	(0.072)	(0.032)	(0.032)	(0.032)	(0.032)
vclocation	−0.101	−0.096	−0.102	−0.090	0.036	0.025	0.037	0.020
	(0.077)	(0.076)	(0.077)	(0.076)	(0.041)	(0.040)	(0.041)	(0.040)
foreigndum	0.020	−0.006	0.005	0.013	−0.100***	−0.095***	−0.092***	−0.107***
	(0.046)	(0.046)	(0.047)	(0.046)	(0.025)	(0.025)	(0.025)	(0.025)
distance	0.051	0.050	0.052	0.049	−0.029	−0.030	−0.030	−0.030
	(0.037)	(0.037)	(0.037)	(0.037)	(0.019)	(0.019)	(0.019)	(0.019)
uncertaintyma12	0.036	0.036	0.040	0.033	0.008	0.009	0.006	0.010
	(0.041)	(0.041)	(0.041)	(0.041)	(0.022)	(0.022)	(0.022)	(0.022)
year&industry	Control	Control	Control	Control	Control	Control	Control	Control
Constant	−2.016***	−2.170***	−2.140***	−2.078***	3.323***	3.393***	3.376***	3.352***
	(0.360)	(0.361)	(0.361)	(0.362)	(0.191)	(0.191)	(0.191)	(0.191)
Observations	7070	7070	7070	7070	7070	7070	7070	7070
Log-likelihood	−3435.979	−3426.501	−3429.335	−3432.307				
AIC	6949.958	6931.003	6936.669	6942.615				
R^2					0.332	0.333	0.333	0.331
Adj_R^2					0.328	0.329	0.329	0.328
Standard errors					0.765	0.765	0.765	0.766
F statistics					91.816***	92.268***	92.384***	91.690***

This table reports the results of the impacts of the degree of matching difference between VCs and startups on the timing of Series A VC financing in entrepreneurial firms. The regressions are estimated by the maximum likelihood method. The standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The detailed definitions of the variables are provided in Table 1.

matching between the two parties is a key driver for VCs' early investment in startups.

Regarding the control variables, the coefficients of the variables of startups' development potential and VCs' preference for early-stage projects are both positive and significant at the 1% level in the first four columns, and are negatively significant at the 1% level in the last four columns. The coefficients of the variable measuring VCs' quality are also significant at the 1% level, except that in column (3) in which the coefficient is significantly positive at the 10% level.

4.2.2. Heterogeneous analysis of the impacts of matching

According to Hypothesis 2, the impacts of matching on the timing of VC investment can vary, depending on VCs' foreign background or state ownership, as well as the state of the IPO market. To test this hypothesis, we divide the entire sample into different subsamples and re-run the regressions based on these subsamples. Table 5 reports the estimation results of Model (4) based on subsamples of VCs with and without a foreign capital background. We note that the estimated coefficients on *mdgree* are all significant for

Table 5
Moderating effects of VCs' foreign background on the impacts of matching on the timing of VC investment.

	Explained variables															
	stagesetup								*stage*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Foreign VC	Local VC	Foreign VC	Local VC	Foreign VC	Local VC	Foreign VC	Local VC	Foreign VC	Local VC	Foreign VC	Local VC	Foreign VC	Local VC	Foreign VC	Local VC
*mdgree*11	0.331**	0.255**							−0.129	−0.158***						
	(0.147)	(0.101)							(0.082)	(0.050)						
*mdgree*22			0.187	0.250**							−0.043	−0.164***				
			(0.152)	(0.103)							(0.085)	(0.051)				
*mdgree*12					0.183	0.257**							−0.064	−0.166***		
					(0.153)	(0.104)							(0.086)	(0.052)		
*mdgree*21							0.362**	0.228**							−0.125	−0.137***
							(0.146)	(0.100)							(0.082)	(0.049)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year&industry	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control
Constant term	−3.107***	−2.248***	−3.172***	−2.350***	−3.094***	−2.323***	−3.223***	−2.258***	3.816***	3.325***	3.872***	3.368***	3.826***	3.366***	3.883***	3.313***
	(0.723)	(0.463)	(0.730)	(0.466)	(0.725)	(0.465)	(0.729)	(0.463)	(0.389)	(0.236)	(0.394)	(0.236)	(0.391)	(0.236)	(0.391)	(0.235)
Observations	2135	4935	2135	4935	2135	4935	2135	4935	2135	4935	2135	4935	2135	4935	2135	4935
Log-likelihood	−1087.423	−2330.132	−1086.855	−2322.422	−1087.357	−2324.241	−1086.478	−2328.803								
AIC	2248.847	4734.264	2247.709	4718.844	2248.713	4722.483	2246.957	4731.605								
R^2									0.233	0.337	0.232	0.338	0.234	0.338	0.232	0.337
Adj_R^2									0.220	0.332	0.219	0.333	0.220	0.333	0.219	0.332
Standard errors									0.803	0.747	0.804	0.747	0.803	0.747	0.804	0.747
F statistics									17.733***	69.145***	17.626***	69.537***	17.764***	69.467***	17.597***	69.124***

