



UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

**The venture capital advantage in technology firms:
An IPO analysis**

Saiteja Sriramagiri (gussrirs@student.gu.se)

Xuan Zhou (guszhoxu@student.gu.se)

Supervisor: Dr. Elias Bengtsson

Master's thesis in Economics, 30 hec

Fall 2021

**Graduate School, School of Business, Economics and Law, University of
Gothenburg, Sweden**

Abstract

The goal of this research is to investigate the level of influence venture capital (VC) firms have on their technology portfolio companies' public shares after their initial public offering (IPO). While there has been substantial research within the certification roles that underwriters and auditors take to ameliorate the information asymmetry problem, we seek to employ a similar framework within a VC-backing context. VCs invest significant time and resources to choose companies they back as their success is further linked to their return and esteem of the fund and partners. Their reputation is often described as an 'intangible' asset used to indicate their unobserved abilities and create expectations for the future. We first quantify this intangible asset of reputation, and then we analyse how the reputation impacts the post-IPO market performance in the short-term and long-term through their certification and reputation effects through econometric methods. While we do not find strong evidence that there exists a significant signalling effect from the backing of reputable VCs in the long-term, we do find evidence of moderate significance in the initial returns. Our findings appear to be in line with existing literature and complement the recent shift in dynamics we observe in the VC ecosystem.

Keywords: venture capital ("VC"), reputation, initial public offering ("IPO"), asymmetric information, technology

Acknowledgements

We would like to express our sincere gratitude to Dr. Elias Bengtsson who has been incredibly generous and helpful in offering his comments and suggestions throughout the study period.

We would like to thank Dr. Katarina Nordblom and the Graduate School for all their support with the administration of the thesis.

We would like to thank our peers for their valuable feedback and perspectives at every stage of the process.

Last, but not least, we would like to thank our parents for their persistent support in making this possible.

Contents

The venture capital advantage in technology firms	1
Abstract	2
Contents	4
List of figures	5
List of tables	7
1. Introduction	8
1.1 Venture capital	8
1.2 Reputation and certification	10
2. Theoretical framework	13
2.1 Asymmetric information	13
2.2 Venture capital reputation	14
2.3 VC-backed IPO performance	19
2.4 Hypothesis	20
3. Methodology	21
3.1 Data collection and sample construction	21
3.2 Market performance measurement	22
3.3 VC reputation	24
3.4 Control variables	27
3.5 Data processing	31
4. Results	33
4.1 Preliminary analysis	33
4.2 Regressions	35
4.3 Regressions with control variable conditions	39
4.4 Robustness check	42
5. Conclusion	44
References	46
Appendix A: Key variables	50
Appendix B: Additional tables	51

List of figures

Figure 1. Total invested capital and number of deals

Figure 2. Number of VC-backed IPOs on NASDAQ by year

Figure 3. Mean market cap at IPO (close of first day trading) by region and by year

Figure 4. Overview of literature review

Figure 5. Distribution Density Graph of VC reputation before and after processing

Figure 6. IPO distribution by industry classification

Figure 7. Buy-and-hold return and VC reputation

List of tables

Table 1. Number of IPO transactions by year

Table 2. VC Reputation score construction

Table 3. Correlation matrix of independent and control variables

Table 4. Descriptive statistics

Table 5. Univariate regression with 1-day, 6-month, and 1-year return

Table 6. Multivariate regression with 1-day, 6-month, and 1-year return

Table 7. Multivariate regression with 1-day returns under the conditions of $\text{syn} = 1$, $\text{hedgefund} = 1$ and $\text{phd} = 1$

Table 8. Regression results without and with robustness standard errors

1. Introduction

1.1 Venture capital

The internet boom since the 2000s has created an incredible amount of successful technology companies. Facebook, Twitter, Skype and Netflix are household names and have penetrated all economies - from North America to Uganda and nearly every person on earth is either a user or has heard of these tech giants. One of the drivers, amongst the generally favorable market conditions, is the ease and accessibility of institutional money in the early stages of a company's growth, or more commonly known as VC funding (Henton and Held, 2013). Superior returns have made venture capital an attractive (risk-compensated) investment vehicle, resulting in an all time high in available VC capital (Simon, 2016). The first half of 2021 has attracted 5 times more invested capital than the entire year of 2011 as shown in Figure 1.

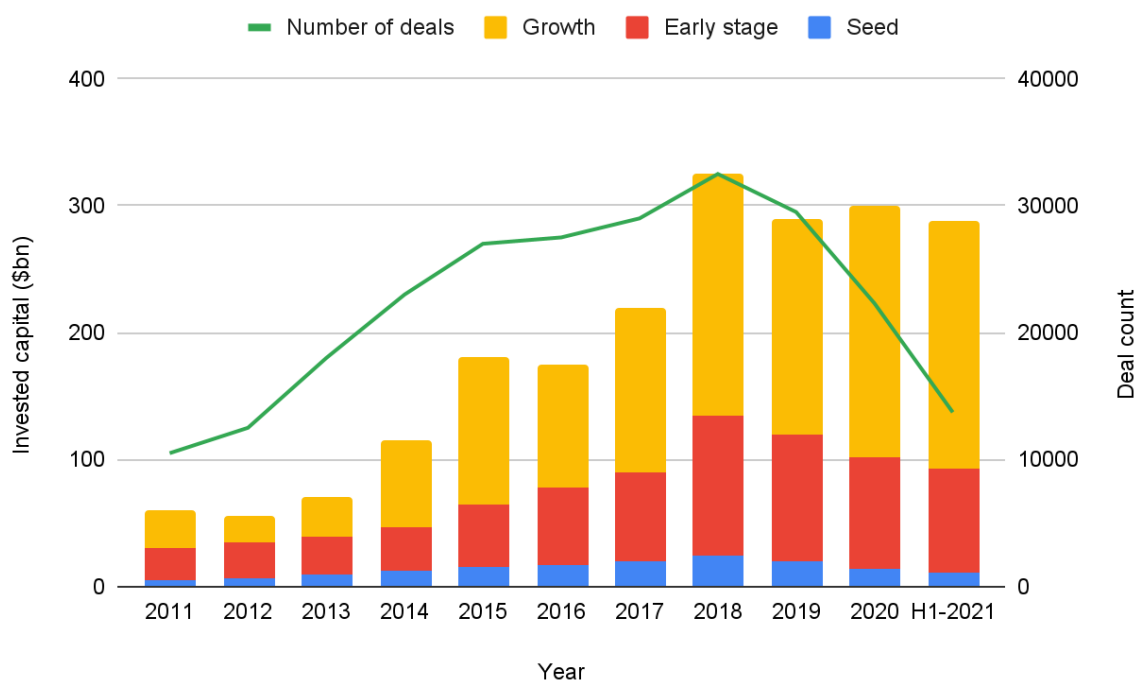


Figure 1. Total invested capital and number of deals

Paired with the recent uptick in VC-backed companies, is the parallel graduation of these companies from privately-held to being publicly-listed to fund their next phase of growth. In spite of the massive uncertainty due to the Covid-19 crisis, there has been a record 82%

growth in the number of IPOs in 2020, of which circa. 54% have been VC-backed ones. Notable companies like Airbnb, DoorDash and Palantir have listed with exceptional first day trading gains of nearly 150%+. 2020 was clearly a landmark year for IPOs and there are no signs of it slowing down. Figure 2 plots the number of IPOs per year on the tech-heavy NASDAQ.

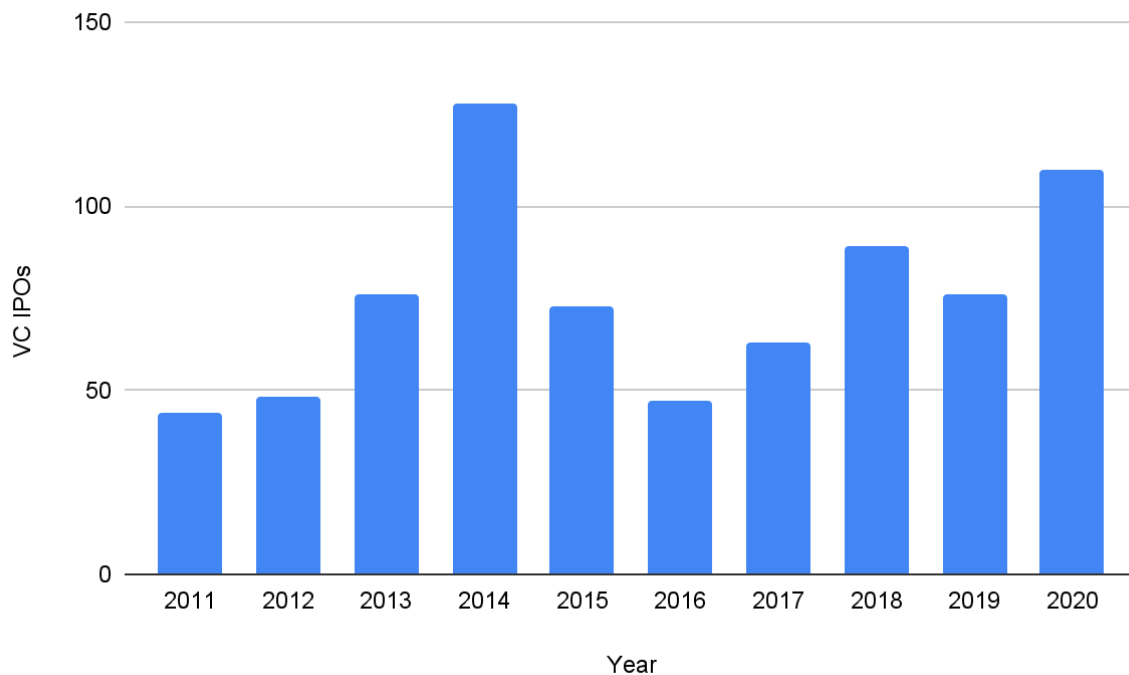


Figure 2. Number of VC-backed IPOs on NASDAQ by year

After decades of pouring money into private capital markets, the attractive public markets have drastically swung the pendulum in the other direction. Venture-backed tech companies are taking advantage of the bull markets to raise whopping amounts in the public markets. It should come as no surprise that the capital raised at IPO has been rapidly growing year over year. Figure 3 exhibits this trend and it's quite impressive to see that the mean market cap at IPO has increased by 510% since 2011. Valuations, net proceeds and market performances are at all time high and desperately calls for investigation.

“With the ample supply of VC money from sovereign wealth funds and mutual funds buying pre-IPOs it's pushed up the private market valuations. That's allowed companies like Airbnb to raise private capital on attractive terms, and they've been in no rush to go public as a result. So far this year, there have

been 127 operating-company initial public offerings in the U.S. and on an average, those offerings have produced an average first-day pop of 38%”
- Jay Ritter, Professor of Finance at University of Florida

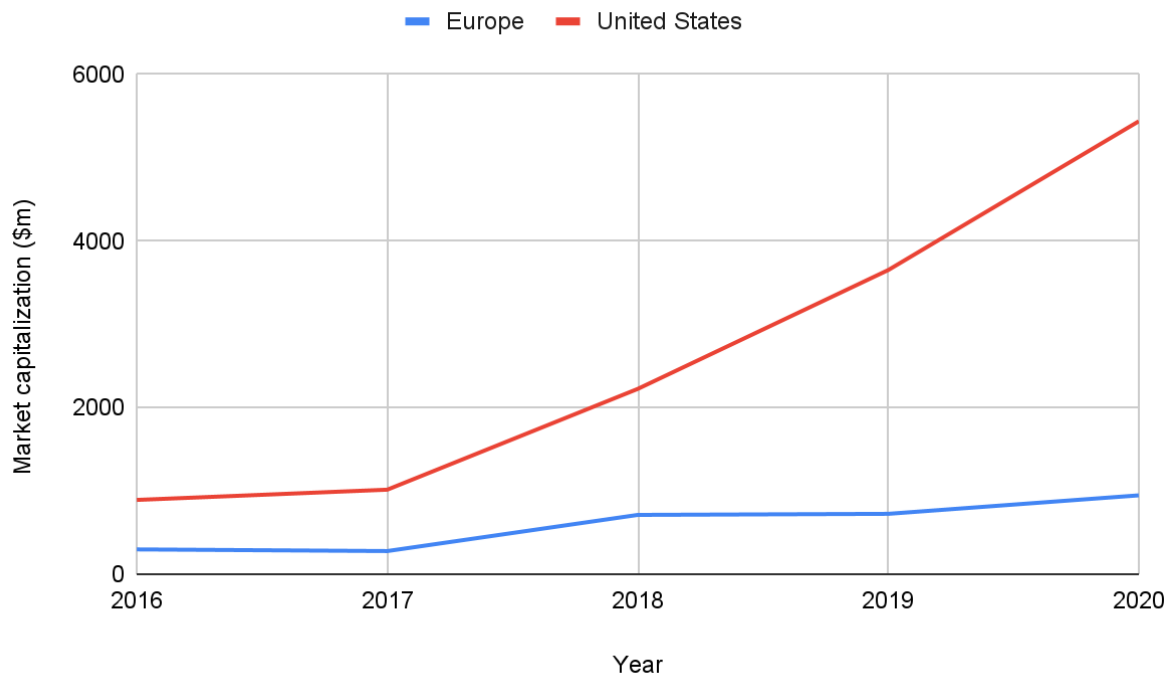


Figure 3. Mean market cap at IPO (close of first day trading) by region and by year

The venture capital field, however, is severely under-studied and under-researched due to the lack of publicly available information of unlisted companies. Our primary goal with this research is to study the intersection of these mega-trends in the financial industry, and particularly understand the role of VC reputation in explaining the short to mid-term performance of venture-backed companies going public. This research would give a deeper and updated insight into our understanding of initial public offerings in the age of overflowing venture capital backing. To a retail investor, it will give new found insight into whether they are right in leveraging the reputation of the venture capital backer as a proxy for the quality of the company.

