Does overconfidence affect venture capital firms' investment?

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Abstract

In this paper, we examine the effect of overconfidence bias on VC firms' investment. Using a sample of U.S. venture capital exits by IPOs and M&As between 2000 and 2019, we construct an overconfidence index and find a strong positive relationship between the follow-on funds and the degree of overconfidence. We also find that the higher the VC's overconfidence, the shorter the time of raising new capital. Further, we show that overconfident VCs are more likely to exit their investments via IPOs rather than M&As and that the degree of overconfidence negatively and significantly affects the time to exit.

JEL classification: G11; G24; G30; G32

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"*Being an expert in a particular field can make biases more difficult to identify, more resistant to change, and lead to greater harm*"

Dr. Brad Klontz, Leading expert in financial psychology[1]

1. Introduction

Past research has shown that psychological and financial aspects are closely linked. The growing literature in behavioral corporate finance suggests that cognitive biases have an important impact on financial decision-making. One specific common bias with great practical importance is overconfidence. The cognition literature defines overconfidence as the tendency of individuals to consider themselves "better than the average" or more intelligent than others (Kruger, 1999; Alicke, 1985). In the context of business and financial decisions, overconfidence is defined as an overestimation of one's own skills relative to others. Individuals are too optimistic about their own future outcomes, and as a result, they underestimate the likelihood of failure (Kunda, 1987; Weinstein and Klein, 2002).

Investor overconfidence literature has explored the link between this behavioral bias and firm performance. Malmendier and Tate (2005) argue that overconfident managers overestimate the returns of their investment projects and the accuracy of their beliefs. They find those overconfident CEOs significantly affect corporate policies, including capital expenditures. Malmendier and Tate (2008) find that overconfident CEOs are more likely to overpay for target companies and undertake value-destroying acquisitions. Campbell et al. (2011) find a strong relationship between CEO's likelihood of forced turnover and the optimism level. Adebambo (2017) focuses on overconfidence among mutual fund

[1] Interviewed by Bob Pisani (CNBC senior markets correspondent), available at https://www.cnbc.com/2021/05/15/nobel-winner-daniel-kahnemans-new-book-is-all-about-your-money-.html?&qsearchterm=overconfidence (May 15, 2021).

managers. She finds that firms with more overconfident investors are relatively overvalued, exhibit lower subsequent stock returns, issue more equity, and invest more. Forman et al. (2019) use relative position size as an indicator of overconfidence. They find that when traders take larger positions, they reveal increased trade timing impairment.

The venture capital industry is not immune to the overconfidence bias. Venture capitalists are, by nature, optimistic, enthusiastic, and risk-taking individuals. On the one hand, VCs need to be more confident to be able to raise sufficient capital from their limited partners, identify high potential new ventures and take their portfolio firms to a successful exit through IPO or M&A. On the other hand, being too optimistic may lead VCs to overestimate the likelihood that a funded company will succeed. Therefore, it is important to examine the effect of overconfidence bias on VC firm's performance. Our analysis of this cognitive bias will contribute to our understanding of how VCs make decisions. The main objective of this study is to test whether VC overconfidence can explain differences in VC fundraising, the likelihood of a successful exit, and the time a VC takes to exit from its portfolio firm.

Using a sample of U.S. venture capital exits by IPOs and M&As between 2000 and 2019, we find a strong positive relationship between the next fundraising and the degree of overconfidence, suggesting that the flow of capital into the venture capital firm is positively associated with its level of overconfidence. Our results show that the higher the VC's overconfidence, the shorter the time of raising new capital. Thus, each additional successful venture leads to higher overconfidence, which gives VC firms incentives to start the process of raising new funds more quickly. Our empirical results also show that the degree of VC overconfidence influences the behavior of venture capital exits. Specifically, we find that overconfident VCs are more likely to exit their investments via IPOs rather than M&As, and that the degree of overconfidence negatively affects the time to exit. When we investigate further the effect of overconfidence, we find that the relationship between VC investment (VC performance) and VC overconfidence is nonlinear and exhibits an inverse U-shaped relationship.

Our paper makes two main contributions. First, we contribute to the literature on overconfidence in the corporate context, which few prior studies have examined (Roll (1986); Malmendier and Tale (2006); Adebambo et al. (2018)). These studies analyze overconfidence effects on M&As, mergers and capital structure decisions, and mutual funds, respectively. Surprisingly few academic papers have examined the case of VCs. Two papers similar to our stream of research are Zacharakis and Shepherd (2001) and Graves et al. (2018). Zacharakis and Shepherd (2001) use a policy capturing experiment (a method common in cognitive psychology) on 53 VCs to examine their investment decision process. They confirm that VCs are overconfident and that the level of overconfidence depends on the amount of information, the type of information, and VCs' strong belief about the success or failure of the venture. Since any relevant information is important in the decision-making process, overconfident VCs may rely on their existing knowledge, limiting information search, which could have a negative effect on their decision quality. Graves et al. (2018) examine the effects of overconfidence in venture capital investing. Using a measure of the predictive accuracy of VCs, they find that the level of disappointment experienced by venture capital investors decreases when the true predictive accuracy increases. In this study, we complement previous literature by examining whether overconfidence among venture capital can explain differences in VC fundraising, the likelihood of a successful exit, and the time a VC takes to exit from its portfolio firm.

Second, we contribute to the literature on VC performance. Prior literature examines factors driving VC fundraising (Gompers et al., 1998; Gompers, 1996; Jeng and Wells, 2000; Mayer et al., 2004; Hasan et al., 2018; Crain, 2018, among others). These studies have found that fundraising is influenced by economic growth, research and development expenditures, reputation and holding directorships in mature public companies, and aggregate fund performance. Previous studies suggest that the time to exit may be linked to grandstanding purposes (Gompers, 1996), economic activity (Wang and Wang, 2012), and cross-border investments (Espenlaub et al., 2015). Gompers et al. (2020) confirm that for VCs, exit considerations are the most important factor in deciding on the valuation they offer. Further, a large body of literature has concluded that the likelihood of exit is influenced by VC firm's characteristics (Félix et al., 2014); legal environment and economic conditions (Cumming et al., 2006; Cumming and MacIntosh, 2003), VC syndication (Lerner, 1994) and directorships in S&P 1500 companies (Hasan et al., 2018). To the best of our knowledge, the relationship between the human capital determinants of VC managers and VC investment performance has not been explored. This study extends prior literature by examining the effect of VC overconfidence on VC activity and performance.

The rest of this paper is organized as follows: Section 2 presents a brief review of the literature and our testable hypotheses. Section 3 describes our data and method. Section 4 describes our empirical tests and results. Section 5 provides additional tests, and Section 6 concludes.

2. Literature review and hypothesis development

Previous studies have shown that overconfidence is a cognitive bias that significantly influences an individual's decision-making. For example, Forbes (2005) examines why entrepreneurs exhibit more overconfidence than non-entrepreneurs. He finds that entrepreneurs are not cognitively homogeneous and that individual age, firm decision comprehensiveness and external equity funding affect the overconfidence's degree. Pak and Chatterjee (2016) suggest that older adults are more prone to overconfidence bias and that older overconfident portfolio managers continue holding risky assets with time. Liu et al. (2016) examine the overconfident trading behavior of individual versus institutional investors and the impact of their overconfident trading on stock return volatility in Taiwan. They find that both types of investors trade more overconfidently when the market is up, less volatile, and more liquid. However, they specify that individual investors trade with more overconfidence than institutional investors in these market conditions. Pikulina, Renneboog, and Toble (2017) examine the relation between overconfidence and investment choices. They find that overconfidence is associated with overinvestment, while underconfidence is associated with underinvestment, and moderate overconfidence is associated with accurate investments.

Gao, Shi, and Zhao (2021) examine investors' trading behaviour after they got lucky by winning the IPO allotment lottery in China. They find that the experience of good luck makes people overconfident about their investment choices. Overconfident investors trade more frequently and lose more money relative to other investors. This cognitive bias is remarkably present when investors are inexperienced.

VCs, as many decision makers, are not immune from the overconfidence bias that could significantly affect the quality of their decisions. For VC, raising money is a long and challenging process and being overconfident is important for attracting new investors. In reality, believing that they are better than others is advantageous because it increases their credibility, ambition, and probability of success. Thus, we expect overconfidence to improve VC firms' ability to raise new capital. Our first hypothesis is the following:

Hypothesis 1. We expect a positive relationship between VCs'overconfidence and their abilities to raise new capital.

One of the challenges of raising new funds is the length of time to complete the process. Gompers (1996) shows that new venture capital firms raise money sooner for follow-on funds for reputational concerns, suggesting that reputation affects fundraising in the venture capital market. Overconfidence may also explain the facility of VC firms to raise new capital since overconfident VCs rely on their prior success, experience, and connection to convince potential investors as soon as possible. We, therefore, propose our second hypothesis as follows:

Hypothesis 2. Overconfident VCs take less time to raise new capital than less overconfident VCs.