This table reports the results for the impacts of degree of matching on the timing of Series A VC financing in entrepreneurial firms on subsamples of those VCs with and without a foreign background. The regressions are estimated by the maximum likelihood method. The standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The detailed definitions of the variables are provided in Table 1.

Table 6
Moderating effects of VCs' state ownership on the impacts of matching.

	Explained variables															
	stagesetup								*stage*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	State-owned	Non-State	State-owned	Non-State	State-owned	Non-State	State-owned	Non-State	State-owned	Non-State	State-owned	Non-State	State-owned	Non-State	State-owned	Non-State
*mdgree*11	0.138	0.316***							−0.067	−0.173***						
	(0.210)	(0.089)							(0.116)	(0.045)						
*mdgree*22			0.021	0.256***							−0.034	−0.149***				
			(0.220)	(0.090)							(0.119)	(0.045)				
*mdgree*12					0.140	0.251***							−0.075	−0.151***		
					(0.221)	(0.091)							(0.121)	(0.046)		
*mdgree*21							−0.035	0.331***							−0.009	−0.166***
							(0.210)	(0.088)							(0.115)	(0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year&industry	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control
Constant term	−2.518*	−2.292***	−2.478*	−2.368***	−2.554*	−2.335***	−2.474*	−2.338***	3.605***	3.432***	3.625***	3.499***	3.631***	3.463***	3.608***	3.466***
	(1.339)	(0.385)	(1.336)	(0.388)	(1.342)	(0.387)	(1.335)	(0.386)	(0.730)	(0.203)	(0.733)	(0.203)	(0.733)	(0.203)	(0.729)	(0.202)
Observations	869	6201	869	6201	869	6201	869	6201	869	6201	869	6201	869	6201	869	6201
Log-likelihood	−444.015	−2978.061	−443.836	−2970.298	−443.563	−2972.210	−444.229	−2975.697								
AIC	964.031	6032.121	963.672	6016.596	963.127	6020.420	964.458	6027.393								
R^2									0.281	0.340	0.282	0.340	0.282	0.341	0.282	0.339
Adj_R^2									0.249	0.336	0.250	0.336	0.250	0.337	0.250	0.335
Standard error									0.805	0.760	0.804	0.759	0.805	0.759	0.805	0.760
F statistics									8.792***	85.637***	8.835***	85.840***	8.803***	86.137***	8.825***	85.272***

This table reports the results for the impacts of degree of matching on the timing of Series A VC financing in entrepreneurial firms on subsamples of those VCs with and without a state background. The regressions are estimated by the maximum likelihood method. The standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The detailed definitions of the variables are provided in Table 1.

Table 7
Moderating effects of state of IPO markets on the impacts of matching.