1.2 Reputation and certification

In the absence of perfect information, reputation can be a strong and reliably proxy factor for decision making. This is a ubiquitous and fundamental observation in human psychology

(Duradoni, et. al, 2020). Reputation of a firm can give prospective customers important information regarding their competencies while also setting them apart from their competitors. Hence, it should come as no surprise that there is strong empirical evidence that reputation is a valuable asset under information asymmetry and that there are many theoretical models of reputation in the financial services market (Holmstrom and Tiróle, 1997). Of particular interest to academia has been the role reputation plays in the context of IPOs, where the reputation of underwriters, auditors and such have been important for investors to assess the quality and credibility of the companies¹. We seek to apply a scientific framework and methodology to understand what level of an influence VCs have on IPOs and market performance of their portfolio firms. The primary motivation for is to reflect on the notion that since VCs assess large numbers of companies and proceed to invest only in a select few. Additionally, VCs spend a sufficient amount of time monitoring companies in the pre-IPO stage and also facilitate their growth stages. Hence, it is not irrational to posit that these selection of companies to be of higher quality than the non-VC-backed ones and in turn, have superior market performance.

Until recently, financial literature did not differentiate between VCs by reputation, but rather treated them homogeneously through a mere dummy variable. Under this simple setting, highly reputable funds such as Andreessen Horowitz, with a 1000+ investments, and 200+ exist are treated equally to a small fund with significantly lesser experience, capital and network. Lerner (1994), Gompers (1996), and Krishnan, Masulis, and Singh (2006) have provided the groundwork for quantifying VC reputation and assessing their impact on post-IPO performance. Building on existing analyses and theory in this research area, our motivation with this research is to see how these results hold in today's funding environment and market conditions. To carry out this study, we create a VC reputation index which involves creating a standardised and weighted system of underlying VC firm characteristics which typically proxy for reputation. In our case, it is a weighted function of M&A exits, IPO exits, total investments and age of the fund. Then, we create a multivariate regression model of market-adjusted returns on our regressors and general control variables based on previous research on IPO returns. We run statistical and econometric tests using market returns to investigate the relationships between the venture capital characteristics and short and

¹ Papers in this study area include Beatty (1989), Menon and Williams (1991), Feltham, et. al (1991), and Michaely and Shaw (1995) on auditor reputation, Beatty and Ritter (1986), Titman and Trueman (1986), Carter and Manaster (1990), and Carter, et. al (1998) on investment bank reputation and IPO underpricing, Lerner (1994), Gompers (1996), and Krishnan, Masulis, and Singh (2006) on influence of venture capital reputation on initial public offerings

long-term market performance. Finally, we benchmark our results against the market to analyse the impact of VC backing.

This paper consists of 5 main sections. It begins with exploring the theoretical framework, followed by a literature review to understand the level and scope of prior research within the field and also understand the main findings and conclusions to act as a benchmark. This is succeeded by the data and methodology where we present in detail our processes and reasoning behind the organisation of our study method and analyses. Results are presented in Section 4, and finally is concluded by an extensive discussion to put into context our findings by tying together the findings with existing theory.

2. Theoretical framework

Due to the lack of publicly available information around private companies, there exists a severe problem of information asymmetry between issuers and investors. Insider parties, i.e. the companies, possess superior information about their future financial performance than the information available to investors. Thus, investors are incapable of truly assessing whether the issuing company is of high or low quality. In this gaping absence, they are forced to rely on proxy indicators such as reputation of the company's financial stakeholders such as underwriters, auditors and institutional investors, in our case VCs. Paired with prior literature surrounding post-IPO performance, we are able to understand the fundamental theories in this research area and make more detailed considerations and conclusions in the study. This section outlines seminal works and theories within the scope of our research. We begin with an overview of how asymmetric information plagues the venture capital markets. This is followed by a brief on how and why reputation is relevant in the presence of information gaps. Finally, to tie it all together is the overview of literature tackling to understand how venture capital backing plays a role in the IPO process.



Figure 4. Overview of literature review

2.1 Asymmetric information

Information asymmetry is defined as:

“a situation where some participants in an economic transaction have access to more, or better, relevant information than other participants.” - Hashimzade, 2017

Information in the real world is never distributed equally. In financial markets and transactions, the asymmetry of information is compounded with parties with conflicting interests which leaves room for unfair advantages to some parties at the cost of others. Literature traditionally describes two forms of asymmetric information:

The adverse selection problem stems from hidden information, which is a situation when one party has access to lesser information than the other (insider) party (e.g., overstating the profitability and potentials). Investors are essentially unable to distinguish accurately the higher quality projects from the underperforming ones. The problem can be tackled by introducing more informed investors (Chan. 1983), conducting more intensive proposal screening, due diligence, syndication and specification of VCs (Joshi et al. 2015). Additionally, Rock (1986) mentioned that the extent of underpricing is dependent on the degree of problems related with adverse selection.

Moral hazard on the other hand, is connected with hidden actions, which is the situation when one party in a transaction is unable to observe the actions of other parties (or cannot legally verify these actions). Investors cannot continuously ensure whether the founders are actively devoting their efforts to the success of the project or if they are simply slacking. To tackle side-effects stemming from moral hazard, VCs can take a more active role in the portfolio company's operations through enhanced corporate governance strategies. (Gompers 1995)

It is quite evident, the role venture capital funds can play in the IPO process, particularly in ameliorating the potential effects of the asymmetric information problem. It should also come as no surprise that these effects are not homogeneous across all investors, but instead vary depending on the different characteristics of the fund in concern. To understand this fully, we need to understand what reputation means in a VC context, and then how it ties in with the effects VCs have in improving the situation of asymmetric information.

2.2 Venture capital reputation

General definition

Organisational reputation is able to decrease perceived uncertainties since they stem from observed histories of repeated behaviour, features and quality of provided products or services (Lee et. al, 2011). More importantly, they provide competitive benefits by supplying actors in the transaction with more information. All market participants have the incentive to contribute their own skills and resources to enhance the firm's future prospects and potential. Thus, reputation is defined as "*an intangible asset based on broad public recognition of the quality of a firm's activities and output, which is further used to indicate the unobserved abilities and creates the expectations for future performance*" (Dimov et al. 2007).

Determinants of reputation

Many have attempted to quantify the reputation and expertise of venture capital firms through various methods. Some of the various methods used historically have spanned from using the reputation of lead underwriters associated with VCs in IPOs (Baker and Gompers, 2003) to number of investments (Kaplan and Schoar, 2005). But what determines venture capital reputation? Reputation is driven by skill and expertise. The more experience an investor has in investing, growing and exiting companies, the more qualified their assessment framework is likely to be in choosing future companies and hence, delivering returns.

Dimov et. al (2007) suggests that the future performance of VCs is a function of past performance. Gompers and Lerner (1999) state that IPOs are the most successful choice of exit for venture capitalists, often fetching the highest returns. Brau et. al (2002) assess a 22% valuation premium associated with an IPO exit relative to an acquisition. Hence, IPOs can seemingly provide a good proxy of reputation. This stems from the fact that IPOs are the most “visible” strategy for VCs, and repeated successes build compounding credibility. Megginson and Weiss (1991) state that Kleiner Perkins Caufield & Byers (the most reputable fund by their measure) had 10 IPOs in their analysis period of 1983-87. In a similar vein, M&A exits are close runner-ups. Exits to large Fortuner 500 companies and such also build reputation. While the return on investment is lesser than IPO exits, the fact that leading companies value the start-up’s product or services and deem them as an add-on their operations spurs front-page news. Some examples include Square acquiring Afterpay for \$29bn and TIDAL for \$300m. Both with IPOs and M&A exits, repeated successes also increased access to potentially breakout companies, which can be a snowball effect.

However, semantic studies such as Gompers (1996), Hochber et al. (2007) and Sorensen (2007) use proxies such as VC age, number of investments and exits. Other methods also include VC fund return measures such as IRR, or Gross MOIC such as Kaplan and Schoar (2005) and Smith et al. (2009). However, these methods are extremely limiting due to the limited accessibility and poor quality of publicly available information. Table B1 in the Appendix outlines the methods used by researchers to measure reputation.

Benefits of higher reputation

Strong VC reputation is in the interest of both the VCs themselves and their portfolio companies. Entrepreneurs tend to want to be associated with highly reputable VCs for an assortment of reasons, including networking effects, portfolio support, access to talent and

superior funding prospects. Implications of these are direct benefits to the VCs themselves, from the ability to attract more funding from limited partners to higher management fees.

A more reputable fund tends to see larger quantity and quality of deal flow as suggested by Hsu (2004). The higher reputation also helps VCs decrease the costs associated with acquiring equity at a 10-14% discount, and the offers are also more likely to be accepted by entrepreneurs. (David et al. 2005). Additionally, reputable VCs benefit from superior performance as posited by Kaplan and Schoar (2005), and Smith et al (2009). This is partially a consequence of the fact that the reputable VCs have better track records of acquisitions and IPOs of their portfolio companies (Krishnan et al., 2011) and Nahata (2008). Benefits appearing in regards to networking effects are closely related to investors' past experience. One additional investment increases the VCs' information network, either by acquiring important social contacts or gaining experiences in monitoring deals in a particular industrial sector. These reputable VCs are able to attract better co-investors and lead syndication of deals, which improves probabilities of success, but also allows VCs to participate in larger rounds in the growth stage of investments. (Hochberg et al. 2007). The higher reputation, which is a function of past performance, attracts further money inflows for future investments while taking advantage of economies of scale of investment management. (Nahata. 2008).

Monitoring

When VCs decide to invest in firms, they are likely to influence the decision-making process of portfolio companies and provide the value-added services based on their expertise, especially in the case where they have large ownership and board directorship. They have so-called monitoring effects to the target firms, providing the value-added services in the guided direction of human resources, executive compensation design, sales and marketing, whilst ensuring they do not act against the interests of the investors and other stakeholders.

Metrick & Yasuda (2011) summarise the five main monitoring activities, which are connected with VC's reputation. The activities include,

- Board representation: the seats that venture capitalists have on board of directors
- Corporate governance: defining the power-sharing relationship between shareholders and managers, which could be an important input
- Human resources: recruitment and evaluation of management
- Matchmaking: "VCs using their contacts and reputation to make introductions that can lead to new partnerships, customers, and suppliers"
- Strategy: VCs play the strategy role in terms of engaging in strategic decisions

Dimov et al. (2007) also mention that even if VCs are involved in the early-stages of ventures and lack the particular expertise, the reputation can enable them to attract the richer external resources, which is consistent with the “networking effect” of VCs. For the performance of firms with higher reputable VC backing, Nahata (2008) finds that the IPO capitalisation captures VC monitoring expertise, indicating that the firms backed by reputable VCs are more likely to exit successfully, access public markets faster, and have the greater asset productivity at their IPOs. On the other side, firms that are backed by larger VC syndication and received the larger VC funding have lower asset turnover ratio. Shu et al. (2011) based on the sample from the Taiwanese market, find that the IPO firms backed by higher ranked VCs are more likely to have the larger future potential, which is indicated by R&D expenditure ratio. The results are consistent for 3 years post IPOs.

Certification

The certification effects of higher reputable VC’s backing is driven by the expectations of outsider investors towards the close monitoring of portfolio companies by VCs. Hence, this is associated with a decrease in the uncertainty around the quality of the IPO firms, which is also connected with the asymmetric information between outsiders and insiders. The market tends to react positively to the higher reputable VC involvement and the outside investors believe that the firms that VCs invested in would experience higher operating performance after IPOs. Hsu (2005) mentions the reputation as an economic good, and the certification effect can be shown based on the fact that higher reputable VCs have the ability to claim that the projects they backed are not overvalued/overpriced, after their interactions with outsiders. Lee et al. (2011) find the positive relationship between the highly reputable VCs and the better initial market returns, but not the relationship between subsequent operating performance. Thus further indicating that the engagement of VCs helps reduce uncertainty somehow but not necessarily guarantee better performance in the long run.

Grandstanding

Lerner (1994) finds that VCs usually take their portfolio firms public when the market condition is roughly at peaks while the more experienced VCs appear to be more proficient in timing IPOs than their less reputable counterparts. Gomer (1996) suggests that the incentive to shorten time to IPO (i.e., listing firms earlier) may be driven from incentive of grandstanding, although they have a shorter time in board seats and have to bear the costs of underpricing, and further dilution of their ownership stakes.