Various studies have reported that exits are influenced by factors related to the economic conditions (Cumming et al. (2006)), VC syndication (Megginson and Weiss(1993)), geographical distance (Cumming and Dai (2010)) and being on the board of mature public companies (Hasan et al.(2018). The literature in corporate finance decision-making documents that beliefs and investor sentiment are also important when deciding whether an investment goes ahead. Overconfident investors are generally too optimistic about outcomes and thus underestimate the probability of failure. Cognitive differences also influence how VCs make decisions and may lead them to overestimate the likelihood that a funded company will succeed (Malmendier and Tate (2005)). Zacharakis and Shepherd (2001) investigate how VCs make decisions and whether they are overconfident. They confirm that 96% of the 51 participating VCs exhibited significant overconfidence. They argue that judgments and decisions made by overconfident VCs are highly susceptible to cognitive biases due to the nature of the VC task. An overestimation of their tolerance for risk and ability to assess new investments leads to poor decisions by committing funds to inappropriate new ventures and a high probability of failure. However, overconfidence could also be the key to success rather than failure. Thus, recognizing the overconfidence bias could represent an opportunity for VCs to improve their decision quality. Everett and Fairchild (2015) suggest that overconfidence produces two conflicting effects on the probability of a successful exit. It could increase the riskiness of a venture leading to a greater likelihood of failure, but it could also induce higher entrepreneurial efforts, increasing the likelihood of successful exits. Based on the above discussion, we expect a positive relationship between VCs'overconfidence and their investment performance and develop our third hypothesis as follows:

Hypothesis 3. Overconfident VCs perform better than less overconfident VCs.

In this study, we measure VC investment performance by the proportion of successful exits and the time to exit. Nahata (2008) finds that companies backed by more reputable VCs are more likely to exit through IPOs. Das, Jagannathan, and Sarin (2003) find that companies in their later stages of development are more likely to be acquired. Schwienbacher (2008a) suggests that IPO is an exit that may be limited to the most promising ventures, whereas acquisitions appear to be a more general exit route. He argues that the choice of exit route for venture-backed companies is influenced by the number of financing rounds and the investment duration. Following previous studies (Nahata (2008), Cumming and Dai (2010), Dai, Jo, and Kassicieh (2012), Hasan et al. (2018), and Amor and Kooli (2020)), we consider both IPOs and M&As as successful exits. Thus, the percentage of successful exits is calculated by dividing the number of exits via IPO and M&A by the number of investments by VC firms by the end of 2019. The exit timing is calculated as the number of years between the first investment and exit dates as a dependent variable.

3. Data and method

We collect venture capital data from Eikon private equity database. We start with all VC investments in the U.S. from 2000 to 2019. We focus on venture capital exits by taking a firm public in an IPO or selling it to a public acquirer (M&A). Our initial sample contains 6038 exits conducted by 3750 venture capital firms. We are interested in the lead VC when multiple venture investors are in the company. We determine the lead VC as the firm that made the company's largest investment across all rounds of funding. If two firms provide the same amount of funding, we consider the firm with the earliest investment. We exclude all exits for which the lead VC could not be identified.

We hand-collect information on the next fundraising for each lead VC. We eliminate all observations in which information about the amount and the time of the next fundraised is not available. We need information about VC firm age, VC staging, VC investments, and VC executives to be available. Our final sample contains 1,867 U.S. venture-backed companies exited through IPO or M&A.

Our purpose is to test how overconfidence bias influences the fundraising and investment performance of VC firms. Measuring investor overconfidence is challenging as it is related to the preferences and beliefs of each investor. Prior studies have suggested numerous proxies for overconfidence borrowed from the psychology literature and based mainly on experimental and questionnaire methodologies (Biais et al., 2005; Glaser and Weber, 2007; Zacharakis and Shepherd., 2001). The financial literature also proposes several factors that could be correlated with overconfidence. Chen et al. (2019) show that female board representation affects the beliefs and behavior of CEO by reducing male CEO overconfidence. They find that the presence of female directors is associated with less aggressive strategies and improved firm performance in industries with high overconfidence prevalence. In other words, overconfidence could be proxied by gender. Gervais and Odean (2001) argue that traders learn about their ability through experience and a bias in this learning process leads them to become overconfident. Their model shows that successful traders attribute too much of their success to their own abilities, suggesting that prior performance is related to overconfidence. Forbes (2005) finds that individual age affects how entrepreneurs are overconfident and that founder- managers are more overconfident than new venture managers. Pak and Chatterjee (2016) consider a survey to determine overconfidence among participants. Specifically, the confidence score equals the mean of subjective probability judgments across a series of questions without assessing whether the judgment is correct or not.

Although experimental and questionnaires methodologies are widely used in previous studies to measure overconfidence, they are criticized for representing the practices of a particular fraction of the VC industry and not representing the broader VC industry.

To overcome these issues, we construct in this study a robust measure of VC overconfidence by combining different factors into a composite index. Our objective is to provide a large representation of overconfidence since it can be considered as a multidimensional cognitive bias. We use a similar procedure as Gompers et al. (2003) and Adebambo et al. (2018) to construct our overconfidence index. We include in the index seven components: VC firm age, prior VC investments, prior companies the VC firm is invested in, prior successful deals, the percentage of early-stage investments by the VC firm, the percentage of seed-stage investments by the VC firm, and the fraction of female executives. More detailed variable definitions are reported in Appendix A. We construct the percentile ranks for each component, and we rank VC firms based on the rank constructed so that the higher value corresponds to a higher overconfidence level. We attribute a score of 0.01 to the bottom 1% of the lowest value of each variable and a score of 1 to the top 1% of the highest value.[2] The overconfidence index is then constructed by summing the scores of the seven components. Its value ranges between 0 and 7. A higher level of overconfidence corresponds to a higher value of the index.

We use two measures to capture VC fundraising activity. The first measure is the amount of funds raised immediately following the observation year (see Gompers (1996); Gompers (2003); Hasan et al. (2018), among others). The second measure is the time of the follow-on fund, calculated as the number of years between the vintage year of the follow-on fund and the observation year. We also include two measures representing VC investment performance. The first measure is the proportion of successful exits calculated as the

[2] For example, when we rank VC firm on prior VC investments, a score of 0.01 is assigned to the bottom 1% VC firm with the lowest sum of prior investments and a score of 1 is attributed to the 1% top VC firms with the highest sum of prior investments.

percentage of all investments exited through either IPO or M&A during the sample period. We then report the proportion of exit by only IPO and the proportion of exit by only M&A for each VC firm to evaluate whether overconfidence is related to the exit strategy. The second measure we use is the time to exit calculated as the difference between the year the portfolio company received its initial funding and the observation year. Factors such as market condition, economic activity, and the quality of the legal system are found to be linked to the speed of exit (Black and Gilson (1998); Cumming et al. (2006); Wang and Wang (2012)). We also test whether VC overconfidence could explain the relationship between VC investment performance and the time to exit. Further, we include several variables to control VC firms and deal characteristics following the VC literature. See appendix A for more detailed variable definitions.

4. Empirical results

4.1 Descriptive statistics

Table 1 reports descriptive statistics for our sample firm. Panel A presents means, medians, 25^{th} percentiles, 75^{th} percentiles, and standard variation of each VC firm characteristic from 2000 to 2019. The average VC age is 20.92 years, and the average firm size is 1,309.53. These observations confirm that our sample is tilted toward more established firms. In panel B, we present a pair-wise correlations matrix of our set of variables. We find a strong positive correlation between VC firm age and prior successful deals. Older VC firms are indeed more experienced, knowledgeable, and gain more reputation, which will affect their performance positively by taking more portfolio firms public via IPO or M&A. The results also show that the overconfidence index is positively correlated with firm age and prior successful deals, which is consistent with the fact that more experienced VC firms are more likely to be overconfident than younger ones. A positive correlation is also found between the overconfidence index and the next fund raised by the VC firm, suggesting that overconfident VCs may be more able to persuade potential investors to provide money to raise new funds. Our results indicate that overconfident VCs take less time to raise money for follow-on Funds as the overconfidence index exhibits a negative correlation with the next fund time. Exit duration seems to be influenced by the cognitive differences of VC firms explained by the positive correlation between the overconfidence index and the time VC firms take to exit their investments. All these correlations are statistically significant and constitute a piece of initial evidence that VC overconfidence is associated with fundraising activity and performance of venture capital firms.

In Table 2, we analyze whether there is a difference between VC firms with a high and low level of overconfidence in terms of their characteristics. Panel A reports results for the two extreme overconfidence index quarters (25^{th} and 75^{th} percentiles). The first quarter includes VC firms with a low level of overconfidence, and the last quarter represents VC firms with a high level of overconfidence. Comparing these two groups shows that VC firms with a high level of overconfidence are generally older, larger, and conduct more successful IPOs and M&As than those with a low level of overconfidence. We also find that VC firms with a high level of overconfidence tend to be more independent and exhibit larger syndicate sizes than those with a low level of overconfidence.

Panel B of Table 2 reports a quintile analysis of the relationship between VC firm characteristics and the level of overconfidence. Comparing the two extreme quintiles, we find similar results to panel A, confirming that the cognitive differences between VC firms are closely and significantly related to their characteristics.