	Explained variables															
	stagesetup(Probit)								*stage(OLS)*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	IPO suspension	IPO opening	IPO suspension	IPO opening	IPO suspension	IPO opening	IPO suspension	IPO opening	IPO suspension	IPO opening	IPO suspension	IPO opening	IPO suspension	IPO opening	IPO suspension	IPO opening
*mdgree*11	0.102	0.316***							−0.168	−0.165***						
	(0.225)	(0.087)							(0.114)	(0.045)						
*mdgree*22			0.151	0.233***							−0.141	−0.136***				
			(0.229)	(0.088)							(0.114)	(0.045)				
*mdgree*12					0.122	0.233***							−0.110	−0.148***		
					(0.234)	(0.089)							(0.117)	(0.046)		
*mdgree*21							0.101	0.316***							−0.182*	−0.147***
							(0.218)	(0.087)							(0.110)	(0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year&industry	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control
Constant term	−2.651***	−2.106***	−2.962***	−2.163***	−2.880***	−2.115***	−2.710***	−2.159***	3.996***	3.385***	4.097***	3.426***	4.020***	3.411***	4.057***	3.398***
	(0.450)	(0.374)	(0.459)	(0.377)	(0.459)	(0.376)	(0.447)	(0.376)	(0.227)	(0.199)	(0.230)	(0.200)	(0.231)	(0.199)	(0.225)	(0.199)
Observations	1063	6007	1063	6007	1063	6007	1063	6007	1063	6007	1063	6007	1063	6007	1063	6007
Log-likelihood	−477.100	−2941.902	−470.707	−2937.601	−472.344	−2939.783	−475.527	−2939.779								
AIC	1006.201	5957.804	993.415	5949.201	996.688	5953.565	1003.054	5953.559								
R^2									0.404	0.320	0.407	0.321	0.406	0.321	0.405	0.320
Adj_R^2									0.390	0.316	0.393	0.317	0.392	0.317	0.390	0.315
Standard errors									0.779	0.762	0.777	0.762	0.778	0.762	0.779	0.762
F statistics									28.134***	78.014***	28.483***	78.261***	28.401***	78.331***	28.205***	77.879***

This table reports the results for the impacts of degree of matching on the timing of Series A VC financing in entrepreneurial firms on whether IPOs are temporarily suspended at the time of the VC investment. The regressions are estimated by the maximum likelihood method. The standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The detailed definitions of the variables are provided in Table 1.

VCs without a foreign background, while for those with a foreign background, the coefficients are insignificant with the exception of those in columns (1) and (7). Therefore, when a VC (or lead VC) has a foreign background, a high matching degree does not generally promote VCs to invest in early-stage projects. However, when VCs are domestic institutions, a high degree of matching can effectively motivate VCs to invest in startups at an early stage. This represents a piece of evidence in favor of Hypothesis 2-1.

To test Hypothesis 2-2, we divide the total sample of VCs into two subsamples based on their state ownership and run regression Model (4) using the two subsamples. A VC has a state background if the VC (or lead VC) has state ownership, is controlled by the state, or is completely owned by the state. Table 6 reports the results. The odd-numbered columns are the results for the VCs with a state background, and the even-numbered columns are the results for the VCs with no state background. We see that the coefficients on the variable *mdgree* are not significant when VCs have a state background, while these coefficients are all significant and have the same sign as those obtained with the baseline model when VCs have no state background. The results suggest that the effects of the matching degree on the timing of VC investment in startups are less pronounced for the VCs with a state background than for the VCs without a state background, supporting Hypothesis 2-2.

Collectively, the results show that both the degree of information asymmetry between VCs and startups as well as the unique resource and experience advantages of VCs can moderate the relationship between matching and the timing of VC investment in startups.

To test Hypothesis 2-3, we divide the sample into two subsamples based on whether IPOs are temporarily suspended at the time of VC investment events. We then run regression Model (4) using the two subsamples and report the results in Table 7. The results show that the matching degree does not have an impact on the timing of VC investment in startups during the time period in which IPOs are temporarily suspended, as the coefficients on the variable *mdgree* are insignificant in any of the eight models when subsamples from the periods in which IPOs are suspended are used. In contrast, during the time period in which IPOs are active, the matching degree shows a significant and positive effect on whether VCs invest in early development-stage startups. The results suggest that the liquidity risk of VCs' exits plays a moderating role in the relationship between matching of VCs and startups and their choice regarding the timing of investment and financing. The propensity of VCs to invest in early-stage projects as a result of better matching with startups is weaker during IPO suspension periods than during IPO opening periods, which is in favor of Hypothesis 2-3.