Grandstanding is consistent with the VC's degree of experience, which is often signalled by the age of VCs. Gompers and Lerner (2004) explain that the grandstanding incentive is exhibited in the actions of younger VCs (defined as those which are less than six years old) who try to signal their ability of successfully taking companies public. The reasons underlying that incentive is the finite lifecycle of VC funds and the demand for periodic fundraising to maintain operation and hence improve reputation. This is shown by the common situation where they bring the companies to IPO earlier than their older counterparts would. The costs incurred from that (the earlier IPO, not the presence of younger VCs) are the higher underpricing levels and the smaller equity stakes. The incentive of grandstanding is not significant with reputable VCs since their experience and performance have been recognised by market investors for a longer time and have lesser asymmetric information concerns arising from the market.

Gompers and Lerner (2004) also discuss the relationship between grandstanding and certification. Grandstanding model deals with the time to IPO and certification is connected with costs of IPO arising from the market's perception of value-add services to IPO firms. The higher expected performance of VC-backed firms, thus help reduce underwriting costs and the degree of underpricing. Considering the demand to recycle money is for both younger and established VCs, Gomper (1996) states that there should be no difference in IPO timing between them, but the sample indicates otherwise. Whether and how, the costs of listing sooner and hence underpricing can be offset by the effects of certification remains as one for future research.

2.3 VC-backed IPO performance

Short-term performance

In relation to the theoretical framework described above, one school of researchers find a lower level of underpricing in VC-backed IPOs (Barry et al., 1990; Megginson, Weiss, 1991), particularly attributed to the monitoring and certification roles they play and the VCs' ability to attract stronger financial stakeholders in the IPO process. Another explanation is posited by Schöber, 2008, and relates to the financial backers. The ultimate goal of the IPO is a high offering price which implies an as small as possible amount of money in first-day returns being left by the exiting shareholders. In the other school of thought, there is contradicting evidence which finds that VC-backed IPOs are associated with more and not less underpricing (Lee and Wahal, 2004; Rossetto, 2008). Tying this along with Gompers (1996), it can be understood that the grandstanding effect can be responsible for the above findings.

Long-term performance

Beyond initial returns, stock prices are analysed over longer periods of times - from one to three years after listing. There is no standardised measure and different studies take varied approaches towards measurement of return, benchmarking and timeframes. Various studies have assessed underperformance in general. Ritter (1991) and Loughran et al. (1994) consider a period of three years and find that investors tend to overestimate the after-market prospects of companies and hence the initial prices are implications of the optimistic valuation estimates.

With respect to VC-backing, there is no popular consensus within academia, and past research offers mixed conclusions. Brav and Gompers (1997) identify an outperformance of VC-backed firms relative to non-VC-backed firms using equally weighted average returns. Particularly, they observe that the small non-VC-backed IPOs perform poorly, and hence this divergence disappears under value-weighted average returns. Espenlaub et. al (2003) find that VC-backed firms tend to underperform compared to non-backed companies towards the end of the typical lock-up period. Similarly, Bessler and Kurth (2005) test the same with a German focus and find an equivalent overperformance of VC-backed companies over a period of six months and an underperformance over the next 18 months Gompers and Lerner (1998) find superior performance of VC-backed IPO firms up until the complete exit of their investors. The effect was eliminated after the VCs' exit from the company on the public market. On the other side, Cumming, MacIntosh (2000) find that performance of the

VC-backed companies actually declines after an IPO compared to non-backed IPO firms. Campbell and Fry (2004) find no difference in performance of VC-backed and non-backed IPO companies.

2.4 Hypothesis

Based on the above literature and analysis of the theoretical framework, we frame our hypotheses in this section. In the short-term, we suspect there to be a premium at which the market values (be it well-or-not justified) reputable VC-backed companies and hence strong, positive initial and short-term returns. This is a well-noted phenomenon often called the ‘first-day-pop’, which is especially prominent around technology IPOs (DuCharme et. al, 2011). Hence, the first hypothesis related to the initial and short-term return profile of VC-backed IPOs.

1. H_0 : Higher reputation of VC-backers prior to IPO does not have any significant impact on 1-day and 6-month returns

H_a : Higher reputation of VC-backers prior to IPO has a significant positive impact on 1-day and 6-month returns

The second hypothesis related to the longer-term return profile of VC-backed IPO companies. As per the above literature, once the 180 day lock-up period expires, VC’s tend to exit the portfolio companies due to the lack of expertise in trading in public markets. With the VCs no longer having any particular influence or obligation to the companies, they are free to act on their own decision-making. As suggested by Espenlaub et. al (2003), we also suspect the market premium to fade out in the long-term, and expect reputation to not have a significant effect on the long-term prices.

2. H_0 : Higher reputation of VC-backers prior to IPO does not have any significant impact on 1-year returns

H_a : Higher reputation of VC-backers prior to prior to IPO has a significant positive impact on 1-year returns

3. Methodology

3.1 Data collection and sample construction

The primary data sources are S&P Capital IQ, and Crunchbase. The initial list of IPO transactions were obtained from Capital IQ with the following filtering criteria:

- Technology companies,
Technology companies are defined as businesses organisations that are centered around a hardware or software technology product or service. Examples include e-commerce, cloud software, biotechnology and digital electronics.
- Previously backed by external institutional investors
We do not have any inherent assumption on what kind of companies can or cannot carry out the function of VCs. Any firm which leads an investment in the early-stage funding rounds, i.e. Seed, Series A, B or C in exchange for equity stake in the company qualifies as a venture capital investment.
- IPO on any major stock market across North America and Europe
Historically, North America has been a ‘hot market’ for VC funding and choice of public market listing. Hence, most studies to date are focussed on the North American region. With the changing dynamics of VC funding and IPOs, we broaden the scope to understand the implication of existing theories, thus the initial selected IPOs transactions are the major US and all European IPO transactions.
- IPO dates between 01/01/2015 and 31/12/2020
The motivation behind the choice of time period was to find one which was recent, given the rapidly growing funding environment in venture capital.

After exporting this initial list of IPO transactions, we then proceed to clean the list to eliminate irrelevant entries including, but not limited to REITs, SPACs, and Holding Companies. The transaction list has also been cleaned to remove unsuccessful IPO transactions, those without underwriter or returns data. From the summary table below, 583 IPO transactions have been included in the selected sample.

Table 1: Number of IPO transactions by year

Year	2015	2016	2017	2018	2019	2020	Total
Number of IPOs	107	61	83	101	101	130	583

The next step in the process is the collection of VC related information for the calculation of the reputation index. Crunchbase offers high-quality data of public and private companies and information includes investments and funding information, founding members and individuals in leadership positions, mergers and acquisitions, news, and industry trends. For the calculation of the VC Reputation Index, the data we collected from the platform was:

- Total number of funding rounds for a particular which has listed
- Lead VC investor
 - Age of the fund
 - Number of investments since inception
 - Number of M&A exits of portfolio companies since inception
 - Number of IPO exits of portfolio companies since inception

3.2 Market performance measurement

The post-IPO market performance, or after-market performance is the percentage change in price level of the stock from the initial listing price. This is traditionally used as a measure of return and performance of the stock. We consider the stock market performance of the company across three time periods - 1 day, 180 days and 365 days. The initial return, or 1 day performance is to analyse the underpricing or first day outlook of the market. Considering the fact that VCs have to hold the equity stakes of issuers beyond the usual 180-day lock-up periods (Field and Hanka, 2001), short-term return of 180 days and long-term return of 365 days are included.

- Initial return (*return1d*) : the initial return is the return on the first trading day, the 1-day time interval is defined as the offering date to the first closing date.
- Short-term return (*return6m*): the short-term return is the 180 day buy-and-hold returns of the IPO transaction, which is the return from the month of listing to the next 6 months. Computing short-term 6 month returns using weekly data that are calculated by compounding daily returns (126 trading days)
- Long-term return (*return1y*): The long-term return included in analysis is the 365 days buy-and-hold returns. Annual return is the compound daily return from the year of listing to the analysed year (either 1 or 3 month), that is, 252 and 756 trading days while monthly return comes from the compounding daily returns of corresponding 21-trading day periods.

Market adjustment

Considering the potential influence from macroeconomic volatility on the market performance of listed firms, we include the matching benchmark returns to form the market-adjusted buy-and-hold returns. Besides, effects from the general economic environment could pose effects to the VC's decision-making process, including the timing to entry, the size of funding, and the difficulty regarding a successful exit etc. Based on Cumming (2010)'s finding, they find that there is a positive relationship between macroeconomic conditions with the VC investment over the same time periods

To include the consideration of macroeconomic conditions, we fetch the matched S&P 500 returns (1-day; 6-month; 1-year). With IPO transaction market performance, we take the difference between the IPO returns and the benchmark returns as the adjusted buy-and-hold returns to ensure all IPO transactions gains are relatively free from general market environment bias to some extent.

Following the approach of Carter et. al (1998), the initial return is calculated as:

$$return1d = \left[\frac{PFT_i}{OP_i} - \prod_{t=0}^{\min(FT, 3)} (1 + \gamma_{mt}) \right] \times 100,$$

where $t = 0, 1, 2, 3$; PFT = closing price on the first day of trading of the stock; FT = first reported trading day; OP = offer price of the stock; and γ_{mt} = return on the S&P 500 index on day t .

And the long-term buy-and-hold return for 6 months and 1 year are calculated as:

$$return = \left[\left(\prod_t^T (1 + \gamma_{it}) \right) - \left(\prod_t^T (1 + \gamma_{mt}) \right) \right] \times 100$$

where t = offer date; T = offer date + 180 or 365 trading days; γ_{it} = return on the the stock i on day t ; γ_{mt} = return on the S&P 500 index on day t .

3.3 VC reputation

As discussed extensively in the theoretical framework section, we have made our case for using a scoring index to treat VCs of different calibre, non-homogeneously. Historically researchers have used multiple methods of quantifying venture capital reputation. The primary struggle with trying to use a complex model considering all aspects of a venture fund's performance is that there exists significant levels of information opacity. Our method leverages the research conducted by Lee et al. (2011), and is optimised to ensure we do not restrict our dataset. VC reputation is measured based on the previous records of *total number of portfolio firms* the VC invested in, the general proxy *VC age*, and measures of activity intensity with the *number of cumulative IPOs and M&As*, Chahine et al. (2021). The Table 2 below summarizes the factors driving the reputation index. Towards the end of section 3.3., we briefly discuss the general limitations of our methodology.

Lead VC and round

Traditionally, a start-up raising external capital goes through 4-6 rounds of investment - namely: Pre-seed, Seed, Series A, Series B, Series C, Series D and so on, and finally, either IPO or Private Equity financing. On average, a particular round of funding has 1-5 venture funds and multiple angel investors. So the question is: which reputation stands behind a particular company? Our approach to this follows in the likes of Krishnan (2011). Within the definition of VC earlier as Seed to Series C, we use the fund with the highest reputation on the largest dollar-amount round a particular company has raised. This ensures we pick up the funds which are likely to offer the company with the greatest operational support and expertise whilst increasing visibility. Once we identify the particular VC which is associated with each IPO company, we dive into the characteristics for the reputation score.

Table 2. *VC Reputation score construction*

VC Reputation	General measure	VC age
	Activity intensity	Total investments
	Exit expertise	IPO exits
		M&A exits

VC age

Age of VC can be used as one proxy of their experience in the industry, which is defined as the time period between the date of incorporation of the VC and the date of IPO of the portfolio company. The construction is based on the assumption that the longer the fund is in existence, the more experience, intangible assets like networking sources, and expertise is gained from previous investment projects. The measurement is similar to Krishan et. al (2011) and is different from the one of Lee et al. (2011), who calculate it as the difference between the focal year of the first raised fund of that VC and the IPO year.

Total investments

The degree of activity participation can be indicated by the number of deals a VC has invested in over a period. Since the more investment experience indicated by the previous deals and fundings, VCs have more choice to show off their ability and efficiency in their investment, which captures the investment density of venture capitalists. It benefits to increase the exposure in the market, making VCs visible, and getting more contacts with other market participants, further building the reputation of VCs. We define total investments as the number of first-time investments into a company from the inception of the fund till the data in concern.

IPO and M&A exits

As previously discussed, it is well-regarded that IPO exits offer the highest returns and visibility to partner venture capitalists of the portfolio companies. M&A exits are close runner-ups with comparably lesser returns to VCs but also good visibility and reputation if a high-profile company is involved in the transaction (Chahine et al. 2021). Hence we incorporate these factors into the reputation scoring index to allow the reputation to pick up exit expertise as a factor. Funds which are experienced in IPO and M&A exits are more likely to help future investments in the same process with top-percentile valuation and returns.

Calculation

For the calculation of annual VC reputation index, we follow a procedure similar to that of Lee et al. (2011). This involves:

- scaling the variables into z-scores,
- aggregating all standardized scores using a weighting function. indicate annual reputation score of each VC

- standardizing all scores within each year on a 100-point scale.

As we posit in the hypothesis section, we expect that the high reputable VC involvement can bring a positive market reaction in the short term, and slowly fade out in the longer term. If VC reputation has a positive influence on the initial market return (performance), it can be explained that engaged VCs with higher reputation eliminate uncertainty within the IPO market based on the perceived benefits brought by venture capitalists. Selection of measure should be the score one year prior to the listing year to avoid the concern of reverse causality between VC reputation and the post-IPO performance.