Table 3 provides a comparison of VC overconfidence across industries and stages. We find no evidence of different levels of overconfidence of VCs investing in technology, medical or other ventures. However, VC firms focusing on early-stage ventures are more overconfident than those focusing on balanced or later-stage ventures. The results of comparison tests (mean and median) are statistically significant at 5% and 1% levels. Investing in early-stage ventures is inherently high risk. Given the significant challenges and the greater information uncertainty associated with early-stage investments, VC firms focusing on such investments are generally older, larger, and characterized by a high level of expertise and skills (Gompers et al. (1998)). Overconfident VCs with these characteristics may be attracted to these investments as they believe in their abilities.

4.2 Overconfidence and fundraising activity

In this section, we examine whether VCs' overconfidence affects their fundraising activity. First, we focus on the amount of capital raised by VC firms immediately following the observation year. Second, we investigate the length of time it takes to complete the process. We conduct our analysis in two steps. We compare VC firms with a high level of overconfidence with those with a low level of overconfidence to evaluate if any significant differences exist between these two groups. We compute the differences in size and time of the next fund by grouping VC firms into overconfidence index percentiles and quintiles, respectively. We then use multivariate analysis to see whether any selection effect drives the differences observed in our univariate analysis.

4.2.1 Univariate analysis

Table 4 reports a univariate analysis of overconfidence and VC firms' fundraising abilities. Panel A provides a comparison between VC firms with a high level of overconfidence and those with a low level of overconfidence using percentile grouping to test whether a difference exists between them in terms of fund size and time. The next fund size is the amount of funds raised immediately following the observation year. The next fund time is the difference in years between the year of the next follow-on fund and the observation year. Our results show that funds raised by VC firms with a high level of overconfidence are almost 5 times more than that of VCs with a low level of overconfidence. This difference is significant at the 1% level. We also find that overconfident VCs do not wait to raise new funds. The average time between the next fund raised and the observation year is about 3.4 years for overconfident VCs compared to 4.8 years for non-overconfident VCs. The t-test of this difference is significant at the 1% level.

Panel B provides results for quintile grouping. The differences in means between the two extreme quintiles in terms of the next size and time funds are significant at the 1% level, confirming that overconfident VCs have a stronger ability to convince potential investors and raise new capital. These results suggest that overconfidence could be a winning strategy when VC firms need to raise funds for risky investments.

4.2.2 Multivariate analysis

To formalize our univariate analysis, we run a set of regressions using two different dependent variables: (1) the logarithm of the size of the next fund raised by the VC firm and (2) the time from the observation year to the VC firm's next fund.

Regressions on the next fund size:

We use the Heckman two-stage model to control for the selection bias related to the VC's probability of raising new funds. The first equation is the probability of raising new funds by VC firms in the period following the observation year, and the second is the amount of capital raised immediately following that year to test whether overconfidence leads to a better fundraising ability.

The first stage selection equation (Probit):

$$\textit{Likelihood of raising a fund} = a_0 + a_1\ \textit{VC firm age} + a_2\ \textit{VC firm location} + a_3\ \textit{VC prior successful deal} + a_4\ \textit{GDP growth} + \varepsilon \qquad (1)$$

The second stage equation:

$$\begin{aligned}\textit{Size of the next fund} = {} & b_0 + b_1\ \textit{VC overconfidence index} + b_2\ \textit{VC firm age} + b_3\ \textit{VC firm location} \\ & + b_4\textit{VC firm syndicate size} + b_5\ \textit{VC firm type} + b_6\ \textit{VC firm's prior IPOs} \\ & + b_7\ \textit{VC firm's prior M\&As} + b_8\ \textit{IMR} + b_9\ \textit{year dummies} \\ & + b_{10}\ \textit{industry dummies} + \eta \qquad (2)\end{aligned}$$

In the first equation, we consider the VC firm's reputation and the market condition as instrument variables to explain the probability of raising a fund. Prior studies have confirmed that the ability of VC firms to raise new capital is positively associated with their reputation and market conditions (Gompers (1996); Hasan et al. (2018)). We use VC firm age and VC prior successful deals as proxies of VC firm's reputation. GDP growth in the previous year is used to proxy for economic and market conditions.

Our primary explanatory variable is the second equation is VC overconfidence index. We include several control variables and the inverse Mills ratios (IMR) obtained from the first equation. We control for VC firm's experience and reputation by considering VC firm age, VC firm's prior IPOs, and VC firm's prior M&As in regressions. We include VC firm type to indicate a different type of VC firms and VC firm syndicate size because VC syndication is positively associated with reputation and VC firm performance (Krishnan et al. (2011); Lerner (1994)). We also include VC firm location to examine whether the amount of capital raised is associated with VC hotbeds. Although not reported, we include industry and calendar fixed effects in all regressions. T-statistics appear in parentheses and are based on standard errors robust to heteroscedasticity and adjusted for industry clustering.

Table 5 presents the results of the next fund size regressions. The results from the selection equation in column 1 show that the probability of raising funds is significantly related to the VC firm's location, VC firm's prior experience, and economic conditions. In models (1) and (2), the coefficient of the *OC index* is positive and significant at the 1% level, suggesting that overconfident VCs are able to raise more capital. Our results also show that firms located in hotbeds and independent VC firms are more likely to raise more funds, consistent with prior literature. The coefficient of *ln(prior IPO)* in model (1) is positive and significant at the 1% level, indicating that taking firms public through IPOs is a stronger signal of ability, and the amount of capital raised by VC firms is significantly related to the number of IPOs they have financed confirming the grandstanding hypothesis of Gompers (1996). In model (2), we control for all prior successful deals (IPOs and M&As), and we find that the amount of capital raised by VC firms is more sensitive to both IPOs and M&As they have invested in, suggesting that prior experience significantly affects VC fundraising. The inverse Mills ratio derived from the specification equation is statistically significant at the 1% level, confirming the importance to control for the selection bias related to the VC's probability of raising new funds.

Regressions on the next fund time:

In this section, we analyze the likelihood and timing of raising money by VC firms using a Cox hazard model, proposed by Cox (1972), where the logarithm of the time from the observation year to the venture capitalist's next fund is the dependent variable. The basic model assumes the following form:

$$h_i(t)=\lambda_0(t)\, exp\{\beta_1 x_{i1}+....+\beta_k x_{ik}\} \tag{3}$$

Where $h_i(t)$ is the conditional hazard rate defined as the probability of raising money for follow-on funds after the observation year. $\lambda_0(t)$ is the baseline hazard function and the second part of the equation is the exponentiated set of k covariates for firm i. We use the same set of independent variables previously considered. Our variable of interest is OC index that measures the level of overconfidence of VC firms. Since the dependent variable is the logarithm of the hazard rate, a positive (negative) coefficient on an explanatory variable indicates that changes in that variable decrease (increase) the time from the observation year to the next fund raised.

Table 6 reports our results. We find that the level of VC overconfidence has a positive effect on the time of raising new capital by VC firms. This implies that VC firms with a high level of overconfidence seem not to wait long before raising follow-on funds. The coefficient of the *OC index* is positive and significant at the 1% level, indicating that VC overconfidence significantly affects fundraising time. We also find that older VCs take more time to raise new capital, suggesting that VC firms with enhanced networks, experience, and reputation may wait longer to raise a new fund, confirming the results of Gompers (1996). The inverse Mills ratio derived from the specification equation is statistically significant at the 1% level (model 1) and the 5% level (model 2), confirming the importance of controlling for the selection bias.

4.3 Overconfidence and VC firm's performance

In this section, we test whether VC overconfidence affects their investment performance measured by the proportion of successful exits. Thus, the dependent variable is the percentage of successful exits calculated by dividing the number of exits through IPOs and M&As by the number of investments by VC firms by the end of 2019. We also examine the effect of VC overconfidence on exit timing by taking the number of years between the first investment date and the exit date as a dependent variable.

4.3.1. Univariate analysis

Table 7 reports univariate analysis of VC overconfidence and investment performance. Panel A provides percentile results by comparing successful exits of VC firms with a high level of overconfidence with those with a low level of overconfidence. We find that the percentage of all successful exits by VC firms with a low level of overconfidence is 67.2% compared to 6.1% for those with a high level of overconfidence. This result is statistically significant at the 1% level and is consistent with Hypothesis 3. Thus, VC investment decisions are significantly affected by overconfidence. This overconfidence leads to a low accuracy about failure and success predictions resulting in the funding of inappropriate ventures.

As shown in panel A of Table 7, about 17% of firms in which VC firms made investments with a low level of overconfidence went public, compared to 23.5% of firms backed by VC firms with a high level of overconfidence. In terms of M&As, 44.2% of firms in which VC firms made investments with a low level of overconfidence exited through M&As, as opposed to only 3.4% of those backed by VC firms with a high level of overconfidence.

In panel B of Table 7, we report quintile analysis, and the results show a significant difference in success rates when comparing the two extreme quintiles, confirming our percentile results.

Overall, our univaritate results suggest that VC overconfidence significantly affects investment performance. Although overconfident VCs work hard to ensure that firms they funded will succeed, the overestimation of their own knowledge and the precision of information they have when assessing new ventures lead to decision-making errors.