4.2.3. *Matching and the level of VCs' risk-taking*

As argued in Hypothesis 3, matching between VCs and startups affects VCs' risk-taking, thereby affecting the likelihood of VCs' investment in early-stage projects. To test Hypothesis 3-1, we first examine whether the matching degree between the two parties is positively associated with the proportion of capital allocated to a particular investment project by a particular VC. Second, we investigate whether the matching degree at the market level is positively related to the overall allocation of VC funds to early-stage projects in the market. To test Hypothesis 3-2, we explore whether a higher matching degree can better increase the risk-taking level of VCs in stand-alone investment than in syndicated investment.

In our analysis, the proportion of funds allocated by a VC to an individual investment project is used as a proxy for the VC's risk-taking level (the variable *risktaking_individual*). In some investment events, the sum of investment is not disclosed by VCs, and thus these investment samples are excluded from our analysis. In addition, we also exclude the sample of investment events by VCs with no

Table 8
Results for the effects of matching on VCs' risk-taking levels.

	Explained variables							
	risktaking_individual							
	Modified sample with $VC\_exp \geq 6$				Modified sample with $VC\_exp \geq 7$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*mdgree*11	0.050* (0.026)				0.053** (0.026)			
*mdgree*22		0.100*** (0.028)				0.101*** (0.029)		
*mdgree*12			0.042 (0.027)				0.046* (0.027)	
*mdgree*21				0.103*** (0.027)				0.101*** (0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year&industry	Control	Control	Control	Control	Control	Control	Control	Control
Constant term	0.869*** (0.104)	0.955*** (0.109)	0.870*** (0.105)	0.961*** (0.109)	0.842*** (0.105)	0.923*** (0.110)	0.841*** (0.105)	0.930*** (0.109)
Observations	3987	3987	3987	3987	3879	3879	3879	3879
R^2	0.343	0.285	0.342	0.287	0.338	0.282	0.337	0.283
Adj_R^2	0.337	0.279	0.336	0.280	0.332	0.275	0.330	0.276
Standard errors	0.315	0.329	0.315	0.328	0.314	0.327	0.314	0.327
F statistics	55.728***	42.645***	55.406***	42.870***	52.982***	40.702***	52.676***	40.897***

This table reports the results for the impacts of degree of matching on VCs' risk-taking levels. The regressions are estimated by the maximum likelihood method. The standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The detailed definitions of the variables are provided in Table 1.

investment experience. This is because the VCs conducting these investments may be inactive VCs or startup VCs, and thus the fund allocation ratio for individual projects is a poor measure of the risk-taking level of these VCs. When calculating the proportion of VC funding allocated to early-stage projects in a given market (the variable *risktaking_market*), the data on the sum of investment are also required, but the choice of whether or not to exclude these samples does not affect the calculation of this variable. To make the empirical results more reliable, both the full sample and the subsample excluding those with missing investment data are used in the analysis.

Table 8 reports the results for the effects of matching on the level of risk-taking of VCs. Columns (1) to (4) are the results based on the sample excluding those with missing investment amounts and those with VC investment experience (the value of *VC_exp*) <6, while columns (5) to (8) are the results based on the sample excluding those with missing investment amounts and those with investment experience (*VC_exp*) <7. The results show that the coefficient on the variable *mdgree* is positive and significant, indicating that a higher degree of matching between the two parties can lead to a higher proportion of investment allocated by VCs to individual investment projects, supporting Hypothesis 3-1. As a result, the higher the degree of matching between the two parties, the greater the level of risk-taking by VCs.

Table 9 reports the results for the effects of market-level matching on the overall level of risk-taking by VCs in the market. Columns (1) to (4) show the test results of the full sample, while columns (5) to (8) show the results based on the sample excluding those with missing investment data and those VCs with investment experience (*VC_exp*) <6. The results show that the coefficients on the market-level matching variable *mdrankp* are all significantly positive at the 1% level, suggesting that a higher degree of matching promotes VCs' overall risk-taking at the market level and thus increases the proportion of VC funding allocated to early-stage projects in the overall market. Overall, when VCs and startups match with each other following a positive assortative structure, society's total surplus increases and VCs can be better compensated for the high risk inherently involved in early-stage investments, thereby boosting their investments allocated to early-stage startups.

