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VC and abnormal return around lock-up: evidence for downward sloping demand curves?

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ABSTRACT

In this research, I delve into the differences in abnormal returns and volume fluctuations during the lock-up expiration periods between venture capitalist and non-VC-backed Initial Public Offerings. I compile a thorough dataset of USA based IPOs from June 1990 to June 2022, using the Eikon New Issue Database and CRSP database. My findings reveal a marked negative Cumulative Average Abnormal Return and Average Abnormal Returns only within VC-backed firms during the lock-up time frame. Interestingly, these negative returns seem to persist in the long run. On the other hand, I don't observe such effects within non-VC-backed companies. Despite my attempts to counteract selection bias through Propensity Score Matching, I recognise the challenge of definitively confirming the correlation between VC backing and CAAR. I also notice abnormal volume fluctuations in both VC and non-VC backed companies, yet a significant negative relationship between abnormal volumes and CAAR is only visible in the VC-backed sample. I propose several hypotheses to explain these phenomena, such as the loss of monitoring role and stock overvaluation due to the type of investors attracted by VC-backed firms. I underscore the need for more comprehensive studies to conclusively establish causality and investigate other possible factors for abnormal return.

Keywords: IPO, Lockup, Venture Capital, Heterogeneous Believes, Market Efficiency

JEL codes: G140, G240

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CHAPTER 1 Introduction

The phenomenon of a price decline when insiders are allowed to sell their shares for the first time following the lock-up period is intriguing, particularly considering the semi-strong form of market efficiency as proposed by Fama (1970). According to this concept, stock prices should incorporate all publicly accessible information. However, as the recent news article ‘BuzzFeed Shares Drop 41% in Wake of Investor Lock-up Expiration ’(Wall Street Journal) points out, it is not rare for a company to exhibit abnormal returns around the lock-up expiration date. During the initial public offering (IPO) process, investors are made aware of the lock-up expiration date and the number of shares that will become unlocked, albeit not the specific volume of shares that will be sold. This raises questions about the nature of this price decline, considering that the information concerning the lock-up period is publicly available. In addition, the observed price decline may manifest differently for venture capital (VC)-backed companies than those not backed by VC. The lock-up expiration dynamics in these two cases could reveal reasons for abnormal returns after the lock-up period.

Many researchers have studied the performance of companies post-IPO in the past, particularly IPO underpricing; however, more discussion needs to be attributed to the post-lockup abnormal return and the role of downward sloping demand curves in it. The semi-efficient market hypothesis suggests that markets should incorporate all existing information in stock prices (Fama, 1970), and lock-up agreement is known to the market. However, empirical research suggests abnormal returns surrounding lock-up expiration (D. J. Bradley et al., 2001; Brav & Gompers, 2003). The Hong et al. (2006) theoretical model also suggests that abnormal return surrounding the lock-up period is attributed to heterogeneous beliefs of insiders and non-insiders, which in pair with downward sloping demand curves and short scale constraint could lead to price decline after the lock-up period. Venture capitalists often use IPO as an exit strategy; however, it is constrained in selling stocks for a specific period due to lock-up agreements. This research will combine the methodology of Lee & Wahal (2004), who examine the relationship of VC backing on IPO underpricing, with Bradley et al. (2001) who studies the relationship between VC backing and abnormal return post lock-up period.

The main question of this study is, ‘Why do we see abnormal returns around lock-up expiration?’. I study whether there is abnormal return surrounding the lock-up period for VC and non-VC-backed companies and whether VC backing contributes to it. Finally, I will find how the effect of other factors that could contribute to abnormal returns differs under VC backing and non-VC backing to test existing hypotheses on abnormal returns surrounding lock-up expiration. The main question can be studied by examining the price movement of VC and non-VC IPOs during lock-up expiration. I suspect that the primary cause of abnormal returns after the lock-up period is a difference in expectations between insiders and non-insiders coupled with downward-sloping demand curves. Hence, I suspect VC-backed companies experience higher underpricing due to several factors. The exit of VC firms, particularly if unexpected by overconfident investors, may result in higher abnormal returns due to the loss of their monitoring role (Bernstein et al., 2016; Yung & Zender, 2010). Or high selling pressure upon lockup expiration, as VC firms typically use IPO as an exit strategy, could lead to a greater abnormal return on the expiration date (Field & Hanka, 2001; P. Gompers & Lerner, 1998; Hong et al., 2006). This and other reasons are discussed in Theoretical framework section.