Controlling reverse causality

There arises a particular problem of reverse causality when it comes to assessing VC funds. Highly reputable VCs, with the resources and network effects at disposal, are more likely to invest in companies that have a much higher success rate as opposed to the choice of companies the lesser reputable VCs invest in (Nahata, 2008). It is necessary to control the reverse causality - i.e. better performance resulting in better reputation, in order to ensure it does not explain the observed patterns. We measure the reputation of the VC in the year prior to the first investment in the portfolio company. By doing this, we relate the past reputation to the future performance, ensuring there is no “look-ahead” bias.

Limitations

There lies an inherent trade-off between the model’s predictive capability and data quality. A more complicated model requires more quality data, which unfortunately is not prevalent within the VC landscape. This includes the difficulty in finding fund and investment returns of a VC firm, LP commitments and fund sizes, and even the structure of the funds. Hence, we proceed to omit the factors drawing severe restrictions on the data collection and quality and possibly give up some accuracy by not incorporating fund performances. However, this approach is rather self-correcting. If we are unable to find specific information like return profiles of VCs, it would not be an unfair assumption that retail investors do not have access to such specialised information either. Hence, by using simpler factors which are easily accessible, we ensure our model is closer to reality than a highly simulated one.

Another limitation we find by using the simpler approach is that it penalises new-age funds significantly even if they have undertaken few high-quality investments. While we find that the relative scoring across funds remains consistent, the absolute values are skewed lower. Further scope for research in the scoring mode could be increasing the quantity of VC funds

used in the indexing and incorporating other factors for quality of investment to reduce the penalty on funds which are quality over quantity.

3.4 Control variables

Total rounds of investment

The stages of investment are regarded as a method for VCs to control the agency costs and moral hazard (Gomper. 1995). Venture capitalists prefer to provide funding in stages rather than the entire funding at once. This allows them the flexibility to abandon the projects if necessary, while considering the development of the project with regards to the asymmetric information, and acquiring additional information about the portfolio firms at each stage of investment. According to Nahata (2008), the total rounds of investment can be a proxy of the quality of the firm since VCs engage in the executive monitoring and know more about the firm's operating performance than outsiders. Thus the follow-on funding occurs only when the firms are potentially doing well. Additionally, benefits that come from reputable VC-backing and relationships depend on the length of their involvement with the portfolio firms (Peggy M et al. 2011). That is, the earlier engagement is expected to bring a higher degree of monitoring, along with a higher influence on the strategy and operations of the portfolio firms. Hence, these effects can be captured by more total rounds of investment.

A company which has potentially raised multiple growth rounds (Series C to Series H or G) could be a signal of a very high quality company providing top-tier returns to investors. Hence, we include this variable as a proxy of the quality of the company.

Percentage (%) of external board members

Previous studies demonstrate that the corporate governance mechanism of firms backed by more reputable VCs have characteristics including the larger number of board of directors, higher proportion of independent outsiders, are less likely to report their financials aggressively, and involve a lesser degree of earnings management. (Gompers, 2003). Findings of Krishnan et al. (2011), show that the more reputable VCs are more likely to hold a larger proportion of equity stakes and board seats in portfolio firms, which normally continue till three years after the IPOs. They further propose that the superior post-IPO performance is driven from the continuous and stronger corporate governance after the issuer's listing.

Following the setting of Pommet et al. (2017), we define the variable of % of external board members as the proportion of outsiders in the overall board members for each listing firm. The data is obtained from Capital IQ. This setting is followed by one important finding of Lee (2011) - the relatively better performance of PE-backed IPOs is positively related with the proportion of equity held by PE-investors and the level of leverage after the portfolio firm being listed. VCs that prefer to act their monitoring role help nominate and hire relevant outside talent in the board of portfolio firms with a higher probability, thereby strengthening the prospects of the firm's future.

Geographical proximity

Geographical proximity is defined as the distance between headquarters of the portfolio firms and the involved VCs and it is believed to influence the post-IPO operating/market performance, effects of VC reputation, and size of fundings from VCs. Previous research finds that the distance between VCs and the portfolio firms is negatively related with the post-IPO performance and the effects of VC reputation. While Lee, Peggy et al. (2011) find that while the geographical proximity shows no significant relationship with post-IPO performance of portfolio firms, the larger distance between VCs and start-ups does underscore the effects of VC reputation. Cumming (2010) propose that the geographical distance is negatively related with the size of investment. This is attributed to the cost of information dissemination, higher costs for monitoring and negotiation, and also the feasibility of being on board of memberships. Thus, we expect that higher geographical proximity could increase the quality of VC's monitoring activities of portfolio firms. Geographical proximity is defined as a dummy, which is set to "1" when the headquarter of a listing firm is the same as the location of the involved lead VC.

Syndication

Syndication or co-investing with other VCs can be defined as different venture capitalists coming together to invest in a start-ups funding round (Joshi. 2015). This is treated as another way to decrease the investment risks and to share operational monitoring, and thus decreasing the potential loss and deal with the uncertainty of project quality. It also shows that the portfolio firm has experienced more due diligence procedures from more investors. Krishnan et al. (2011) suggest that syndication could measure the benefits and the degree of networking of VCs as well. In this analysis, the syndication situation can be obtained based on the investors (VCs, PEs, hedge funds) engaging in the same round of investment, and the same

entry date. Syndication variable is set as one dummy, if the criteria above is met, equals one, otherwise set it as zero instead.

Industry specification

Cumming (2011) suggests industry specifications that are of particular importance to VC firms include information technology, telecom, medical and health technology, and high (deep) technology. This is consistent with the actual industry-wise distribution of VC investments in recent years. Given the relative consistency of the industry distribution investors tend to focus on, we intend to investigate whether the reputation effect (if any) is particularly emphasised in these industries which attract the majority of VC investments. We categorise the listed companies based on their core business strategy and focus.

Education levels of founders

Miloud et al. (2014) state that the features of the founder and the management team can be important to signal to potential investors that the value comes from human capital in terms of prior entrepreneurship experience, education, further contributing to the future development of the firm. This resource-based notion is connected with the quality and valuation of projects. The education level of founders is defined as the dummy variable, the value is equal to “1” if the founder(s) has earned the PhD degree, it is set to zero if lower or equal to Master degree level.

Underwriter reputation

As discussed before, the highly-reputed underwriters potentially decrease the level of information asymmetry. Thus more established underwriters explicitly certify the validity of documents and implicitly show the quality of the IPO issuers. The certification effect associated with highly-reputed auditors follow the same logic.

In this study, the method of calculating underwriter score follows the one from Jay R. Ritter (scores from 10 to 100) and Carter and Manaster (1990) (ranging from 0 to 9). Both the proxies are highly correlated with underwriter market shares, and match the data with the year of IPO date. Our process of calculating the underwriter reputation score is as follows:

- First, we collect all year net proceeds of all IPO transactions and calculate the relative share for every underwriter in that year.
- Second, we aggregate the relative percent of net proceeds of involved underwriter(s) for each IPO transaction, either take the average or the maximum of net proceeds

percent as the engaged underwriter reputation variable. The involved underwriters for each IPO transaction are collected from database Capital IQ or S-1 Registration Statements shown in SEC filings.

Private equity and hedge fund backing

The operating structure, and goals of buyout funds versus other minority-stake private equity companies are significantly different. One particular difference amongst others which academia finds is that the grandstanding motive is significantly less important when there is a PE investment as they already tend to have established reputations within the industry (Flagg, 2007). For our analysis we define the variable *pe* as a company which has taken in a majority shareholder at some point in their funding journey. In order to control for the potential change in company goals and trajectory associated with these investments, we incorporate a dummy variable which takes the value 1 if there has been a private equity investment..

Another phenomenon which has become increasingly prevalent from the 2009 financial crisis recovery is the participation of multi-billion dollar hedge funds in the pre-IPO private capital investing landscape. Examples of these include Tiger Global Management, an USD 80bn public markets fund which, as of 2021 is the most active VC investor, averaging at about 1.3 deals per day. Aragon et. al (2018) suggest that hedge funds are more successful at picking investments than independent venture capitalists, analysing the IPO and M&A rates. They also tend to deploy complex portfolio management strategies and favorable deal structures which include inflated valuations and zero board seats. Hellman et. al (2008) find that non-traditional investors use the venture capital market as a framework to build early relationships with venture firms. Clearly, the dynamics associated with having a hedge fund investor on a private company cap-table cause a shift in dynamics. To control for the situation, we include a hedge fund dummy, which takes the value 1 if there has been an investment round with hedge fund participation.

3.5 Data processing

To figure out the characteristics of the dependent variable, VC reputation, we analyse the distribution of the variable. The graphs below describe the natural and processed distributions of the variable and the complementary table of percentiles is in the Appendix B (Table B3).

Based on the findings of Moller et al. (2005), most conventional multivariate analysis methods are sensitive to outliers since they are proceeded based on least squares where outliers can have an arbitrarily large effect on the estimate and then influencing the accuracy of the model estimation. By using the robust methods, models are able to be fit for most samples, and outliers are regarded as those observations that have larger residuals from the robust fit. By observing the distribution pattern of the VC reputation variable, the concern of the variable diverging normal distribution arises. This is likely to influence the quality of the independent variable further impact the results of regression analyses.

To tackle the concern, we take a similar methodology of Krishnan et al. (2011). We winsorize the return data at 1% and 99% level. Considering the possible effects coming from outliers of VC reputation data, we restrict the range of VC reputation between 10 and 90. After the restrictions, the VC reputation variable tends to distribute more evenly compared to the previous iteration.

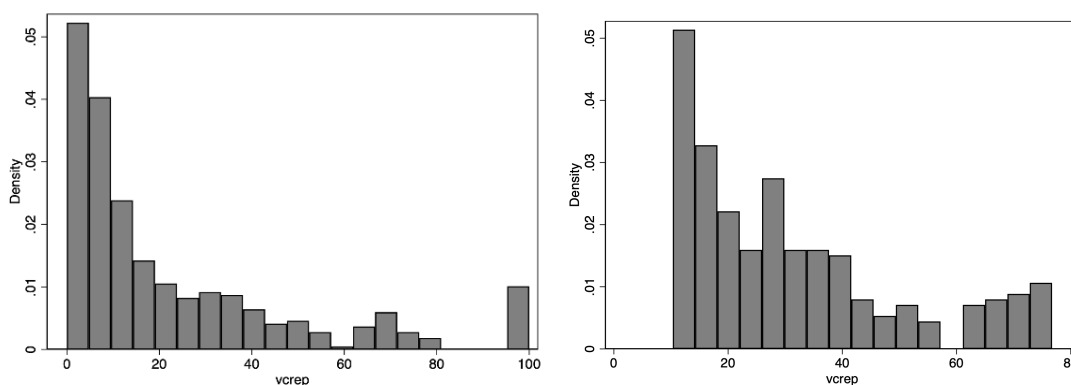


Figure 5. Distribution Density Graph of VC reputation before and after processing (before & after)

From the correlation matrix table, it is clear that all included independent and control variables do not have any concerning levels of correlation. Given the characteristics of the dataset, the likelihood of autocorrelation is small, but the concerns of cross-sectional correlation may be paid more attention to, which is aligned with the calendar-time returns. To

tackle the problem, models within different industries and conditions are presented in the results section.

Table 3. *Correlation Matrix of independent and control variables*

	vcrep	undrep	totrnd	extboard	hedgefund	pe	geo	phd
undrep	0.338							
	(0.0000)							
totrnd	0.233	0.223						
	(0.0000)	(0.0000)						
extboard	-0.064	-0.159	-0.017					
	(0.2597)	(0.0007)	(0.9291)					
hedgefund	0.134	0.32	0.042	-0.152				
	(0.0023)	(0.0000)	(0.1368)	(0.0028)				
pe	0.116	0.125	0.059	-0.101	0.225			
	(0.0071)	(0.0098)	(0.0637)	(0.0562)	(0.0000)			
geo	0.088	-0.018	0.121	0.127	-0.012	-0.04		
	(0.0865)	(0.6590)	(0.0197)	(0.0135)	(0.7486)	(0.4355)		
phd	-0.014	0.045	-0.075	0.054	0.269	0.112	-0.047	
	(0.9688)	(0.3570)	(0.3597)	(0.1450)	(0.0000)	(0.0041)	(0.3045)	
syn	0.085	0.318	0.141	0.011	0.293	0.181	0.019	0.283
	(0.0241)	(0.0000)	(0.0003)	(0.4854)	(0.0000)	(0.0000)	(0.5955)	(0.0000)

For venture capital reputation (vcrep), an independent variable, the highest correlation coefficient is 0.338, with underwriter reputation (undrep). This is followed by total rounds of funding (totrnd, coefficient = 0.233). The positive relation between VC reputation and underwriter reputation is aligned with the supporting theoretical discussion that the deals with better “quality” and prospects for future growth not only attract more rounds of fundings, but also backing from investment bankers and auditors. The total rounds of fundings (totrnd) variable also has high correlation with the underwriter reputation, with the coefficient of 0.223, backing the interpretation as discussed above.