To test Hypothesis 3-2, we divide the entire sample into two subsamples based on whether a VC investment is a syndicated investment. We run the regressions on the two subsamples and report the results in Table 10. For the non-syndicated investment subsample, the coefficients on the variable *mdgree* are all significant and have the same sign as the main results. However, for the syndicated investment subsample, the absolute values of the coefficients of the variable *mdgree* are smaller and are, in fact, not significant in columns (3), (5), (11), and (13). The results indicate that the effect of the matching degree on the level of risk-taking of VCs is more pronounced when VCs invest alone than when they invest jointly with other VCs. Better matching plays a greater role in driving VCs to invest in early-stage projects in the case of non-syndicated investment, because the risk-taking level in syndicated investment for a VC is relatively lower than the risk-taking level in stand-alone investment. This supports Hypothesis 3-2.

4.3. Robustness tests

4.3.1. Alternative measures for the degree of matching

In addition to the real-time quality measure *VC_exp* for VCs, we also consider the total number of times that a VC firm has helped its invested companies successfully achieve IPO before an investment event, denoted as *VC_ipoexp*. At the same time, we consider three

Table 9
Results for the effects of market-level matching on overall VCs' risk-taking levels.

	Explained variables							
	risktaking_market							
	Full sample				Modified sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*mdrankp*11	0.187*** (0.014)				0.118*** (0.020)			
*mdrankp*22		0.172*** (0.013)				0.143*** (0.017)		
*mdrankp*12			0.143*** (0.013)				0.098*** (0.018)	
*mdrankp*21				0.272*** (0.013)				0.203*** (0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year&industry	Control	Control	Control	Control	Control	Control	Control	Control
Constant term	0.460*** (0.023)	0.461*** (0.023)	0.463*** (0.023)	0.447*** (0.022)	0.447*** (0.029)	0.440*** (0.029)	0.448*** (0.029)	0.432*** (0.029)
Observations	7070	7070	7070	7070	3987	3987	3987	3987
R^2	0.819	0.819	0.817	0.825	0.819	0.821	0.819	0.823
Adj_R^2	0.818	0.818	0.816	0.824	0.818	0.819	0.817	0.821
Standard errors	0.091	0.091	0.091	0.089	0.089	0.088	0.089	0.088
F statistics	857.596***	859.186***	848.750***	893.188***	483.878***	489.133***	482.628***	496.206***

This table reports the results for the impacts of market-level matching on overall VCs' risk-taking levels. The regressions are estimated by the maximum likelihood method. The standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The detailed definitions of the variables are provided in Table 1.

Table 10
Impacts of matching for syndicate investment and stand-alone investment.

	Explained variables															
	stagesetup								*stagesetup*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	syndicate	stand-alone	syndicate	stand-alone	syndicate	stand-alone	syndicate	stand-alone	syndicate	stand-alone	syndicate	stand-alone	syndicate	stand-alone	syndicate	stand-alone
*mdgree*11	0.234*	0.324***							−0.114*	−0.237***						
	(0.124)	(0.121)							(0.062)	(0.063)						
*mdgree*22			0.165	0.296**							−0.053	−0.245***				
			(0.115)	(0.123)							(0.057)	(0.064)				
*mdgree*12					0.162	0.262**							−0.066	−0.234***		
					(0.115)	(0.124)							(0.057)	(0.064)		
*mdgree*21							0.281**	0.349***							−0.110*	−0.241***
							(0.123)	(0.119)							(0.060)	(0.062)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year&industry	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control	Control
Constant term	−2.571***	−1.652***	−2.593***	−1.952***	−2.559***	−1.735***	−2.633***	−1.880***	3.629***	3.170***	3.633***	3.322***	3.620***	3.228***	3.647***	3.267***
	(0.466)	(0.630)	(0.466)	(0.641)	(0.466)	(0.633)	(0.466)	(0.639)	(0.235)	(0.340)	(0.236)	(0.341)	(0.236)	(0.340)	(0.235)	(0.341)
Observations	3488	3582	3488	3582	3488	3582	3488	3582	3488	3582	3488	3582	3488	3582	3488	3582
Log-likelihood	−1686.380	−1718.570	−1685.677	−1707.405	−1685.086	−1712.671	−1686.211	−1713.269								
AIC	3448.761	3513.140	3447.355	3490.811	3446.171	3501.343	3448.422	3502.538								
R^2									0.324	0.350	0.323	0.353	0.324	0.352	0.323	0.351
Adj_R^2									0.316	0.343	0.316	0.346	0.317	0.345	0.315	0.344
Standard error									0.744	0.782	0.745	0.781	0.744	0.781	0.745	0.782
F statistics									44.611 ***	51.566***	44.494 ***	52.182***	44.718 ***	51.965***)	44.397***	51.743***