4.3.2 Multivariate analysis

We use a generalized linear model (GLM) to estimate whether the level of VC overconfidence affects the percentage of successful exits. We choose this model as the dependent variable is a proportion that falls between zero and one. Thus, the use of an OLS model could not be appropriate. We estimate the following model for proportions of all successful exits, IPO exits, and M&A exits:

$$\begin{aligned} \textit{Proportion of successful exit} = {} & b_0 + b_1\, \textit{VC overconfidence index} + b_2\, \textit{VC firm age} \\ & + b_3\, \textit{VC firm location} + b_4\, \textit{VC firm syndicate size} \\ & + b_5\, \textit{VC firm type} + b_6\, \textit{venture stage} + b_7\, \textit{year dummies} \\ & + b_8\, \textit{industry dummies} + \eta \end{aligned} \tag{4}$$

The dependent variable is the percentage of successful exits calculated by dividing the number of exits through IPOs and M&As by the number of investments by VC firms by the end of 2019. Our primary independent variable is the VC overconfidence index which measures the degree of overconfidence of a VC firm. VC firm age is measured by the period between the VC firm’s year of incorporation and the observation year. VC firm syndicate is the number of VC firms investing in the portfolio company. VC firm type is a dummy variable that takes the value if the VC firm is independent and zero otherwise. The venture stage is measured by three dummies indicating the stage of the portfolio company when it received its first funding. We include industry and calendar fixed effects in all regressions. We also include the robust option in the GLM model to obtain robust standard errors.

The results reported in column 1 of table 8 show that the level of VC overconfidence is negatively associated with the proportion of all successful exits. The coefficient of the OC index is statistically significant at the 1% level, indicating that overconfidence has a negative effect on VC decision quality.

Columns 2 and 3 of Table 8 present results for the relationship between the level of VC overconfidence and the exit strategy. As shown in the Table, we find that VCs with a low level of overconfidence are more likely to exit through M&As while those with a high level of overconfidence are more engaged in IPO exits. The coefficient of the OC index is negative and statistically significant at the 1% level for the M&A sample and positive and significant at the 5% level for the IPO sample. These multivariate analysis results are consistent with those of the univariate analysis. In terms of other VC characteristics, we find that older VCs are more likely to successfully exit from their investments, while M&A is their preferred exit strategy. We also find that syndication plays an important role in achieving successful exits as the coefficient of syndicate size is positive and significant at the 1% level. The stage of the portfolio company when it received its first funding seems to affect the proportion of successful exits. We find that early-stage ventures are more likely to successfully exit than expansion and later-stage ventures.

Examining the relationship between VC overconfidence and the time to exit, we use an accelerated failure time (AFT) model to test whether the level of overconfidence affects the time to exit. One feature of this model is that the baseline hazard function follows an assumed density function based on prior expectations. Based on Akaike Information

Criterion (AIC) and Bayesian Information Criterion (BIC) results, we assume that the baseline hazard function follows a log-logistic density function. Hence, we estimate a log-logistic AFT model where the dependent variable is the number of years between the exit date and the first investment date by the lead venture capital firm. A positive (negative) coefficient on an explanatory variable indicates both a higher (lower) probability of survival as well as an increasing (decreasing) expected duration. Specifically, we estimate the following AFT model:

$$\begin{aligned} Ln(T) = {} & b_0 + b_1 VC\ overconfidence\ index + b_2 VC\ firm\ age + b_3\ VC\ firm\ location \\ & + b_4 VC\ firm\ syndicate\ size + b_5\ VC\ firm\ type + b_6\ VC\ firm's\ prior\ IPO \\ & + b_7\ VC\ firm's\ prior\ M\&A + b_8 venture\ stage + b_9\ \ year\ dummies \\ & + b_{10}\ \ industry\ dummies + \epsilon \end{aligned} \tag{5}$$

where T is the duration of a VC-backed firm before the exit.

The results in columns 4 and 5 of Table 8 show that the level of VC overconfidence is significantly and negatively associated with the time to exit, indicating that overconfident VCs take companies public earlier than VCs with less level of overconfidence. This result may be attributable to the beliefs of overconfident VCs that they have a greater ability to choose the right time to exit from their investment. The positive and significant coefficient of Ln(VC firm age) suggests that more experienced VCs take their time to bring companies to the market by IPOs or M&As than less established VCs. We also find that the duration before the exit is positively and significantly related to the prior successful deals, confirming that more experienced VCs take their time before the exit. The syndication size is positively and significantly associated with the time to exit, suggesting that a larger syndicate size should have a prolonging effect on the time to exit.

5. Additional tests

5.1. Control for fundraising flows

Prior research has shown that past performance measured by capital flows could be an important determinant of new capital commitments. This evidence is widely documented for mutual funds (Sirri and Tufano,1998; Adebambo, 2017). Venture capital firms could also benefit from their prior fundraising. Gompers (1996) confirms that VCs who have shown no returns in their first fund find it difficult to raise new funds. He argues that VCs without any fundraising experience find it extremely difficult to attract new investors. Gompers and Lerner (1998) find that capital under management as a measure of reputation is positively associated with the ability of a VC to receive larger capital commitments.

As we do not include VC fundraising flows as a prior performance component in constructing the overconfidence index, our results could be driven by the prior fundraising effect. Hence, we repeat all our regressions controlling for this effect to address this concern. We first include LAGFUND, a variable that measures the prior total amount of capital raised by a VC firm. We then add an interactive variable that combines the effect of VC overconfidence with prior fundraising flows. The result reported in Table 9 shows that overconfident VCs are significantly more likely to raise new funds and seem to not wait a long time before raising new capital than less overconfident VCs, even after controlling for their fundraising history. Our results for investment performance are also robust to the control for prior fundraising flows, suggesting that VC overconfidence has a significant effect on the proportion of successful exits and the time to exit.

5.2. Principal Component Analysis (PCA)

In this study, we construct a VC overconfidence index using seven variables related to VC firm characteristics. The primary concern with an index construction is considering a set of variables that could be correlated and have a different weight in explaining the dependent variable. In this section, we use a principal component analysis (PCA) to retain the most valuable parts of our initial set of variables. This statistical technique is used for data reduction. It combines the original set of variables in a specific way to obtain a serie of uncorrelated linear combination of the variables that contains most of the variance.

Table 10 reports the results of PCA analysis. We find that the fourth first principal components explain more than 77% of the variance. However, only the first two have eigenvalues greater than one and explain more than 50% of the variance in the data set. Analyzing the correlation between the original data and the two first components, we find that the first component is strongly correlated with the sum of prior investments, the number of prior successful deals and the total number of companies the VC invested in. This suggests that this first component can be viewed as a measure of VC prior experience which has an important role in explaining the VC overconfidence. As for the second component, we find a strong positive correlation between the percentage of seed-stage investments and the percentage of VC investments in the early stage. We conclude that this component can be viewed as a measure of VC risk aversion as greater investments in the early and seed-stage means a higher ability to deal with risky investments leading to a higher level of overconfidence.

We re-examine the effect of VC overconfidence on fundraising activity and VC firm performance by including each of those two components in our regressions. The results reported in Table 11 confirm that VC prior experience is positively and significantly associated with the amount of capital raised in a new fund and indicate that VC firms with greater prior experience do not need to wait longer to raise a new fund. Table 12 confirms the results that VC overconfidence has a negative and significant effect on their decision accuracy and actively influences their exit strategy. We also find that VC firms with higher prior experience and greater ability to invest in risky investment seem to be able to go public sooner, confirming our previous findings using an overconfidence index.

5.3. U-shaped relationships

So far, we suppose in this study that the relationship between VC overconfidence and VC investment or VC performance is linear, but what if it is not and follows a U-shaped relationship. In the VC context, VCs need to be overconfident to a certain degree to identify and invest in high-potential new ventures. However, we can also suppose that beyond a certain level of overconfidence, they could overestimate the likelihood that a funded company will succeed. Zacharakis and Shepherd (2001, p. 312) point out that: "*More information ideally should enable the VCs to assess any potential pitfalls. However, additional information makes the decision more complex*." Thus, more information positively affects the level of confidence, but it could also negatively affect VC decision accuracy.

In this sub-section, we test the existence of U-shaped relation via quadratic regressions. In Table 13, we present our results. Models 1, 2, and 3 of Table 13 extend previous models 1 and 2 of Table 5 and model 1 of Table 8 by adding a squared overconfidence index term.

Results of models 1, 2, and 3 confirm the existence of a significant nonlinear relationship between VC fundraising (VC performance) and VC overconfidence. The OC term is significantly positive at the 1% level (confirming previous results), and the squared OC term is significantly negative at the 1% level, indicating an inverse U-shaped VC fundraising (VC performance)-VC overconfidence relationship. Figures 1 and 2 illustrate the relationships between VC fundraising and VC overconfidence and between VC performance and VC overconfidence, respectively. We observe that VC overconfidence has a positive effect on VC investment (VC performance) at a certain level. Beyond this level, the effect of VC overconfidence is inverted, and a negative relationship between VC investment (performance) and VC overconfidence is observed at a high level of VC overconfidence.