The negative correlation coefficients that have relatively large magnitude are between underwriter reputation and external board member percentage and, hedge fund investors and external board member percentage (-0.159 and -0.152 respectively). Of particular interest is the correlation coefficient between hedge fund backing and external board members, demonstrating their deal dynamics of not taking board seats along with their equity investment.

4. Results

4.1 Preliminary analysis

The goal with this section is to carry out a preliminary analysis and understand the basic features of the dataset. As a precursor, a comprehensive overview of the variables is attached in Appendix A.

Table 4. Descriptive statistics

	Obs.	Mean	Median	Std. dev	Minimum	Maximum
<i>vcrep</i>	575	22.6155	12.7874	25.9732	0	100
<i>undrep</i>	575	3.7165	5	1.7081	0	5
<i>totrnd</i>	575	4.9930	4	3.4434	1	26
<i>extboard</i>	575	40.4921	25.2600	35.0359	0	100
<i>hedgefund</i>	575	0.4035	0	0.4910	0	1
<i>pe</i>	575	0.2696	0	0.4441	0	1
<i>geo</i>	575	0.7578	1	0.4288	0	1
<i>phd</i>	575	0.5217	1	0.4999	0	1
<i>industry</i>	575	4.7617	6	1.9147	1	8
<i>return1d</i>	575	0.2516	0.125	0.4467	-0.9775	3.1265
<i>return6m</i>	527	0.1948	0.0122	0.8108	-1.1455	5.8874
<i>return1y</i>	460	0.2555	-0.1057	1.1689	-1.2157	5.8977

From the table above, few characteristics of the dataset could be observed. The total sample contains 575 IPO transactions, although the 1-year returns is smaller with 460 deals, considering that at the time of data collection, some companies which listed in 2020 did not trade long enough to get the 1-year market returns.

With a rudimentary analysis, there does not appear to be anything particularly concerning. The numerical variables include *vcrep*, *undrep*, *totrnd*, *extboard*. VC and underwriter reputation are defined as the scores, ranging from 0 to 100, and 0 to 5 respectively. Total rounds of funding are the number of investments the issuers received before their listings, and *extboard* is shown as percentage (%). Other control variables including the *hedgefund*, *pe*, *geo*, *phd* are dummy variables to control for specific conditions as described in the methodology section. *industry* is a categorical variable with 8 different classifications. There appears to be a mild skew of the data with the means greater than the medians.

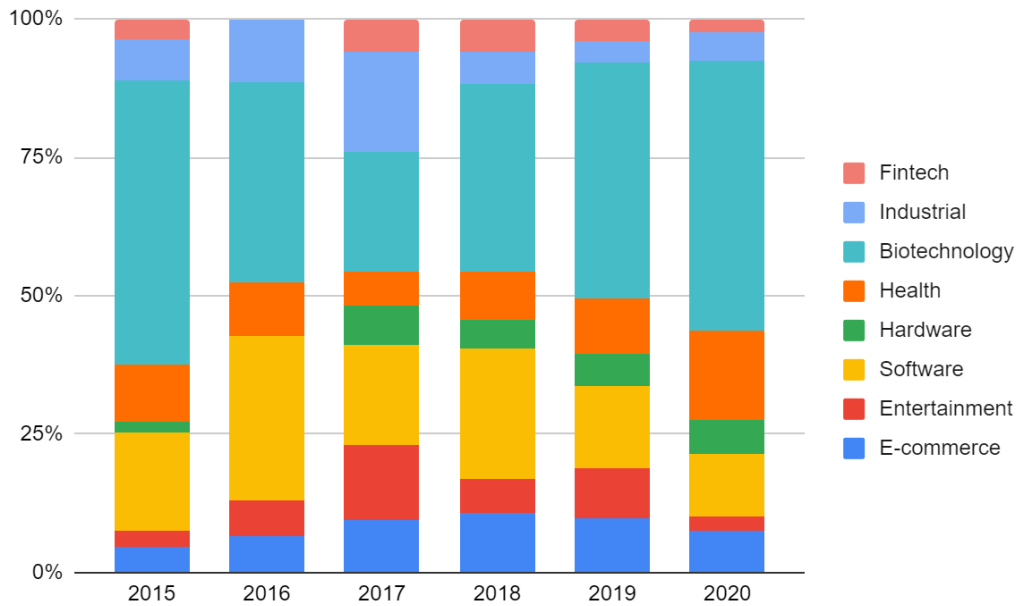


Figure 6. IPO distribution by industry classification

Next, we look at the distribution of IPOs across the time period of our analysis. The most evident finding is the overwhelming majority of biotechnology companies at the beginning and end of the sample period. After a more thorough analysis, we find the young biotechnology companies seek to take advantage of the public markets to fund the extensive research cycles and R&D expenses. It is also interesting to see the spike in health-tech IPOs, from 2019 to 2020, notably accelerated by the COVID-19 crisis. On the other hand, the concentration of e-commerce, and hardware companies have remained consistently on the lower end of the spectrum. The above graph confirms Cummings’ (2011) findings that the focus sectors of venture capital investments lie around information technology and biotechnology. Additionally, it also confirms the increased likelihood of grandstanding in the more research intensive industries, namely biotechnology and health. With the large influx of new venture funds going through the IPO process, it can be presumed only that they are trying to build reputation through these means. Finally, we also see the cyclicity associated in the venture capital investing decisions as suggested by Lerner (2003). Given this understanding of the distribution of the industries across the years, we now seek to analyse the trend in the return profiles from the lenses of the VC reputation index.

Figure 7 plots the yearly trend in median VC reputation and median yearly short to long term returns against year. The goal is to visualize reputation and returns, to identify any potential relationships between them. As we see below, there is a clear upward trend of both venture

capital reputation and returns from 2017 and 2018 respectively. It is also interesting to see that the uptick in the reputation lags behind market-adjusted returns. The trend between *return1d* and *vcrep* seems more in line as compared to *return6m* and *return1y*. These results are in line with our expectation and prior literature. This could potentially suggest venture capital reputation to be a driving factor of the adjusted-returns, particularly *return1d* but requires further rigorous analysis in the next section.

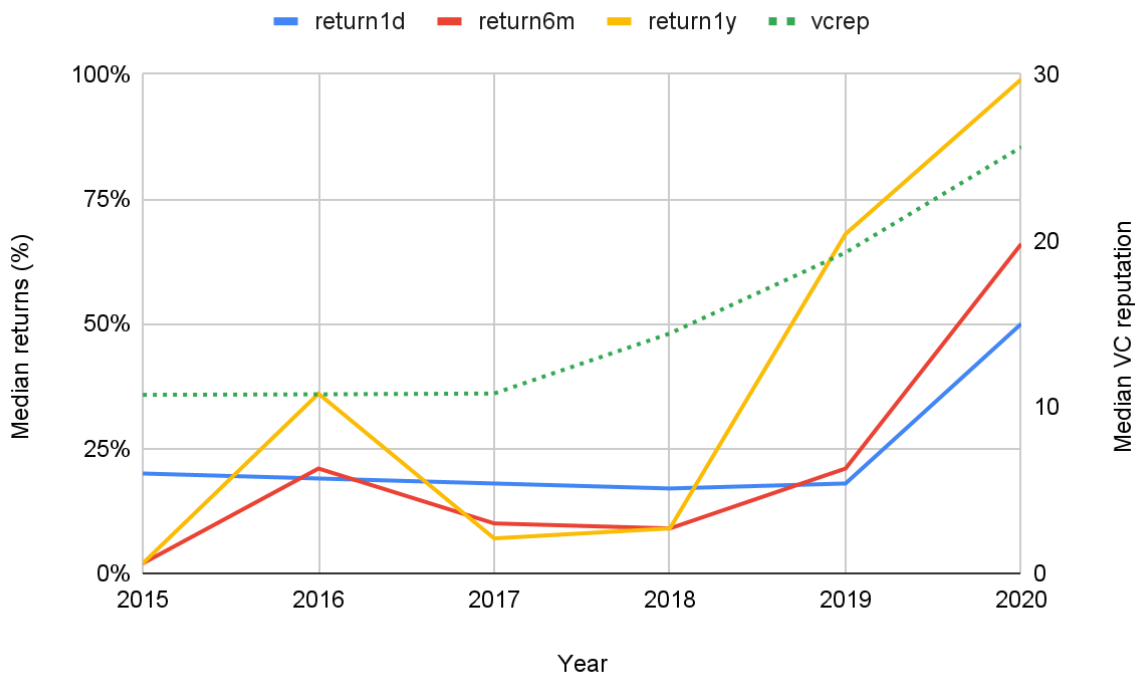


Figure 7. Buy-and-hold return and VC reputation

4.2 Regressions

As initially posited, we suspect the market would proxy reputable VCs’ choice of investments as “good” companies and proceed to associate a market premium to portfolio companies. According to prior literature, there has been evidence of the market premium for VC-backed listed companies in both the short and long-term, mainly attributable to the operating support, monitoring and certification effects. We now tackle the hypothesis with regression analyses.

Univariate regression

We start with a rudimentary univariate regression, using our independent variable, *vcrep*, to assess the general magnitude and direction of the coefficient. The model specification below denotes the univariate regression of IPO transaction market returns with respect to *vcrep*, where *R* stands for the returns of 1-day, 6-month, or 1-year post-IPO market performance.

$$R = \beta_0 + \beta_1 vcrep + \varepsilon,$$

We observe that variable VC reputation is significant for one-day returns but not for six month and one year buy-and-hold returns. Supporting the initial hypothesis and prior literature in VC-backed IPO underpricing, the results suggest that a unit increment in the VC reputation score, increases the one-day return by 0.00162. Although the coefficients of VC reputation become statistically insignificant in the longer run return (6-month and 1-year), the positive signs of independent variable still support our initial expectation, that is, more reputable VCs are more beneficial for the higher post-IPO market returns. However, the simplicity of the model prevents us from making any statistically meaningful conclusions.

Table 5. Univariate regression with 1-day, 6-month, and 1-year return

	(1)	(2)	(3)
VARIABLES	return1d	return6m	return1y
<i>vcrep</i>	0.00162** (0.000726)	0.00175 (0.00135)	0.00243 (0.00208)
Constant	0.216*** (0.0247)	0.157*** (0.0467)	0.205*** (0.0726)
Observations	572	527	460
R-squared	0.009	0.003	0.003
Adjusted R-squared	0.007	0.0012	0.0006

Multivariate regression

We succeed the initial analysis with the multivariate regression with all included independent and control variables, as per the linear specification below. Table 6 shows the results of 1-day return, 6-month return, and 1-year return, as shown in (1), (2), and (3), respectively.

$$R = \beta_0 + \beta_1 vcrep + \beta_2 undrep + \beta_3 geo + \beta_4 totrnd + \beta_5 extboard + \beta_6 hedgefund + \beta_7 pe + \beta_8 phd + \beta_9 syn + \varepsilon,$$

Table 6. Multivariate regression with 1-day, 6-month, and 1-year return

	return1d	return6m	return1y
vcrep	0.00429***	0.00318	0.00286
	(0.00157)	(0.00256)	(0.00449)
undrep	0.0132	-0.0113	-0.0241
	(0.0226)	(0.0363)	(0.0642)
geo	0.0408	0.0481	0.0838
	(0.0716)	(0.113)	(0.199)
totrnd	0.00762	0.00219	0.00581
	(0.00788)	(0.0130)	(0.0226)
extboard	0.000979	0.00211	-0.00351
	(0.000836)	(0.00141)	(0.00280)
hedgefund	-0.0164	-0.193*	-0.593***
	(0.0610)	(0.0999)	(0.180)
pe	-0.0566	0.0425	0.129
	(0.0634)	(0.102)	(0.185)
phd	-0.00281	-0.0156	-0.0850
	(0.0602)	(0.0977)	(0.173)
syn	0.108	0.140	0.327
	(0.0773)	(0.123)	(0.217)
Constant	-0.0837	-0.0295	0.324
	(0.122)	(0.195)	(0.342)
Observations	272	246	220
R-squared	0.060	0.040	0.064
Adjusted R-squared	0.0278	0.0029	0.0242

Prior literature lends support to the idea that VCs help the information asymmetry problem and are a value-add to portfolio companies. While the regression results suggest a premium for VC-backed companies, it does not support the entire narrative. The regression results suggest that for an incremental unit in *vcrep*, the initial 1-day return increases by 0.00429. The coefficients are not significant for the other two time periods. This resounds with our

analyses so far, that the venture capital premium is significant only in the initial return, (*return1d*).

For the control variables in models, the underwriter reputation variable is not statistically significant for three model settings, with the coefficients of 0.0132, -0.0113, and -0.0241 respectively. The latter two appear to diverge from prior literature which states that with more reputable underwriter' backing, the IPO issuers perform better at least in the short term after being listed in the capital market. The correlation table of all independent and control variables show the positive relation between VC reputation index and underwriter reputation, with the value of 0.338. But based on the general insignificance of the *return6m* and *return1y* regressions, we can make a satisfactory reading of *return1d* regression.