This table reports the results for the impacts of degree of matching on the timing of Series A VC financing in entrepreneurial firms on subsamples of whether a VC investment is a syndicate investment. The regressions are estimated by the maximum likelihood method. The standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The detailed definitions of the variables are provided in Table 1.

Table 11
Results for the effects of matching based on alternative measures of the degree of matching.

	Explained variable											
	stagesetup						*stage*					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
mdgree11a	0.3280***						−0.1384***					
	(0.0789)						(0.0411)					
mdgree22a		0.1540*						−0.0647				
		(0.0805)						(0.0425)				
mdgree12a			0.2934***						−0.1166***			
			(0.0804)						(0.0418)			
mdgree21a				0.2214***						−0.0978**		
				(0.0789)						(0.0417)		
mdgree13a					0.2915***						−0.1059**	
					(0.0799)						(0.0415)	
mdgree23a						0.1736**						−0.0621
						(0.0794)						(0.0419)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year&industry	control	control	control	control	control	control	control	control	control	control	control	control
Constant	−2.3585***	−2.2320***	−2.3060***	−2.2973***	−2.2263***	−2.1623***	3.4569***	3.4149***	3.4308***	3.4449***	3.4029***	3.3906***
	(0.3674)	(0.3656)	(0.3673)	(0.3654)	(0.3667)	(0.3648)	(0.1943)	(0.1951)	(0.1945)	(0.1945)	(0.1943)	(0.1947)
Observations	7070	7070	7070	7070	7070	7070	7070	7070	7070	7070	7070	7070
Log-likelihood	−3436.0840	−3442.8060	−3438.6760	−3439.8650	−3437.5280	−3441.5970						
AIC	6948.1690	6961.6120	6953.3520	6955.7300	6951.0560	6959.1930						
R^2							0.3298	0.3278	0.3295	0.3281	0.3296	0.3280
Adj_R^2							0.3263	0.3243	0.3260	0.3246	0.3261	0.3244
Standard error							0.7663	0.7675	0.7665	0.7673	0.7664	0.7674
F statistics							93.5427***	92.6809***	93.4141***	92.8040***	93.4580***	92.7537***

This table reports the results for the impacts of matching between VCs and startups on the timing of Series A VC financing in startups, based on alternative measures of the degree of matching constructed using real-time quality measures for VCs and startups. The regressions are estimated by the maximum likelihood method. The standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The detailed definitions of the variables are provided in Table 1.

Table 12
Results for the effects of matching based on alternative measures of the degree of matching with consideration of VCs' industry preferences.

	Explained variable							
	stagesetup				*stage*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mdgree11ind	0.3266*** (0.0795)				−0.1799*** (0.0414)			
mdgree22ind		0.1783** (0.0796)				−0.1303*** (0.0415)		
mdgree12ind			0.1855** (0.0817)				−0.1352*** (0.0424)	
mdgree21ind				0.2661*** (0.0782)				−0.1666*** (0.0411)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year&industry	control	control	control	control	control	control	control	control
Constant	−2.3184*** (0.3629)	−2.3093*** (0.3644)	−2.3070*** (0.3645)	−2.2945*** (0.3630)	3.4941*** (0.1930)	3.5156*** (0.1937)	3.5069*** (0.1938)	3.4993*** (0.1931)
Observations	7070	7070	7070	7070	7070	7070	7070	7070
Log-likelihood					0.3301	0.3303	0.3307	0.3294
AIC					0.3265	0.3268	0.3272	0.3259
R^2	−3440.9570	−3437.9000	−3438.1050	−3443.3870				
Adj_R^2	6957.9130	6951.8000	6952.2100	6962.7730				
Standard error					0.7662	0.7661	0.7658	0.7666
F statistics					93.6377***	93.7442***	93.9097***	93.3713***