6. Conclusion

In this paper, we seek to understand better the effect of overconfidence bias on VC firms' investment. Using a sample of U.S. venture capital exits by IPOs and M&As between 2000 and 2019, we construct an overconfidence index and find a strong positive relationship between the follow-on funds and the degree of overconfidence, suggesting that the flow of capital into the venture capital firm is positively associated with its level of overconfidence. We also find that the higher the VC's overconfidence, the shorter the time of raising new capital. When we investigate further the effect of overconfidence, we find that the relationship between VC investment (VC performance) and VC overconfidence is, however, nonlinear and exhibits an inverse U-shaped relationship.

Our paper makes two main contributions. First, we contribute to the literature on overconfidence in the corporate context and confirm the importance of this cognitive bias in VC decision-making. Second, we contribute to the literature on VC performance. We show that the degree of VC overconfidence influences the behavior of venture capital exits.

Specifically, we find that overconfident VCs are more likely to exit their investments via IPOs rather than M&As and that the degree of overconfidence negatively and significantly affects the time to exit.

Our results are potentially relevant for entrepreneurs interested in relying on VC financing for their growth and development. They are also important for VCs to better understand the effect of overconfidence on their decision-making process and for investors to evaluate their investment strategies better.

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Figure 1: Relationship between VC fundraising activity and VC overconfidence index

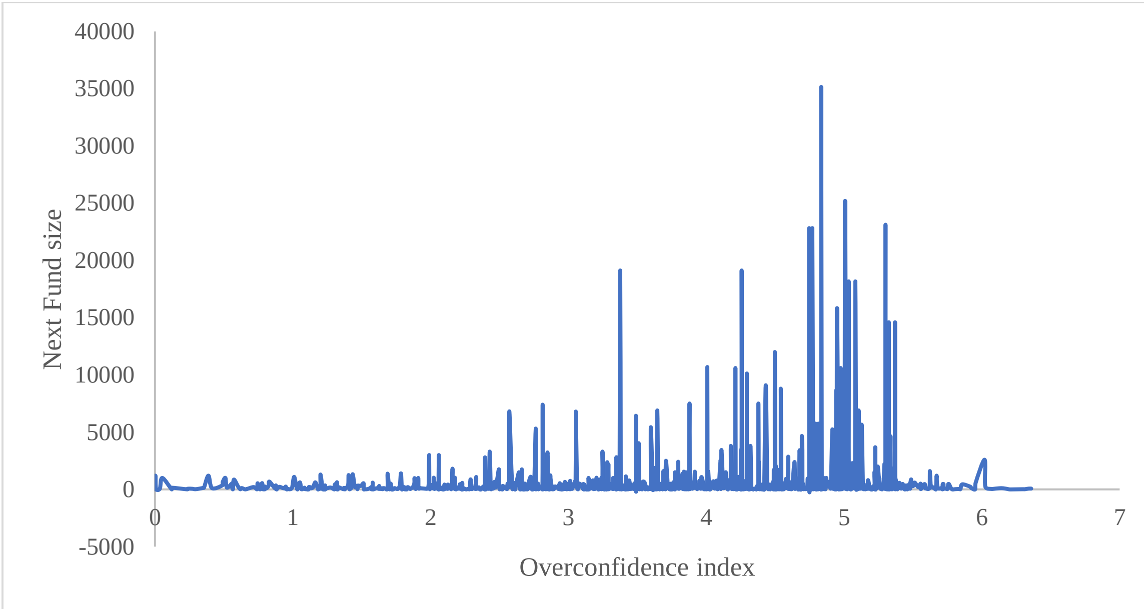
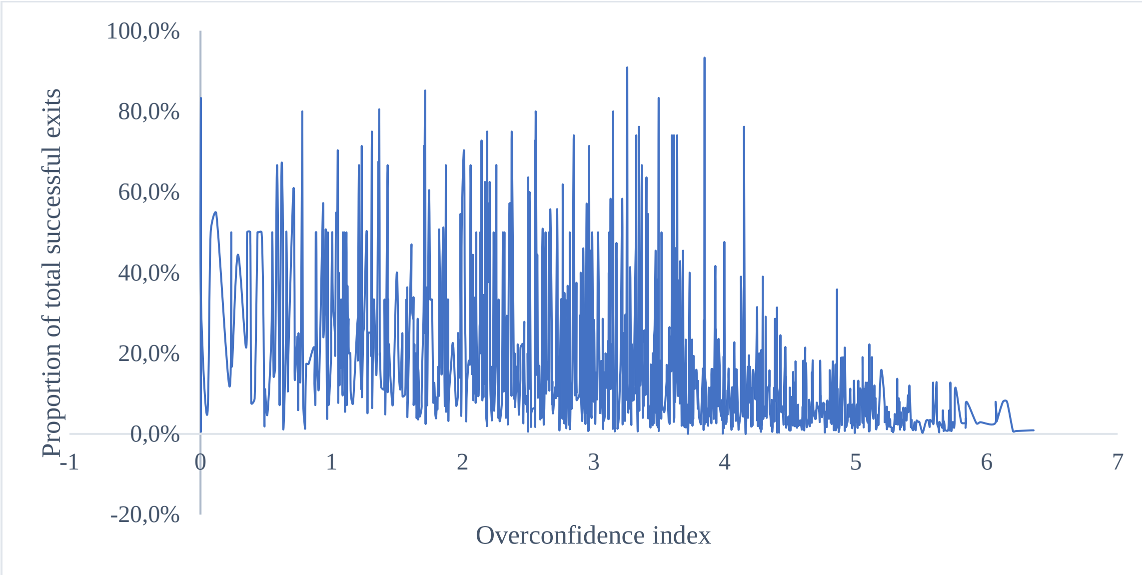


Figure 2: Relationship between VC investment performance and VC overconfidence index



Appendix A
Definition of variables

Variable name	Definition of variable
Panel A: VC firm characteristics	
OC index	Overconfidence index constructed from seven components (see more details below) and taken on values between 0 and 7.
VC firm age	The difference in years between the deal year and the year the VC firm was founded
VC firm size	The VC firm s' capital under management in a particular year is calculated by taking the sum of all previous funds raised by the VC firm
Firm type	A dummy variable takes the value of one if the VC firm was not affiliated with any other entities (independent VC firm), and zero otherwise.
Firm Location	A dummy variable that takes the value of one if the VC firm was based in venture hotbeds that is either New York or California, and zero otherwise.
Syndicate size	The total number of VC firms invested in the portfolio company
Prior IPO	The number of IPOs exits by the VC firm prior to the observation year
Prior M&A	The number of M&As exits by the VC firm prior to the observation year
Prior succ. deals	The number of successful exits (IPO and M&As) by the VC firm prior to the observation year
GDP growth in the previous year	The GDP growth of the United States in the previous year
Early-stage venture	A dummy variable takes the value of one if the venture was in the early stage when it received its initial funding and zero otherwise.
Expansion stage venture	A dummy variable that takes the value of one if the venture was in the expansion stage when it received its initial funding, and zero otherwise
Later stage venture	A dummy variable takes the value of one if the venture was in the later stage when it received its initial funding and zero otherwise.
Panel B: Overconfidence index components	
VC firm age	The difference in years between the deal year and the year the VC firm was founded
Early-stage investments	The percentage of VC firm's investments in early-stage
Seed stage investments	The percentage of VC firm's investments in seed stage
Prior VC investments	The sum of all investments by the VC firm prior to the observation year
Prior companies invested in	The sum of all companies that the VC firm invested in prior to the observation year
Prior successful deals	The sum of all exits by the VC firm prior to the observation year
Gender	The fraction of female executives in the VC firm

Table 1
Summary statistics

This table presents summary statistics of lead VC firms. Panel A describes time-series averages of cross-sectional statistics for all VC firms. Panel B presents cross-correlations among VC firm characteristics of the sample. * indicates statistical significance at the 10% level.

Panel A: Descriptive statistics

Variables	Mean	25th percentile	Median	75th percentile	Std.dev
OC index	3.013	1.73	3.12	4.342	1.62
Firm size ($ millions)	1309.53	15.05	77.95	507.3	5359.51
Firm age (in years)	20.92	10	16	26	20.66
Prior succ.deals	36.67	1	7	30	88.06
Firm location	0.23	0	0	0	0.42
Frim type	0.74	0	1	1	0.44
Syndicate size	7.08	3	5	10	5.73
Next fund size ($ millions)	521.18	0	45.8	245.5	2178.39
Next fund time (in years)	4.43	1	3	5	6.78
Time to exit (in years)	6.41	3	5.2	8.7	4.71

Panel B: Correlation matrix

	OC index	Firm size	Firm age	Prior IPO	Prior M&A	Prior-succ deal	Firm location	Firm type	Syndicate size	Next fund size	Next fund time	Time to exit
OC index	1											
Firm size	0.26*	1.00										
Firm age	0.40*	0.37*	1.00									
Prior IPO	0.51*	0.63*	0.60*	1.00								
Prior M&A	0.59*	0.54*	0.55*	0.93*	1.00							
Prior-succ deal	0.57*	0.58*	0.58*	0.97*	0.99*	1.00						
Firm location	0.01	0.11*	0.19*	0.21*	0.12*	0.16*	1.00					
Firm type	0.06	-0.12*	-0.31*	-0.15*	-0.05	-0.09*	-0.23*	1.00				
Syndicate size	0.28*	-0.05	0.04	0.13*	0.17*	0.16*	0.11*	-0.03	1.00			
Next fund size	0.15*	0.64*	0.25*	0.41*	0.32*	0.35*	0.16*	-0.13*	-0.09*	1.00		
Next fund time	-0.10*	-0.11*	0.15*	-0.12*	-0.12*	-0.12*	-0.04	-0.15*	-0.04	-0.09	1.00	
Time to exit	0.25*	0.00	0.21*	0.11*	0.15*	0.14*	0.03	-0.02	0.27*	-0.08	0.03	1.00

Table 2
Overconfidence bias and VC firm's characteristics

This table presents an analysis of VC firms' characteristics based on two groups: VC firms with a high level of overconfidence and VC firms with a low level of overconfidence. Panel A presents percentile analysis. Column 3 is the difference between column 1 and column 2. Column 4 is t-statistics and column 5 is the *p*-value. Panel B presents a quintile analysis. Q5-Q1 indicates firms' characteristics differentials between the most overconfident VCs (Q5) and the least overconfident VCs (Q1). *** represent statistical significance at the 1% level.