Another control variable which stands out is the hedge fund dummy variable. In the full regression, hedge fund is not significant in the case of short-term return (1-day return), but then it is significant in 6-month and 1-year return regression (at 95% and 99% statistical levels), with the coefficients of -0.193 and -0.593, showing the negative relationship between the presence of hedge fund investors and the market returns of IPO firms.

Also contrary to Miloud et. al (2012) is the insignificance of the PhD dummy across all three time frames of returns. We feel this insignificance stems from a vast difference in sample periods. Miloud et al. consider a sample from 1980-2007 whereas ours is from 2015-2020. In the current startup ecosystem, educational background seems less relevant as it did during the dot-com bubble. While educational background still does matter, from a start-up context, an MBA probably equips management with better skills in running a business successfully. Pinelli et. al (2020) confirm these suggestions where they use other metrics of measuring educational background in addition to the PhD degree.

We find that model fit, which we assess through the adjusted R-squared measure, is relatively the same for the *return1d* and *return6m* regressions but falls for *return1y*. This is not too surprising as the predictive capabilities of the model tend to fall as the time frame gets longer. Overall, we find the multilinear regression model resounds with our preliminary findings. There is a significant excess return on the initial day but insignificant market-adjusted excess return on the short-term and long-term returns. There are two possible explanations: (1) VCs do little to aid the information asymmetry, and it is merely a market "expectation". Thus, we see the significant first-day jump, followed by a quick correction of the market hype. (2) The market has trended towards valuing VC-backed start-ups at a premium that before, implying that the offer price at the IPO incorporates this effect. This could explain the higher initial return followed by the quick correction. These oppose some literature from earlier time

periods but they do not disqualify ours as they highlight the market's adaptability and implications of the trends in this new VC boom. Espenlaub et. al (2003) finds that the companies start to underperform towards the end of the lock-up period, and Campbell and Fry (2004) also find no significant difference between VC-backed and non-VC-backed long-term returns.

4.3 Regressions with control variable conditions

In addition to the full regression above which includes all variables, we attempt to further diagnose the results with the addition of some conditions. These include (1) VC syndicated rounds ($syn = 1$), (2) there are hedge fund investors involved in the deal ($hedgefund = 1$), and (3) there are PhD holders on boards ($PhD = 1$). The idea with this experiment is to understand if any of these conditions particularly amplify the coefficient and impact of $vcrep$ on $return1d$. We have already discussed the particular importance of syndication, hedge fund backing and educational background in the previous sections and we complement it with this analysis. We choose to highlight the results of the 1-day post-IPO market return model in this part (with full regression results in the Appendix). The model specifications are shown in the equations below, while the regression results with respect to three conditions are shown in Table 7.

$$(1) R_{1d} = \beta_0 + \beta_1 vcrep + \beta_2 undrep + \beta_3 geo + \beta_4 totrnd \\ + \beta_5 extboard + \beta_6 hedgefund + \beta_7 pe + \beta_8 phd + \varepsilon$$

$$(2) R_{1d} = \beta_0 + \beta_1 vcrep + \beta_2 undrep + \beta_3 geo + \beta_4 totrnd \\ + \beta_5 extboard + \beta_6 pe + \beta_7 phd + \beta_8 syn + \varepsilon$$

$$(3) R_{1d} = \beta_0 + \beta_1 vcrep + \beta_2 undrep + \beta_3 geo + \beta_4 totrnd \\ + \beta_5 extboard + \beta_6 hedgefund + \beta_7 pe + \beta_8 syn + \varepsilon$$

Syndication

Syndication is also called co-investment, in the thesis, represents several VCs co-investing in a funding round. Krishnan et al. (2011) mention there might be the positive relationship

between the returns and size of syndication as the highly reputable VCs are likely to attract more non-lead counterparts. Syndication is also considered as a way for VCs to mitigate the concerns of risks generated from asymmetric information, as Joshi et al. (2015) state. Under this condition, the transactions included in the regression are 217. When VC investors are syndicated in one single deal, the VC reputation variable has a positive relationship with the 1-day after listing market returns. Statistically significant at 95% level, and with a coefficient of 0.0044, it shows that when VC investors syndicate on one deal in the portfolio company's funding rounds, the 1-day market return would rise by 0.0044 correspondingly.

Table 7. *Multivariate regression with 1-day return under the conditions of (1) syn = 1, (2) hedgefund = 1 and (3) phd = 1*

	(1)	(2)	(3)
	return1d	return1d	return1d
vcrep	0.00440** (0.00191)	0.00423* (0.00232)	0.00409* (0.00226)
undrep	0.00198 (0.0316)	0.00941 (0.0441)	0.0488 (0.0358)
totrnd	0.00534 (0.00918)	0.00376 (0.0116)	0.00757 (0.0110)
extboard	0.00150 (0.000986)	0.00203* (0.00115)	0.00102 (0.00117)
hedgefund	-0.0182 (0.0695)		0.0376 (0.0847)
pe	-0.0626 (0.0735)	-0.0708 (0.0817)	-0.0655 (0.0843)
geo	0.0648 (0.0874)	0.147 (0.100)	0.257** (0.102)
phd	-0.00611 (0.0708)	0.0677 (0.0844)	
syn		0.0480 (0.156)	0.0233 (0.139)
Constant	0.0495	-0.168	-0.360*
Observations	217	122	140
R-squared	0.051	0.091	0.117
Adjusted R-squared	0.0147	0.0272	0.0629

Hedge fund dummy

The IPO deals under the hedge fund condition equals to one are 122, which is relatively smaller. Hedge fund and PE dummies show if the hedge fund and PE investors are involved in that IPO deals, which are denoted as the dummy variables. In the model of post-IPO one day return regression, VC reputation variable is at 90% level significant, with the coefficient of 0.00423, which means when hedge fund investors are engaged in the deal, one more score that the VC investor has, the after listing one day return rises by 0.00423. Besides, variable external board member percentage is also significant at 90% level, it has the positive coefficient of 0.00203, meaning that with one more percent rising for the share of external members on boards, the 1-day post-IPO market return increases by 0.00203.

PhD holders

PhD dummy variable is used to describe whether the management of the IPO companies have the PhD degree, regardless if the members are internal or external. This serves to show the educational background of management further demonstrating the positive relationship with after-listing operating and market performance, as suggested by Milound et al. (2014). When regressing 1-day post-IPO market return under the condition that PhD dummy equals to one, VC reputation is significant at 90% statistical level, with the positive coefficient of 0.00409, the positive relationship between VC reputation score and 1-day post-IPO market performance is consistent for the three models. Besides, the coefficient of geographical proximity dummy is 0.257, which is significant at 95% level, showing that when there are PhD holders, and lead VC investor(s) are in the same locations as the IPO issuers', the 1-day market return would increase by 0.257.

We do not find any particular evidence that the above conditions cause any emphasised relationship between returns and reputation. Hence, our findings remain as previously discussed.

4.4 Robustness check

Robustness tests can help confirm the validity of the results. Using the robust standard errors, the standard error estimates are calculated with a sandwich estimator of variance and hence would be unbiased and not suffer from heteroscedasticity. If the variances meet the conditions of homoscedasticity, the assumptions of the Gauss-Markov theorem would be satisfied. Thus although the OLS estimators are unbiased, also consistent, the variances would not be “BLUE” and the formulae for the standard errors would not hold. Thus in the following part, we present the full regression results with the robust standard errors (Brooks, C, 2019). The table below presents the regression results of full regression (the first three rows) and the regressions with robustness standard errors (the last three rows).

Table 8. Regression results without and with robustness standard errors

	return1d	return6m	return1y	return1d	return6m	return1y
vcrep	0.00429***	0.00318	0.00286	0.00429*	0.00318	0.00286
	(0.00157)	(0.00256)	(0.00449)	(0.00247)	(0.00280)	(0.00410)
undrep	0.0132	-0.0113	-0.0241	0.0132	-0.0113	-0.0241
	(0.0226)	(0.0363)	(0.0642)	(0.0380)	(0.0376)	(0.0553)
geo	0.0408	0.0481	0.0838	0.0408	0.0481	0.0838
	(0.0716)	(0.113)	(0.199)	(0.0726)	(0.106)	(0.199)
totrnd	0.00762	0.00219	0.00581	0.00762	0.00219	0.00581
	(0.00788)	(0.0130)	(0.0226)	(0.00851)	(0.0114)	(0.0222)
extboard	0.000979	0.00211	-0.00351	0.000979	0.00211	-0.00351
	(0.000836)	(0.00141)	(0.00280)	(0.000909)	(0.00147)	(0.00260)
hedgefund	-0.0164	-0.193*	-0.593***	-0.0164	-0.193*	-0.593***
	(0.0610)	(0.0999)	(0.180)	(0.0608)	(0.104)	(0.183)
pe	-0.0566	0.0425	0.129	-0.0566	0.0425	0.129
	(0.0634)	(0.102)	(0.185)	(0.0627)	(0.106)	(0.200)
phd	-0.00281	-0.0156	-0.0850	-0.00281	-0.0156	-0.0850
	(0.0602)	(0.0977)	(0.173)	(0.0640)	(0.0990)	(0.184)
syn	0.108	0.140	0.327	0.108	0.140	0.327*
	(0.0773)	(0.123)	(0.217)	(0.0885)	(0.107)	(0.184)
Constant	-0.0837	-0.0295	0.324	-0.0837	-0.0295	0.324
	(0.122)	(0.195)	(0.342)	(0.171)	(0.191)	(0.292)
Observations	272	246	220	272	246	220
R-squared	0.060	0.040	0.064	0.060	0.040	0.064
Adjusted R-squared	0.0278	0.0029	0.0242			

We can easily find out that the coefficients of independent and control variables for three models remain the same, but the statistical significance level of VC reputation decreased to 90% rather than the 99% in the results of the ordinary standard error version regression. For control variables, the hedge fund dummy remains at its significant level, though the standard errors increase in the later case. Worth mentioning that syndication dummy changes at 90% level of significance when using robustness standard errors, remains its positive sign of coefficient, demonstrating the positive effects come from the situation when IPO issuers and VC investors located in the same areas, which aligned with our previous theoretical discussion.

5. Conclusion

The goal of this study was to investigate if VC reputation in VC-backed companies contributed to excess market-adjusted initial to long-term returns after the company's IPO. This was particularly motivated by the significant boom in VC funding and VC-backed IPOs in the past couple of years. This hypothesis is attributed to the various value additions venture capitalists bring to the table, and also the different roles they play in ameliorating the information asymmetry in private companies and IPOs. Initially, we suspected that this effect lasts only as long as the lock-up period of 180 days. After the lock up period, the VCs tend to exit the boards and sell their public holdings due to their inexperience in the public markets and wish to realise their return on investments. Hence, we hypothesized that there would be significant excess returns in *return1d* and *return6m* but not in *return1y* regressions. However, as per our analysis and regressions above, we can reject the first null hypothesis but we are unable to reject the latter with significance.

These findings, as previously discussed, have two possible explanations. The first is the VCs do not in fact have a significant impact on the market performance. Previous literature, although in a minority, does support this explanation where Campbell and Fry (2004) amongst others do find no significant difference between VC and non-VC backed stock performance in the long term. If we go down this route of explanations, our findings imply that the VC-backing is merely an expectation of quality driven by public market investors. It also ties in with practical findings of the "first day pop" as suggested by DuCharme et. al (2001). Once the hype fades out, the market is quick to correct, and drive down the trading price to its "true" value.

The other explanation relates to the new dynamics and adaptability of the public technology markets. Paired with the potential assumption that VC-backed companies are indeed of higher quality, it could be the case that VC-backed IPOs are now valued at a premium at the source, i.e. IPO pricing. This explanation is further reinforced by the fact that IPO valuations are at an all time high, with many suspecting that we could potentially be a stone's throw away from another internet bubble. With lesser underpricing, this could well explain the significance evident only in the initial returns, and insignificance in all the other time frames.

Our study also comes with inherent limitations due to the data quality and period of study. Due to the availability of data, the VC reputation score is a rather simplistic score with sufficient performance. Conducted on a larger longitudinal and latitudinal scale, the scoring model could be more normally distributed and improve significance. Another potential tweak which could improve significance is using the reputation of the largest VC stakeholder or average reputation of all VCs on the capitalisation table. This would eliminate any proxy effects in the reputation. Another possible source of insignificance to this study comes from the regulatory changes in the time period. While we adjust merely on the market return, stronger macroeconomic and regulatory control variables could be leveraged to make a stricter regression framework as suggested by Krishnan (2011).

While we can say VCs may not have a direct impact on the market performance of the company, it does also warrant more holistic analysis on how and where VCs add value (if any). Throughout the study, we have suggested that VC-backed companies could be of higher quality and more “successful”, which we measure by the means of post-IPO returns. For further investigation, one could expand the definitions of “success” for a portfolio company and investment, and investigate the impact on other metrics such as operating performance and proxy measures of information asymmetry. By doing this, we could potentially analyse if VCs in any way, influence the fundamental quality of the business as opposed to the market outlook.