This table reports the results for the impacts of matching between VCs and startups on the timing of Series A VC financing in startups, based on alternative measures of the degree of matching constructed using quality measures for VCs with the consideration of their industry preferences. The regressions are estimated by the maximum likelihood method. The standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The detailed definitions of the variables are provided in Table 1.

real-time quality measures for startups, including *EN_numberAcum*, *EN_numberA*, and *EN_ratio*. *EN_numberAcum* is the total number of VCs participating in a startup' all rounds of financing up to the point of Series A financing. *EN_numberA* is the number of VCs participating in a startup's Series A financing. *EN_ratio* is the average number of VCs participating in each round of funding for a startup from the round of its angel funding until its Series A financing by VCs, calculated as *EN_numberAcum* divided by the total number of rounds until Series A financing by VCs. As our sample contains only Series A financing events in startups, these indicators are all real-time (ex-ante) quality measures for startups at the time when a VC investment event occurs, reflecting the comprehensive evaluation and investment judgement of VCs regarding the startups in which they invest.

Based on the quality measures *VC_exp* and *VC_ipoexp* for VCs, as well as *EN_numberAcum*, *EN_numberA*, and *EN_ratio* for startups, we re-calculate various alternative matching degree measures (*mdgree11a, mdgree22a, mdgree12a, mdgree21a, mdgree13a, mdgree23a*) and reconduct the analysis. We report the results in Table 11. The results show that the estimated coefficients on the matching degree are significant in 10 out of 12 regressions considered, and for the other two regressions, the significance level is slightly higher than 10%. Thus, the results remain qualitatively the same as our previous findings.

The previous analysis does not consider VCs' potential industry preferences. It is possible that some VCs may specialize in a specific industry, while others may have preferences for multiple industries. To take into account the heterogeneity in industry preferences among VC firms, we construct two variables *VC_total_exp_ind* and *VC_exp_ind*. *VC_total_exp_ind* represents the total times of a VC firm's investment over the entire sample period in the industry to which a particular startup belongs, while *VC_exp_ind* represents the real-time investment times of a VC firm in the industry of a startup at the time of investment. In this case, investment experience in other industries is not considered. Based on *VC_total_exp_ind* and *VC_exp_ind*, we recalculate various matching degree variables, denoted as *mdgree11ind*, *mdgree22ind*, *mdgree12ind*, and *mdgree21ind*. We re-run the regressions and report the results in Table 12. The results show that the estimated coefficients on the matching degree measures in the 8 regressions are all significant at either the 1% or 5% level.

4.3.2. Alternative measures of main variables

We first consider an alternative measure for the timing of VC investment in startups. In the above analyses, we measure the timing of VC investment based on the development stage of startups at which VC financing is secured. The classification of development stages of startups can be subjective and lack precision. As a robustness check, we use the number of years from the founding year of a startup to the year of VC investment as a measure of the timing of VC investment.[7] The results are qualitatively unchanged.[8]

We then consider alternative measures for the matching degree, directional mismatching, the growth potential of startups, the

[7] In the cases where the startup's disclosed time of establishment is later than the time of financing, the year of establishment is assigned a value of 0. In the cases where the startup's time of establishment is not disclosed, a random value is assigned according to the criteria used by Zero2IPO database to classify the development stages, with seed stage assigned a value of 0 to 1, startup stage assigned a value of 1 to 3, expansion stage assigned a value of 3 to 10, and mature stage assigned a value of 10 or more.

[8] The test results in Sections 4.3.2 to 4.3.4 are not reported for brevity, but are available upon request.

quality of VCs, and VCs' preference for early-stage projects. Phased investment allows VCs to diversify risk, and can help alleviate the agency problem between the management of VCs and startups, thereby improving the VCs' decision making (Kaplan and Strömberg, 2003). Since all the variables measuring the matching degree, matching difference, the growth potential of startups, the quality of VCs, and VCs' preference for early-stage projects in the above analyses are constructed based on the number of VC investments, they may be affected by the phased investing behavior of VCs. To provide a robustness test, we recalculate these variables by excluding the cases in which the same VC invests multiple times in the same startup. The regression results based on these revised variables confirm our previous findings.