Panel A: Percentile analysis

	VC firm with a high level of overconfidence (1)	VC firm with a low level of overconfidence (2)	Difference (3) = (1) – (2)	*t*-statistics	*p*-value
Firm size	3764.245	38.148	3726.097	6.676	0.000***
Firm age	32.993	10.030	22.963	15.579	0.000***
Prior IPO	39.270	0.204	39.065	16.593	0.000***
Prior M&A	76.549	1.106	75.443	20.157	0.000***
Prior succ deals	115.820	1.019	114.801	21.847	0.000***
Firm Location	0.266	0.150	0.115	4.4285	0.000***
Firm type	0.807	0.696	0.111	3.975	0.000***
Syndicate size	9.234	5.245	3.988	11.099	0.000***
Duration	8.033	4.994	3.038	9.775	0.000***

Panel B: Quintile analysis

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Q5 -Q1	p-Value
Firm size	13.791	88.000	361.805	1019.667	4424.422	4410.631	0.000***
Firm age	9.466	14.517	18.677	24.450	34.291	24.824	0.000***
Prior IPO	0.143	0.716	2.679	9.481	45.917	45.774	0.000***
Prior M&A	0.956	2.389	12.265	20.349	89.005	88.049	0.000***
Prior succ deals	0.793	3.097	14.944	29.830	134.923	134.129	0.000***
Firm Location	0.158	0.193	0.262	0.301	0.267	0.109	0.002***
Firm type	0.678	0.703	0.746	0.765	0.803	0.124	0.000***
Syndicate size	5.293	5.732	6.954	7.941	9.501	4.207	0.000***
Time to exit	5.011	5.332	6.119	7.347	8.218	3.207	0.000***

Table 3

Overconfidence bias by industry and stage preferences

This table presents overconfidence bias according to the industry and stage preferences of VC firms. In panel A, we categorize VC firms into three groups based on their industry focus. In panel B, we categorize VC firms into three groups based on their stage focus. If the firm is at seed or early stage, we define it as early-stage VC. *p*-values of comparison tests across groups are reported. ** and *** denote significance at the 5% and 1% levels, respectively.

	Mean	25th percentile	Median	75th percentile	Std.dev
Panel A: Overconfidence bias by industry preferences					
Full sample	2.692	1.351	2.642	4.058	1.622
Information technology (IT)	2.653	1.277	2.551	4.078	1.686
Medical/Health	2.675	1.134	2.951	3.893	1.743
Others	2.729	1.495	2.672	4.030	1.537
Comparison tests across groups – p-Value					
IT - Medical/Health	0.925		0.896		
IT - Others	0.603		0.562		
Medical/Health - Others	0.806		0.873		
Panel B: Overconfidence bias by stage preferences					
Early stage	3.280	2.170	3.415	4.563	1.619
Balanced stage	3.024	1.783	3.015	4.403	1.619
Later stage	2.947	1.573	3.008	4.257	1.603
Comparison tests across groups – p-Value					
Early - Balanced	0.034**		0.026**		
Early - Later	0.001***		0.000***		
Balanced - Later	0.488		0.472		

Table 4

Overconfidence bias and VC fundraising: Univariate analysis

This table presents a univariate analysis of overconfidence and VC fundraising. Panel A compares VC firms with a high level of overconfidence with those VC firms with a low level of overconfidence using percentiles. Panel B displays results of a quintile analysis comparing the most overconfident VCs (Q5) to the least overconfident VCs (Q1). *** indicates statistical significance at the 1% level.

Panel A: Percentile analysis

	All VC firms		VC firm with a high level of overconfidence		VC firm with a low level of overconfidence		Differences in mean	
	N	Mean	N	Mean	N	Mean	t-Statistics	p-Value
Next fund size	1867	521.177	473	1562.415	472	324.206	4.160	0.000***
Next fund time	1867	4.432	473	3.421	472	4.808	-3.321	0.001***

Panel B: Quintile analysis

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Q5 -Q1	p-Value
Next fund size	274.495	437.995	632.629	1146.226	1522.191	1247.696	0.005***
Next fund time	4.840	4.806	5.215	4.510	3.126	-1.714	0.001***

Table 5
Overconfidence bias and VC fundraising: Multivariate analysis

This table displays the results of the multivariate regressions of overconfidence bias and VC fundraising. All models are estimated using the Heckman two-stage model, with the first regression is the probability of raising a fund in a given year, and the second stage is the next amount raised, given a particular year. The dependent variable is the natural logarithm of the following fund raised after the observation year. Model 1 includes the number of prior IPOs and the number of prior M&As. Model 2 includes the number of prior successful deals. OC index measures the level of VC overconfidence. VC firm age is measured by the number of years between VC firm's year of incorporation and the observation year. Firm location is a dummy variable that takes the value of one if the VC firm was based in venture hotbeds that are either New York or California and zero otherwise. Syndicate size is the natural logarithm of the total number of VC firm invested in the portfolio company. Firm type is a dummy variable that takes the value of one if the VC firm was not affiliated with any other entities (independent VC firm) and zero otherwise. All regressions include industry and year fixed effects. *, ** and *** indicate statistical significance at 10%, 5% and 1% level respectively.

	First stage: likelihood of raising funds	(1)	(2)
Constant	-0.329*	4.260***	1.617
	(-1.911)	(4.063)	(1.350)
OC index		0.238***	0.230***
		(3.008)	(2.924)
Ln(VC firm age)	0.089*	-0.339***	-0.374***
	(1.718)	(-5.106)	(-5.626)
Firm Location	0.338***	0.869***	1.090***
	(3.552)	(5.450)	(6.855)
Syndicate size		-0.633***	-0.619***
		(-7.827)	(-7.689)
Firm type		0.383***	0.378***
		(3.071)	(3.042)
Ln (prior IPO)		0.351***	
		(4.257)	
Ln (prior M&A)		0.186	
		(1.557)	
Ln (prior succ. Deals)	0.014***		0.736***
	(4.216)		(6.143)
Inverse Mills ratio		-3.921**	-8.181***
		(-2.319)	(-6.96)
GDP growth in the previous year	0.133***		
	(4.117)		
Industry and year fixed effects		Yes	Yes
Adjusted R^2		0.32	0.31
No. of observations		1,867	1867

Table 6

Overconfidence bias and fundraising time: Multivariate analysis

This table presents a regression analysis of overconfidence bias and VC fundraising time. All models are estimated using the Heckman two-stage model, with the first regression is the probability of raising a fund in a given year, and the second stage is the time between the next raised fund and the observation year. The dependent variable is the logarithm of the time from the observation year to the venture capitalist's next fund. A Cox hazard model is used to estimate the likelihood and timing of raising money by VC firms. Model 1 includes the number of prior IPOs and the number of prior M&As. Model 2 includes the number of prior successful deals. OC index measures the level of VC overconfidence. VC firm age is measured by the number of years between VC firm's year of incorporation and the observation year. Firm location is a dummy variable that takes the value of one if the VC firm was based in venture hotbeds that are either New York or California and zero otherwise. Syndicate size is the natural logarithm of the total number of VC firms invested in the portfolio company. Firm type is a dummy variable that takes the value of one if the VC firm was not affiliated with any other entities (independent VC firm) and zero otherwise. All regressions include industry and year fixed effects. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	First stage: likelihood of raising funds	(1)	(2)
OC index		0.127***	0.123***
		(2.812)	(2.739)
Ln(VC firm age)	0.089*	-0.141**	-0.165***
	(1.718)	(-2.218)	(-2.741)
Firm Location	0.357***	0.090	0.146
	(4.703)	(0.870)	(1.412)
Syndicate size		0.021	0.015
		(0.333)	(0.238)
Firm type		-0.147	-0.122
		(-1.410)	(-1.170)
Ln (prior IPO)		0.116**	
		(2.030)	
Ln (prior M&A)		0.124*	
		(1.832)	
Ln (prior succ. Deals)	0.014***		0.224***
	(4.216)		(5.018)
Inverse Mills ratio		-0.688***	-1.463**
		(-2.867)	(-2.128)
GDP growth in the previous year	0.133***		
	(4.117)		
Industry and year fixed effects		Yes	Yes
Wald_test		65.26	67.60
Log_likelihood		-3954.207	-3953.036
No. of observations		1,867	1,867

Table 7

Overconfidence bias and VC investment performance: Univariate analysis

This table presents a univariate analysis of overconfidence bias and VC investment performance. Panel A compares VC firms with a high level of overconfidence with those VC firms with a low level of overconfidence using percentiles. Panel B displays the results of a quintile analysis comparing the most overconfident VCs (Q5) to the least overconfident VCs (Q1). *** indicates statistical significance at the 1% level.