We find satisfactory implications of the study on academia and practise. From an academic perspective, we find that evidently what has held in the early ages of the internet does not seem to hold sufficient significance. We show this with our above findings which appear to be complementary to what we observe in practice and working in VC. There is enough evidence to explore aspects of this study in depth such as building a rigorous reputation model and assessing the value addition of venture capital investors. From a more practical standpoint, our findings suggest that venture capital is prone to significant hype. It puts forward a general awareness that VC-backing is not a proxy of a high-quality company or investment, and they are just as susceptible to market corrections based on their inherent quality as an investment and operating performance.

References

- Aragon, George O. and Li, Emma and Lindsey, Laura Anne, Exploration or Exploitation? Hedge Funds in Venture Capital (2018).
- Baker, M., and P. A. Gompers. "The Determinants of Board Structure at the Initial Public Offering." *Journal of Law and Economics*, 46 (2003), 569-598.
- Barry, C. B.; C. J. Muscarella; J. R. Peavy III; and M. R. Vetsuypens. "The Role of Venture Capital in the Creation of Public Companies: Evidence from the Going-Public Process." *Journal of Financial Economics*, 12(1990), 447-471.
- Beatty, R. P. "Auditor Reputation and the Pricing of Initial Public Offerings." *Accounting Review*, 64 (1989), 693-709.
- Beatty, R. P., and I. Welch. "Issuer Expenses and Legal Liability in Initial Public Offerings." *Journal of Law and Economics*, 39 (1996), 545-602.
- Bebchuk, L.; A. Cohen; and A. Ferrell. "What Matters in Corporate Governance?" *Review of Financial Studies*, 22 (2009), 783-827.
- Brau, J. C.; F. Francis; and N. Kohers. "The Choice of IPO versus Takeover: Empirical Evidence." *Journal of Business*, 76 (2003), 583-612.
- Brav, A., and P. A. Gompers. "Myth or Reality? The Long-Run Underperformance of Initial Public Offerings: Evidence from Venture and Non-venture Capital-Backed Companies." *Journal of Finance*, 52(1997), 1791-1822.
- Brooks, C. (2019). *Introductory econometrics for finance* (Fourth ed.).
- Campbell, Terry L., and Melissa B. Fry, 2004, Venture Capitalist Involvement in the Long-Run Performance of IPOs, *Journal of Private Equity* 10, 7-17.
- Carter, R. B.; I. H. Dark, and A. K. Singh. "Underwriter Reputation, Initial Returns, and the Long-Run Performance of IPO Stocks." *Journal of Finance*, 53 (1998), 265-311.
- Carter, R. and S. Manaster. "Initial Public Offerings and Underwriter Reputation". *Journal of Finance*. 45(1990), 1045-1067.
- Cumming, Douglas J., Jeffrey G. MacIntosh, 2000, The Extent of Venture Capital Exits: Evidence from Canada and the United States, Working Paper, University of Alberta.

Das, P. . *Econometrics in Theory and Practice*. Singapore: Springer Singapore Pte. Limited. (2019)

DuCharme, Larry and Rajgopal, Shivaram and Sefcik, Stephan E., *Lowballing for 'Pop': The Case of Internet IPO Underpricing* (2001).

Elango, B.; V. H. Fried; R. D. Hsinchu; and A. Polonchek. *How Venture Capital Firms Differ*. *Journal of Business Venturing*, 10(1995), 157-179.

Espenlaub, Susanne K. and Goergen, Marc and Khurshed, Arif and Renneboog, Luc, *Lock-In Agreements in Venture Capital-Backed UK IPOs* (2003).

Fama, E. F. "Market Efficiency, Long-Term Returns, and Behavioral Finance." *Journal of Financial Economics*, 49 (1998), 283-306.

Field, L. C., and G. Hanka. "The Expiration of IPO Share Lockups." *Journal of Finance*, 56 (2001), 471-500.

Frosch, Stina, Von Frese, Juergen, and Bro, Rasmus. (2005). *Robust methods for multivariate data analysis*. *Journal of Chemometrics*. 19. 549 - 563.

Gompers, P. A. "Optimal Investment, Monitoring, and the Staging of Venture Capital." *Journal of Finance*, 50 (1995), 1461-1489.

Gompers, P. A. "Grandstanding in the Venture Capital Industry." *Journal of Financial Economics*, 42 (1996), 133-156.

Gompers, P., and J. Lerner. "Venture Capital Distributions: Short-Run and Long-Run Reactions." *Journal of Finance*, 53 (1998), 2161-2183.

Gompers, P., and J. Lerner. "Money Chasing Deals? The Impact of Fund Inflows on Private Equity Valuations." *Journal of Financial Economics*, 55 (2000), 281-325.

Hanley, K. W. "The Underpricing of Initial Public Offerings and the Partial Adjustment Phenomenon." *Journal of Financial Economics*, 34 (1993), 231-250.

Helwege, J., and N. Liang. "Initial Public Offerings in Hot and Cold Markets." *Journal of Financial and Quantitative Analysis*, 39 (2004), 541-569.

Hochberg, Y. V.; A. Ljungqvist; and Y. Lu. "Whom You Know Matters: Venture Capital Networks and Investment Performance." *Journal of Finance*, 62 (2007), 251-301.

Jain, B. A., and O. Kini. "The Post-Issue Operating Performance of IPO Firms." *Journal of Finance*, 49(1994), 1699-1726.

- Joshi, K. and Bala Subrahmanya Mungila Hillemane. "Information Asymmetry Risks in Venture Capital (VC) Investments: Strategies of Transnational VC Firms in India." (2019).
- Kreps, D. M., and R. Wilson. "Reputation and Imperfect Information." *Journal of Economic Theory*, 27 (1982), 253-279.
- Krishnan, C. N. V., and R. Masulis. "Venture Capital Reputation." In *The Oxford Handbook of Venture Capital*, ch. 4, D. Cumming, ed. New York: Oxford University Press (2011).
- Krishnan, C. N. V.; R. Masulis; and A. Singh. "Does Venture Capital Reputation Affect Subsequent IPO Performance?" Working Paper, Vanderbilt University (2006).
- Lee, P. M., and S. Wahal. "Grandstanding, Certification and the Underpricing of Venture Capital Backed IPOs." *Journal of Financial Economics*, 73 (2004), 375-407.
- Lerner, Joshua, 1994, Venture Capitalists and the Decision to Go Public, *Journal of Financial Economics* 35, 293–316.
- Loughran, T., and J. Ritter. "Why Has IPO Underpricing Changed Over Time?" *Financial Management*, 33 (2004), 5-37.
- Masulis, R. W.; C. Wang; and F. Xie. "Corporate Governance and Acquirer Returns." *Journal of Finance*, 62 (2007), 1851-1889.
- Masulis, R. W.; C. Wang; and F. Xie. "Agency Problems at Dual-Class Companies." *Journal of Finance*, 64 (2009), 1697-1727.
- Meggison, W. L., and K. A. Weiss. "Venture Capitalist Certification in Initial Public Offerings." *Journal of Finance*, 46 (1991), 879-903.
- Michaely, R., and W. H. Shaw. "Does the Choice of Auditor Convey Quality in an Initial Public Offering?" *Financial Management*, 24 (1995), 15-30.
- Miloud, T., Aspelund, A., & Cabrol, M. (2012). Startup valuation by venture capitalists: An empirical study. *Venture Capital (London)*, 14(2-3), 151-174.
- Moeller, S. B.; F. P. Schlingemann; and R. M. Stulz. "Firm Size and the Gains from Acquisitions." *Journal of Financial Economics*, 73 (2004), 201-228.
- Moskowitz, T. J., and M. Grinblatt. "Do Industries Explain Momentum?" *Journal of Finance*, 54 (1999), 1249-1290.

- Nahata, R. "Venture Capital Reputation and Investment Performance." *Journal of Financial Economics*, 90 (2008), 127-151.
- Pompilio, D. "Do Venture Capital Firms Promote 'Good' Governance at IPO Companies? An Examination of the Decision to Adopt a Classified Board." Working Paper, Cornell University (2007).
- Ritter, J. R. "The 'Hot Issue' Market of 1980." *Journal of Business*, 57 (1984), 215-240.
- Shapiro, C. "Premiums for High Quality Products as Returns to Reputations." *Quarterly Journal of Economics*, 98 (1983), 659-680.
- Shleifer, A., and R. W. Vishny. "Large Shareholders and Corporate Control." *Journal of Political Economy*, 94 (1986), 461-88.
- Sorensen, M. "How Smart Is Smart Money? A Two-Sided Matching Model of Venture Capital." *Journal of Finance*, 62 (2007), 2725-2762.
- Teoh, S. H.; I. Welch; and T. J. Wong. "Earnings Management and the Long-Run Market Performance of Initial Public Offerings." *Journal of Finance*, 53 (1998), 1935-1974.
- Titman, S., and B. Trueman. "Information Quality and the Valuation of New Issues." *Journal of Accounting and Economics*, 8 (1986), 159-172.
- Verbeek, M. *Guide to Modern Econometrics*. Hoboken: Wiley. (2005)

Appendix A: Key variables

Variables	Type	Definition	Source	Operationalisation
Control Variables				
vcrep	Integer	Reputation score of the lead VC fund which backed the IPO company	Calculated	Regression
undrep	Integer	Reputation score of the underwriter of the IPO company stock	Calculated	Regression
totrnd	Integer	Total number of funding rounds from founding to IPO	Crunchbase	Regression
extboard	Integer	Percentage of board members who are external	Capital IQ	Regression
hedgefund	Dummy	1 if IPO company has a hedge fund investor in the private funding rounds	Crunchbase	Regression
pe	Dummy	1 if IPO company has been backed by a majority equity investor	Crunchbase	Regression
geo	Dummy	1 if IPO company and VC firm are in the same country	Crunchbase	Regression
phd	Dummy	1 if IPO company management has any PhD qualifications	Capital IQ	Regression
syn	Dummy	1 if IPO company has had syndicated investors in funding rounds	Crunchbase	Regression
industry	Categorical	Classification taking values of 1 to 8 based on industry	Capital IQ	Descriptive analysis
Independent Variables				
return1d	Integer	1 day market-adjusted return of IPO stock	Calculated	Regression
return6m	Integer	180 day market-adjusted return of IPO stock	Calculated	Regression
return1y	Integer	365 day market-adjusted return of IPO stock	Calculated	Regression
VC Reputation Index				
VC age	Integer	Years between founding and year prior to IPO of portfolio company	Crunchbase	VC Reputatation Index
Total investments	Integer	Number of first-time investments from inception to year prior to IPO	Crunchbase	VC Reputatation Index
IPO exits	Integer	Number of IPO exits from inception to year prior to IPO	Crunchbase	VC Reputatation Index
M&A exits	Integer	Number of M&A exits from inception to year prior to IPO	Crunchbase	VC Reputatation Index
Others				
Stock, S&P 500 return	Integer	Percentage difference between opening and closing prices based on time frame	Capital IQ	Market-adjusted return
Net proceeds	Integer	Net proceeds from IPOs of an underwriter to calculate market share	Capital IQ, SEC Filings	Auditor reputation

Appendix B: Additional tables

Table B1. VC reputation measures used in existing literature

Studies	Sample Period	VC Reputation Measure
Gompers (1996)	1978–1987	VC age
Gompers, Lerner (1999a)	1969–1994	VC capital under management
Baker, Gompers (2003)	1978–1987	Reputation of underwriters associated with VCs
Lee, Wahal (2004)	1980–2000	Average first-day returns of VC-backed IPOs
Kaplan, Schoar (2005)	1980–2001	VC fund returns
Krishnan et al. (2006)	1993–2002	VC rolling-window IPO market share
Gompers et al. (2006)	1975–1998	VC's industry experience
Hochberg et al. (2007)	1980–1999	VC's network centrality
Sorensen (2007)	1975–1995	VC number of investment rounds
Nahata (2008)	1991–2001	VC cumulative IPO capitalization market share
Smith et al. (2009)	1980–2006	VC fund IRR and cash-on-cash return
Krishnan et al. (2011a)	1993–2002	VC rolling-window IPO market share
Lee et al (2011)	1990–2000	VC scoring index

Table B2. The distribution of sample industries

Industry	2015	%	2016	%	2017	%	2018	%	2019	%	2020	%
E-com	5	4.7%	4	6.6%	8	9.6%	11	10.9%	10	9.9%	10	7.7%
Entertain	3	2.8%	4	6.6%	11	13.3%	6	5.9%	9	8.9%	3	2.3%
Software	19	17.8%	18	29.5%	15	18.1%	24	23.8%	15	14.9%	15	11.5%
Hardware	2	1.9%	0	0.0%	6	7.2%	5	5.0%	6	5.9%	8	6.2%
Health	11	10.3%	6	9.8%	5	6.0%	9	8.9%	10	9.9%	21	16.2%
Biotech	55	51.4%	22	36.1%	18	21.7%	34	33.7%	43	42.6%	63	48.5%
Industrial	8	7.5%	7	11.5%	15	18.1%	6	5.9%	4	4.0%	7	5.4%
Fintech	4	3.7%	0	0.0%	5	6.0%	6	5.9%	4	4.0%	3	2.3%
Obs	107		61		83		101		101		130	

Table B3. *The percentile distribution of vcrep*

Percentiles	%
1%	0.053
5%	0.5299
10%	1.3886
25%	4.7698
50%	13.2013
75%	32.9773
90%	65.6393
95%	76.7245
99%	100
Standard Deviation	25.8495
Mean	22.8783