4.3.3. Alternative classifications of VC markets

In our previous analysis, the VC markets are classified based on the location of a startup and the year in which an investment event occurs. To investigate whether the findings remain unchanged under different market classification standards, we adjust market division standards to redefine the markets. When classifying markets along the geographical dimension, we now consider three regions: Beijing-Tianjin-Hebei region, Jiangsu-Zhejiang-Shanghai region, and Pearl River Delta region. We also treat half a year as the time interval when classifying markets along the time dimension, the same as the choice in Sørensen (2007). Crossing 38 half-years with 3 regions, we now have 114 sub-markets. We re-calculate the degree of matching and the degree of matching difference, and then re-estimate the regression models. The regression results are qualitatively the same, supporting earlier findings.

4.3.4. Sample selection bias due to matching

In the VC market, we observe matches of VCs and startups that have successfully achieved an investment relationship. In fact, before a VC and a startup reach an investment agreement, there is a possibility that the VC or startup could match with another partner in the market. The set of realized matches used in our analysis is just a subset of the set of all potential matches between VCs and startups in the market. To address the possible sample selection bias arising from matching, we re-examine our research issues using a two-stage Sørensen-Heckman regression with bilateral selection effects. In the first stage regression, the explained variable *match* is equal to 1 for actual matching outcomes, and 0 for other potential matching outcomes, while the main explanatory variable *density* measures the density of VCs in the market. The control variables remain the same as previous regressions except that the year dummies are not included. To run the first-stage regression, the unrealized potential matches are constructed based on the actual matches in the market. We then run the Probit regression based on a mixed sample of actual and potential matches. We finally calculate the probability of both parties reaching an actual match, which is used to calculate the inverse Mills ratio *IMR*. In the second-stage regression, we examine the impacts of matching on the timing of VC investment in startups with the estimated inverse Mills ratio *IMR* being added as one additional explanatory variable.

The results show that the coefficients on the exogenous variable of the density of VCs' *density* in the first-stage regression are all positive and significant at the 1% level. In the second stage of the regression, the coefficients of the matching variable are still significant, but the inverse Mills ratio *IMR* is not significant, indicating that there is no sample selection bias in the baseline regression model.

5. Conclusions

This paper investigates whether balanced matching between VCs and startups helps promote early VC investment in startups. We find that with a higher degree of matching between the two parties, startups are more likely to secure their first round of funding at an early stage of development and VCs are more likely to invest in early-stage projects. We further show that the impacts of matching on the timing of VC investment in startups are particularly pronounced for VCs with no state-owned capital background and VCs with no foreign capital background. In addition, the impacts are more pronounced during the periods when IPOs are not suspended than when IPOs are suspended. Finally, we demonstrate that a high matching degree increases the level of risk-taking by VCs, thus enhancing their investment in early-stage projects.

This research studies the timing of VC investment in entrepreneurial firms from a new perspective and confirms the causal relationship running from matching to the timing of VC investment. Early-stage VC investment in startups plays an important role in promoting the growth and success of startups; it can help VCs improve their professional services and maximize their value-adding effects. We highlight that matching efficiency between VCs and startups is the key driver for VCs' early investment in startups. Our findings have important policy implications for the development of VC markets. Governments should facilitate information exchange between VCs and startups and help increase matching efficiency in the VC market, thereby enhancing the proportion of VC funds allocated to early-stage startups. It is also important for VCs to improve their capabilities of identifying good investment projects and improve their relevant value-adding functions, so they are more willing to invest in startups at early stages as well as maximize the exit performance of VCs and the growth potential of startups.

CRediT authorship contribution statement

Hui Fu: Conceptualization, Formal analysis, Funding acquisition, Methodology, Project administration, Software, Supervision, Writing – original draft. **Huilan Qi:** Data curation, Software, Writing – original draft. **Yunbi An:** Conceptualization, Methodology, Supervision, Writing – review & editing.

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