Panel A: Percentile analysis

	All VC firms	VC firm with a high level of overconfidence	VC firm with a low level of overconfidence	Differences in mean	
	Mean	Mean	Mean	t-Statistics	p-Value
All successful exits	0.281	0.061	0.672	11.847	0.000***
IPO exits	0.181	0.235	0.169	-3.025	0.002***
M&A exits	0.184	0.034	0.442	12.721	0.000***

Panel B: Quintile analysis

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Q5 -Q1	p-Value
All successful exits	0.718	0.374	0.224	0.115	0.056	-0.661	0.000***
IPO exits	0.164	0.141	0.160	0.196	0.230	0.066	0.004***
M&A exits	0.482	0.252	0.141	0.068	0.032	-0.450	0.000***

Table 8

Overconfidence bias and VC investment performance: Multivariate analysis

This table presents a regression analysis of overconfidence bias and VC investment performance, measured by the proportion of exits or the time to exit. Models 1, 2 and 3 are estimated using a generalized linear model (GLM). In model 1, the dependent variable is the percentage of all successful exits calculated by dividing the number of exits through IPOs and M&As by the number of investments by VC firms by the end of 2019. In model 2, the dependent variable is the percentage of successful IPOs, and in model 3, the dependent variable is the proportion of successful M&As. In models 4 and 5, the dependent variable is the time to exit measured by the number of years between the exit date and the first investment date by the lead venture capital firm. The OC index measures the level of VC overconfidence. VC firm age is measured by the number of years between VC firm's year of incorporation and the observation year. Firm location is a dummy variable that takes the value of one if the VC firm was based in venture hotbeds that are either New York or California and zero otherwise. Syndicate size is the natural logarithm of the total number of VC firms invested in the portfolio company. Firm type is a dummy variable that takes the value of one if the VC firm was not affiliated with any other entities (independent VC firm) and zero otherwise. Venture stage variable is included to control for the new venture stage. All regressions include industry and year fixed effects. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Proportion of successful exits			Time to exit	
	(1)	(2)	(3)	(4)	(5)
Constant	-0.914***	-2.149***	-0.942***	-0.307***	-0.303**
	(-4.846)	(-8.786)	(-4.396)	(-2.591)	(-2.558)
OC index	-0.643***	0.092**	-0.634***	-0.145***	-0.127***
	(-17.473)	(2.031)	(-14.663)	(-4.217)	(-3.595)
Ln (VC firm age)	0.357***	0.056	0.256***	0.261***	0.255***
	(5.888)	(0.517)	(3.804)	(7.680)	(7.449)
Firm Location	-0.392***	0.424***	-0.705***	-0.020	-0.053
	(-4.054)	(3.758)	(-6.290)	(-0.332)	(-0.910)
Syndicate size	0.249***	0.461**	0.212***	0.535***	0.520***
	(3.902)	(2.331)	(2.892)	(13.737)	(13.451)
Firm type	-0.003	-0.355***	-0.181	0.121**	0.137**
	(-0.029)	(-2.977)	(-1.524)	(2.144)	(2.412)
Ln (prior IPO)				-0.083**	
				(-2.224)	
Ln (prior M&A)				0.229***	
				(5.139)	
Ln (prior succ. Deals)					0.131***
					(3.603)
Early stage venture	0.467***	0.068	0.689***	0.126	0.124
	(3.257)	(0.371)	(4.432)	(1.576)	(1.544)
Expansion stage venture	-0.286*	0.175	-0.162	-0.507***	-0.531***
	(-1.825)	(0.938)	(-1.025)	(-6.184)	(-6.468)
Later stage venture	0.043	0.156	0.217	-0.062	-0.057
	(0.359)	(1.064)	(1.487)	(-0.605)	(-0.551)
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes
Wald test				629	621.3
Log_likelihood	-454.6	-513.4	-386	-2105	-2113
Observations	1,867	1,867	1,867	1,867	1,867

Table 9

VC Overconfidence, fundraising activity, investment performance: controlling for fundraising flows

This table reports regression results for overconfidence bias, fundraising activity, and investment performance of VC firms. See Appendix A for the definitions of variables. LAGFUND measures the natural logarithm of the prior total amount of capital raised by the VC firm. All regressions include industry and year fixed effects. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Fundraising activity analysis							
		VC next fund size			VC next fund time		
	First stage:	(1)	(2)	(3)	(1)	(2)	(3)
Constant		7.278***	7.311***	7.195***			
		(9.901)	(9.451)	(9.441)			
OC index		0.414***			0.023		
		(8.370)			(0.671)		
LAGFUND		0.226***			0.084***		
		(9.113)			(6.768)		
OC index*LAGFUND			0.039***	0.037***		0.018***	0.018***
			(6.015)	(5.673)		(5.449)	(5.292)
Ln(VC firm age)	0.089*	-0.467***	-0.405***	-0.446***	-0.129**	-0.159***	-0.158***
	(1.718)	(-6.231)	(-5.423)	(-5.990)	(-2.549)	(-3.225)	(-3.208)
Firm Location	0.357***	-0.002	0.124	0.109	-0.053	-0.002	-0.030
	(4.703)	(-0.011)	(0.675)	(0.595)	(-0.651)	(-0.030)	(-0.367)
Syndicate size		-0.363***	-0.394***	-0.414***	0.031	-0.001	-0.009
		(-4.452)	(-4.771)	(-5.038)	(0.600)	(-0.014)	(-0.185)
Firm type		0.318**	0.418***	0.408***	0.096	0.072	0.093
		(2.519)	(3.277)	(3.226)	(1.110)	(0.830)	(1.085)
Ln (prior IPO)			0.081			-0.068	
			(0.922)			(-1.464)	
Ln (prior M&A)			0.331***			0.099**	
			(3.983)			(2.037)	
Ln (prior succ. Deals)	0.014***			0.431***			0.040
	(4.216)			(7.791)			(1.131)
Inverse Mills ratio		-4.729***	-4.230***	-4.168***	-0.874***	-0.802***	-0.812***
		(-7.874)	(-6.387)	(-6.453)	(-4.567)	(-4.106)	(-4.197)
GDP growth in the previous year	0.133***						
	(4.117)						
Industry and year fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2		0.38	0.36	0.37			
Wald_test					131.1	135.7	132.7
Log_likelihood					-5790	-5787	-5789
No. of observations		1,867	1,867	1,867	1,867	1,867	1,867

Table 9 : (Continued)

Panel B: Investment performance analysis									
	Proportion of successful exits						Time to exit		
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)
Constant	-0.668***	-2.092***	-0.653***	-0.464***	-1.979***	-0.493**	1.364***	1.130***	1.123***
	(-3.620)	(-8.614)	(-3.115)	(-2.583)	(-8.927)	(-2.376)	(8.791)	(6.640)	(6.740)
OC index	-0.558***	0.033	-0.525***				-0.080**		
	(-13.800)	(0.664)	(-11.295)				(-2.536)		
LAGFUND	-0.090***	0.055***	-0.127***				-0.090***		
	(-5.843)	(3.347)	(-6.999)				(-9.572)		
OC index* LAGFUND				-0.045***	0.013***	-0.055***		-0.019***	-0.019***
				(-14.227)	(4.173)	(-14.728)		(-6.978)	(-7.215)
Ln (VC firm age)	0.292***		0.171***	-0.099**		-0.188***	0.168***	0.206***	0.208***
	(4.937)		(2.596)	(-2.143)		(-3.643)	(2.882)	(3.507)	(3.477)
Firm Location	-0.313***	0.356***	-0.610***	-0.321***	0.369***	-0.651***	-0.140**	-0.147**	-0.132**
	(-3.258)	(3.010)	(-5.433)	(-3.248)	(3.147)	(-5.861)	(-2.304)	(-2.382)	(-2.195)
Syndicate size	0.211***		0.168**	-0.072		-0.068	-0.049	-0.030	-0.024
	(3.250)		(2.268)	(-1.178)		(-0.943)	(-1.156)	(-0.717)	(-0.586)
Firm type	-0.047	-0.383***	-0.213*	-0.190*	-0.374***	-0.350***	-0.004	0.016	0.004
	(-0.482)	(-3.183)	(-1.852)	(-1.932)	(-3.156)	(-3.065)	(-0.053)	(0.198)	(0.046)
Ln (prior IPO)								0.017	
								(0.435)	
Ln (prior M&A)								-0.106***	
								(-2.597)	
Ln (prior succ. Deals)									-0.090**
									(-2.560)
Early stage venture	0.040	0.148	0.229	0.200*	0.143	0.367***	-0.040	-0.043	-0.041
	(0.338)	(1.001)	(1.584)	(1.689)	(0.969)	(2.578)	(-0.561)	(-0.622)	(-0.593)
Expansion stage venture	0.411***	0.089	0.618***	0.400***	0.071	0.597***	-0.093	-0.092	-0.085
	(2.970)	(0.484)	(4.120)	(2.668)	(0.386)	(3.702)	(-0.910)	(-0.912)	(-0.839)
Later stage venture	-0.296*	0.166	-0.179	-0.162	0.149	-0.096	0.083	0.131	0.123
	(-1.871)	(0.879)	(-1.117)	(-1.117)	(0.788)	(-0.613)	(0.812)	(1.283)	(1.201)
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald test							169.8	211.5	210
Log_likelihood	-444.4	-511	-374.3	-471.3	-511.2	-394.4	-1360	-1352	-1353
Observations	1,867	1,867	1,867	1,867	1,867	1,867	1,867	1,867	1,867