Table B4. 1-day return regressions with industry constraints

	E-com	Entertain	Software	Hardware	Health	Biotech	Industrial	Fintech
vcrep	0.00200	0.00316	0.00244	-0.00116	0.00558*	-0.000486	0.00394	-0.00736
	(0.00294)	(0.00287)	(0.00235)	(0.00474)	(0.00309)	(0.000971)	(0.00431)	(0.00797)
undrep	-0.0523	0.0218	0.0158	0.0923	0.0714	0.0269	-0.0638	0.000559
	(0.0511)	(0.0420)	(0.0339)	(0.0560)	(0.0506)	(0.0201)	(0.0590)	(0.0851)
syn	0.0858	-0.237	-0.0473	0.0451	0.0659	0.0843	0.346	0.275
	(0.197)	(0.146)	(0.122)	(0.198)	(0.157)	(0.0929)	(0.206)	(0.265)
totrnd	0.0365**	-0.0196	-0.00750	0.0293	0.0121	0.00474	-0.0431	-0.0123
	(0.0167)	(0.0222)	(0.0128)	(0.0218)	(0.0232)	(0.0100)	(0.0336)	(0.0312)
geo	-0.0474	0.248*	0.128	0.253	-0.0295	0.0459	-0.577*	0.372
	(0.146)	(0.140)	(0.141)	(0.268)	(0.172)	(0.0641)	(0.288)	(0.324)
extboard	-0.000115	-0.000705	0.00187	0.000460	0.00622***	0.00257***	-0.00131	0.00381
	(0.00181)	(0.00190)	(0.00141)	(0.00268)	(0.00205)	(0.000832)	(0.00268)	(0.00469)
phd	-0.0138	-0.0998	0.381**	0.341*	0.104	-0.0606	-0.0762	-0.169
	(0.129)	(0.160)	(0.150)	(0.175)	(0.156)	(0.0785)	(0.217)	(0.286)
hedgefund	0.342**	-0.0960	-0.132	-0.00883	-0.0250	0.0434	0.562*	0.218
	(0.131)	(0.189)	(0.123)	(0.215)	(0.155)	(0.0649)	(0.323)	(0.341)
pe	-0.0533	-0.0734	-0.00210	0.0946	-0.0312	-0.0314	-0.626**	0.124
	(0.147)	(0.196)	(0.117)	(0.282)	(0.168)	(0.0617)	(0.262)	(0.286)
Constant	0.0404	0.313*	0.0871	-0.670*	-0.416	-0.0983	0.926***	-0.0210
	(0.224)	(0.153)	(0.184)	(0.349)	(0.298)	(0.110)	(0.323)	(0.545)
Observations	44	33	96	26	55	230	39	22
R-squared	0.342	0.327	0.127	0.472	0.269	0.081	0.361	0.345

Table B5. 6-month return regressions with industry constraints

	E-com	Entertain	Software	Hardware	Health	Biotech	Industrial	Fintech
vcrep	0.00355	0.00276	0.00162	0.00967	0.00555	-0.000412	0.00254	0.00218
	(0.00630)	(0.00407)	(0.00383)	(0.00864)	(0.00648)	(0.00211)	(0.00403)	(0.0137)
undrep	0.0153	0.0520	-0.0315	0.0671	0.0682	0.0605	0.0207	-0.0763
	(0.111)	(0.0589)	(0.0568)	(0.100)	(0.113)	(0.0440)	(0.0595)	(0.157)
syn	0.534	-0.128	-0.158	0.252	-0.106	0.139	0.0996	1.091**
	(0.402)	(0.200)	(0.208)	(0.369)	(0.327)	(0.201)	(0.202)	(0.453)
totrnd	-0.0435	-0.0363	-0.0279	-0.0249	0.0603	0.0203	-0.0716**	-0.0557
	(0.0532)	(0.0306)	(0.0212)	(0.0414)	(0.0483)	(0.0214)	(0.0326)	(0.0525)
geo	-0.327	0.334*	0.155	0.267	0.506	0.236*	-0.531	0.440
	(0.325)	(0.192)	(0.244)	(0.492)	(0.365)	(0.139)	(0.342)	(0.553)
extboard	-0.000194	-0.00419	0.00256	-0.000183	0.00738	0.00378**	-0.00148	0.0134
	(0.00405)	(0.00261)	(0.00247)	(0.00483)	(0.00482)	(0.00190)	(0.00286)	(0.00881)
phd	-0.222	-0.189	0.0348	0.386	0.409	-0.00842	0.114	-0.339
	(0.289)	(0.219)	(0.259)	(0.352)	(0.318)	(0.176)	(0.228)	(0.482)
hedgefund	0.0611	-0.473*	-0.0328	-0.170	-0.171	0.0114	0.0581	0.446
	(0.326)	(0.262)	(0.209)	(0.415)	(0.361)	(0.142)	(0.339)	(0.633)
pe	-0.466	0.327	0.255	0.101	0.252	-0.0985	-0.480	0.0371
	(0.351)	(0.269)	(0.202)	(0.537)	(0.364)	(0.137)	(0.292)	(0.508)
Constant	0.217	0.158	0.417	-0.633	-1.272**	-0.586**	0.816**	-0.508
	(0.495)	(0.214)	(0.310)	(0.634)	(0.587)	(0.237)	(0.333)	(0.961)
Observations	38	32	91	23	47	213	37	21
R-squared	0.194	0.499	0.072	0.353	0.279	0.071	0.297	0.551

Table B6. 1-year return regressions with industry constraints

	E-com	Entertain	Software	Hardware	Health	Biotech	Industrial	Fintech
vcrep	0.0105	0.00281	0.00595	-0.0228	0.00329	-0.00235	0.00311	0.0109
	(0.0128)	(0.00884)	(0.00647)	(0.0366)	(0.0105)	(0.00289)	(0.00648)	(0.0142)
undrep	0.0338	0.228*	0.0186	0.295	0.0379	0.0534	-0.00848	-0.238
	(0.223)	(0.128)	(0.0939)	(0.210)	(0.202)	(0.0589)	(0.0919)	(0.162)
syn	1.262	0.117	0.0758	0.608	-0.559	0.0545	0.193	0.672
	(0.805)	(0.435)	(0.356)	(0.846)	(0.506)	(0.277)	(0.312)	(0.497)
totrnd	-0.131	-0.0504	-0.0303	0.0500	0.147	-0.0155	-0.00739	-0.0117
	(0.112)	(0.0664)	(0.0361)	(0.0967)	(0.0944)	(0.0289)	(0.0492)	(0.0560)
geo	-0.336	0.243	0.539	-0.491	0.851	0.356*	-0.406	0.188
	(0.691)	(0.417)	(0.397)	(1.065)	(0.549)	(0.193)	(0.532)	(0.578)
extboard	0.000536	-0.00963	-0.00430	0.00492	0.00340	0.000738	-0.00347	-0.00790
	(0.00890)	(0.00567)	(0.00467)	(0.0126)	(0.0102)	(0.00307)	(0.00432)	(0.0104)
phd	-0.258	-0.833*	-0.246	0.737	0.302	0.240	0.382	-0.197
	(0.572)	(0.476)	(0.437)	(0.848)	(0.516)	(0.239)	(0.348)	(0.508)
hedgefund	-0.359	-1.358**	-0.482	-0.302	-0.558	-0.0438	-0.361	-0.689
	(0.690)	(0.569)	(0.347)	(1.078)	(0.602)	(0.200)	(0.528)	(0.652)
pe	-1.030	1.101*	0.514	1.153	0.567	-0.132	-0.293	0.00324
	(0.744)	(0.583)	(0.342)	(1.739)	(0.602)	(0.191)	(0.477)	(0.569)
Constant	0.248	0.329	0.129	-1.035	-1.163	-0.385	0.334	0.732
	(0.981)	(0.465)	(0.502)	(1.508)	(1.005)	(0.310)	(0.544)	(0.994)
Observations	36	32	83	20	39	172	35	19
R-squared	0.188	0.601	0.091	0.303	0.267	0.044	0.106	0.366

Table B7. Regressions with (1) *hedgefund = 1* and (2) *pe = 1*

	return1d	return6m	return1y	return1d	return6m	return1y
vcrep	0.00423*	0.00217	-0.000753	0.00384	0.00396	8.82e-05
	(0.00232)	(0.00392)	(0.00496)	(0.00250)	(0.00468)	(0.00864)
undrep	0.00941	-0.00752	0.0524	0.145***	0.169*	0.218
	(0.0441)	(0.0714)	(0.0937)	(0.0502)	(0.0932)	(0.175)
totrnd	0.00376	-0.00937	-0.0129	0.0165	-0.00263	-0.0151
	(0.0116)	(0.0195)	(0.0249)	(0.0126)	(0.0223)	(0.0393)
extboard	0.00203*	0.00202	-0.00626*	-0.00143	0.000278	-0.00801
	(0.00115)	(0.00208)	(0.00361)	(0.00163)	(0.00314)	(0.00731)
geo	0.147	0.126	0.0923	0.137	0.0422	0.100
	(0.100)	(0.157)	(0.213)	(0.121)	(0.210)	(0.378)
pe	-0.0708	0.0416	0.112			
	(0.0817)	(0.131)	(0.173)			
phd	0.0677	0.137	0.186	0.0594	-0.145	-0.317
	(0.0844)	(0.139)	(0.174)	(0.103)	(0.185)	(0.335)
syn	0.0480	-0.211	-0.391	-0.0652	-0.0321	0.0857
	(0.156)	(0.251)	(0.310)	(0.159)	(0.283)	(0.537)
hedgefund				-0.0721	-0.197	-0.566*
				(0.102)	(0.178)	(0.326)
Constant	-0.168	0.0287	0.171	-0.629**	-0.511	0.0134
	(0.267)	(0.433)	(0.557)	(0.292)	(0.539)	(0.979)
Observations	122	103	88	83	77	69
R-squared	0.091	0.049	0.075	0.194	0.101	0.138

Table B8. Regression with $geo = 1$ constraint

	(1)	(2)	(3)
VARIABLES	return1d	return6m	return1y
vcrep	0.00139 (0.00172)	0.00259 (0.00298)	0.000983 (0.00531)
undrep	0.0628** (0.0244)	0.0160 (0.0411)	-0.0127 (0.0740)
totrnd	0.0198** (0.00858)	0.0166 (0.0150)	0.0192 (0.0265)
extboard	0.00144* (0.000865)	0.00269* (0.00152)	-0.00269 (0.00301)
hedfund	-0.0235 (0.0651)	-0.213* (0.112)	-0.666*** (0.203)
pe	-0.0217 (0.0683)	0.0520 (0.116)	0.157 (0.212)
phd	0.101 (0.0662)	0.152 (0.113)	0.114 (0.204)
syn	0.0283 (0.0866)	0.0306 (0.146)	0.325 (0.264)
Constant	-0.249** (0.125)	-0.181 (0.210)	0.242 (0.375)
Observations	217	193	171
R-squared	0.094	0.053	0.072

Table B9. Regression with $phd = 1$ constraint

	return1d	return6m	return1y
vcrep	0.00409*	0.00376	0.00317
	(0.00226)	(0.00381)	(0.00631)
undrep	0.0488	0.0143	-0.0646
	(0.0358)	(0.0589)	(0.101)
totrnd	0.00757	0.000611	0.00717
	(0.0110)	(0.0178)	(0.0290)
extboard	0.00102	0.00204	-0.00223
	(0.00117)	(0.00202)	(0.00410)
hedgefund	0.0376	-0.0705	-0.287
	(0.0847)	(0.140)	(0.238)
pe	-0.0655	-0.0964	-0.0734
	(0.0843)	(0.139)	(0.235)
geo	0.257**	0.329**	0.491*
	(0.102)	(0.166)	(0.286)
syn	0.0233	0.195	0.164
	(0.139)	(0.225)	(0.395)
Constant	-0.360*	-0.447	0.102
	(0.194)	(0.326)	(0.551)
Observations	140	126	105
R-squared	0.117	0.072	0.063

Table B10. Regressions with $syn = 1$ constraint

	(1)	(2)	(3)
VARIABLES	return1d	return6m	return1y
vcrep	0.00440** (0.00191)	0.00293 (0.00314)	-0.000202 (0.00558)
undrep	0.00198 (0.0316)	-0.00253 (0.0516)	0.00894 (0.0919)
totrnd	0.00534 (0.00918)	0.00122 (0.0153)	-0.000851 (0.0267)
extboard	0.00150 (0.000986)	0.00322* (0.00166)	-0.00230 (0.00336)
hedgefund	-0.0182 (0.0695)	-0.242** (0.114)	-0.678*** (0.207)
pe	-0.0626 (0.0735)	0.0390 (0.118)	0.145 (0.213)
geo	0.0648 (0.0874)	0.0296 (0.139)	0.174 (0.250)
phd	-0.00611 (0.0708)	0.0306 (0.116)	-0.0998 (0.205)
Constant	0.0495 (0.171)	0.0616 (0.278)	0.583 (0.488)
Observations	217	194	172
R-squared	0.051	0.054	0.070