Table 10
Principal component analysis

This table presents the results of the principal component analysis. Panel A reports the eigenvalues and the proportion of variance that the component explains. Panel B indicates the correlation between the original variables including in the index and the first two principal components.

Panel A

Component	Eigenvalue	% Variance Explained	%Cumulative Variance Explained
1	2.19799	0.3140	0.3140
2	1.35143	0.1931	0.5071
3	.999037	0.1427	0.6498
4	.875603	0.1251	0.7749
5	.698484	0.0998	0.8746
6	.645417	0.0922	0.9669
7	.232035	0.0331	1.0000

Panel B

Variable	PC1	PC2
% early stage investments	0.0317	0.6977
% seed stage investments	0.0095	0.6775
Sum prior investments	0.4472	-0.1402
Sum companies invested in	0.6044	0.0123
Prior successful deals	0.5797	0.0870
Fraction female executives	0.0666	-0.1581
VC age	0.3052	-0.0433

Table 11

Overconfidence bias and VC fundraising: PCA analysis

This table presents a multivariate analysis of overconfidence bias and VC fundraising activity.VC overconfidence is measured by the first two components of PCA analysis. Component 1 is a measure of prior VC experience, and component 2 is a measure of VC risk aversion. The dependent variable in model 1 is the natural logarithm of the amount of the next fund raised following the observation year. The dependent variable in model 2 is the logarithm of the time from the observation year to the venture capitalist's next fund. VC firm age is measured by the number of years between VC firm's year of incorporation and the observation year. Firm location is a dummy variable that takes the value of one if the VC firm was based in venture hotbeds that are either New York or California and zero otherwise. Syndicate size is the natural logarithm of the total number of VC firms invested in the portfolio company. Firm type is a dummy variable that takes the value of one if the VC firm was not affiliated with any other entities (independent VC firm) and zero otherwise. All regressions include industry and year fixed effects. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Fundraising size	Fundraising time
	(1)	(2)
Constant	5.560***	
	(12.693)	
Prior experience	0.409***	0.097***
	(7.305)	(3.042)
VC risk aversion	-0.031	0.030
	(-0.704)	(0.949)
Ln(VC firm age)	-0.102	-0.592***
	(-1.129)	(-11.508)
Firm Location	0.555***	0.176*
	(3.365)	(1.785)
Syndicate size	-0.467***	-0.504***
	(-5.266)	(-9.854)
Firm type	0.529***	-0.228***
	(3.719)	(-2.963)
Inverse Mills ratio	-2.763***	0.637***
	(-10.279)	(2.624)
Industry and year fixed effects	Yes	Yes
Wald test	443.5	458
Log likelihood		-6640
Observations	1,867	1867

Table 12

Overconfidence bias and VC investment performance: PCA analysis

This table presents the regression analysis of overconfidence bias and VC investment performance. VC overconfidence is measured by the first two components of PCA analysis. Component 1 is a measure of prior VC experience, and component 2 is a measure of VC risk aversion. The dependent variable of model 1 is the percentage of all successful exits calculated by dividing the number of exits through IPO and M&A by the number of investments by VC firms by the end of 2019. In model 2, the dependent variable is the percentage of successful IPOs, and in model 3, the dependent variable is the proportion of successful M&As. The dependent variable of model 4 is the time to exit measured by the number of years between the exit date and the first investment date by the lead venture capital firm. VC firm age is measured by the number of years between VC firm's year of incorporation and the observation year. Firm location is a dummy variable that takes the value of one if the VC firm was based in venture hotbeds that is either New York or California and zero otherwise. Syndicate size is the natural logarithm of the total number of VC firms invested in the portfolio company. Firm type is a dummy variable that takes the value of one if the VC firm was not affiliated with any other entities (independent VC firm) and zero otherwise. Venture stage variable is included to control for the new venture stage All regressions include industry and year fixed effects. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Proportion of successful exits	Proportion of IPO exits	Proportion of M&A exits	Time to exit
	(1)	(2)	(3)	(4)
Constant	0.389***	0.065	0.369***	-0.600***
	(9.133)	(1.522)	(8.955)	(-4.313)
Prior VC experience	-0.036***	0.016***	-0.026***	-0.087***
	(-9.849)	(3.902)	(-8.878)	(-3.235)
VC risk aversion	0.009	-0.008	0.012	-0.106***
	(1.139)	(-1.200)	(1.577)	(-4.850)
Ln (VC firm age)	-0.044***	0.008	-0.053***	0.467***
	(-4.147)	(0.758)	(-5.319)	(11.149)
Firm Location	-0.056***	0.045**	-0.070***	-0.030
	(-3.957)	(2.509)	(-6.242)	(-0.458)
Syndicate size	-0.003	0.066***	-0.004	0.434***
	(-0.258)	(5.568)	(-0.392)	(10.372)
Firm type	-0.071***	-0.066***	-0.082***	0.275***
	(-4.075)	(-3.495)	(-4.937)	(4.406)
Ln (prior succ. Deals)				0.057*
				(1.954)
Early-stage venture	0.039*	-0.006	0.054***	0.289***
	(1.941)	(-0.306)	(2.800)	(3.524)
Expansion stage venture	0.046	0.005	0.063**	-0.391***
	(1.522)	(0.198)	(2.209)	(-4.229)
Later stage venture	-0.008	-0.032	0.008	-0.024
	(-0.415)	(-1.131)	(0.542)	(-0.225)
Industry and year fixed effects	Yes	Yes	Yes	Yes
Wald test				397.3
Log likelihood	-419.247	-447.628	-352.660	-1851
Observations	1,867	1867	1,867	1867

Table 13
Results for inverted U-shaped relationships

This table displays the results of quadratic regressions. The dependent variable in models (1) and (2) is the natural logarithm of the following fund raised after the observation year. Model 1 includes the number of prior IPOs and the number of prior M&As. Model 2 includes the number of prior successful deals. In model 3, the dependent variable is the percentage of all successful exits calculated by dividing the number of exits through IPOs and M&As by the number of investments by VC firms by the end of 2019. OC index measures the level of VC overconfidence. VC firm age is measured by the number of years between VC firm's year of incorporation and the observation year. Firm location is a dummy variable that takes the value of one if the VC firm was based in venture hotbeds that are either New York or California and zero otherwise. Syndicate size is the natural logarithm of the total number of VC firms invested in the portfolio company. Firm type is a dummy variable that takes the value of one if the VC firm was not affiliated with any other entities (independent VC firm) and zero otherwise. All regressions include industry and year fixed effects. *, ** and *** indicate statistical significance at 10%, 5% and 1% level respectively.

	Fundraising activity		Investment performance
	(1)	(2)	(3)
Constant	7.687***	7.964***	0.361***
	(9.950)	(10.682)	(9.834)
OC index	1.331***	1.175***	-0.101***
	(7.702)	(6.851)	(-5.410)
OC index squared	-0.183***	-0.164***	0.003
	(-6.449)	(-5.973)	(1.270)
Ln (VC firm age)	-0.524***	-0.529***	0.043***
	(-6.929)	(-7.013)	(4.393)
Firm Location	-0.230	-0.269	-0.047***
	(-1.254)	(-1.468)	(-3.778)
Syndicate size	-0.473***	-0.457***	0.028***
	(-5.627)	(-5.465)	(3.076)
Firm type	0.422***	0.404***	-0.016
	(3.265)	(3.150)	(-0.993)
Ln (prior IPO)	0.273***		
	(3.032)		
Ln (prior M&A)	0.326***		
	(3.291)		
Ln (prior succ. Deals)		0.555***	
		(6.819)	
Inverse Mills ratio	-5.948***	-6.184***	
	(-9.332)	(-10.121)	
Early stage venture			0.010
			(0.563)
Expansion stage venture			0.066***
			(2.672)
Later stage venture			-0.032*
			(-1.743)
Industry and year fixed effects	Yes	Yes	Yes
Log_likelihood			212.3
R-squared	0.366	0.367	
Observations	1,867	1,867	1,867