My dataset will contain the American market from 1990 to the 2022 year. The dependent variable of research interest is CAR for the 5-day window (-2;2). I estimate daily stock returns post-lockup period based on the market model, using CRSP value weighted index return as market return, and then calculate actual abnormal returns as residuals of this model. Then I calculate cumulative abnormal return (CAR), average abnormal return (AAR) and cumulative average abnormal return (CAAR). I also estimate abnormal volume and average abnormal volume (AAV). Details of calculations are present in Section 4. All data come from the Eikon New Issue database and CRSP database. The treatment variable of interest is a dummy variable that takes one if the company was VC backed and zero otherwise. The data come from the Eikon New Issue database, distinguishing between VC and non-VC IPO. First, I do an event study analysis to check whether companies in the American market experience abnormal returns after the lock-up period. Nevertheless, because VC backing is nonrandom and only some companies can attract VC firms, I would like to know how the abnormal return of VC-backed companies would have changed if they did not obtain VC investment. Hence, I perform propensity score matching (Austin, 2011; Rosenbaum & Rubin, 1985) to estimate the average treatment effect on the treated. Using logistic regression, I will estimate propensity score or, in other words, the probability of being selected by VC. Then match the treatment and control group using nearest neighbour matching and Kernel matching method, then find the average treatment effect on the treated. For multivariable analysis, I perform multivariate OLS regression with a complete set of controls and a VC dummy. By comparing the results of these methods, I can assess the robustness and validity of my findings.

From this research, I expect to deepen understanding of abnormal returns surrounding lock-up expiration. The last papers on lock-up abnormal expiration in USA are not new, so I plan to contribute existing knowledge by studying newer data sets and adjusting for selection bias which has yet to be done. I suspect to find out that both VC and non-VC-backed companies experience negative abnormal returns due to differences in the beliefs of insiders and non-insiders. I expect that VC companies will experience higher negative abnormal returns due to being more sensitive to information asymmetry between insiders and non-insiders; also, I expect that positive post-IPO performance and locked per cent of shares will have a higher effect for VC-backed companies than for non-VC backed ones in line with the theoretical model of Hong et al. (2006).

This thesis provides a exploration of the influence of venture capital on post-IPO performance, focusing specifically on the role of lock-up agreements and their impact on abnormal returns. Starting with a investigation of venture capital, I highlight its various functions and crucial role during the IPO stage. Then explore lock-up agreements, illustrating the reasons behind their implementation and why insiders may choose to exit investments. Furthermore, I present a discussion on abnormal return, its causes, empirical evidence surrounding it, and how it is affected during lock-up expiration. Special attention is paid to the role of venture capital in relation to abnormal return and volume, and other potential variables contributing to abnormal returns. Following this, I introduce the dataset used for this study, presenting the methods applied in analysis, such as calculating abnormal returns and volumes, propensity score matching, and regression analysis. The resulting chapter then synthesizes and presents the results from this analysis. Ultimately, the thesis concludes with an overall interpretation of the findings.

CHAPTER 2 Theoretical Framework

2.1 Venture Capital

The field of venture capital has evolved significantly over the years. The first two venture capital firm, American Research and Development Corporation (ARDC) and and J.H. Whitney & Company were established in 1946. Over the years, the field has grown and diversified, with different types of venture capital firms emerging, including corporate venture capital and independent venture capital firms (Gompers & Lerner, 2001). Venture Capital is part of a private equity form of financing. However, in comparison to traditional PE firms VC companies usually provide capital to early-stage startups. In comparison to debt financing VC firms usually exchange capital to equity and participate in decision making of the firms. Venture Capital is like Angel Investing as both invest in early-stage companies in exchange for equity, however angel investors are typically individuals. Venture capital is usually studied in the context of investment decision making, its functions and exit strategies.

2.1.1 Venture Capital functions

In venture capital, investors typically occupy the role of General Partners. These individuals receive a compensation for their administrative responsibilities of fund management. Nevertheless, their most substantial wealth accrual materialises with the firm's divestiture. Enterprises that benefit from the financial backing of VC investors tend to be privileged within the investment community, mainly attributable to their discernible superiority in performance relative to other initial public offerings and the overarching market, as corroborated by the work of Brav & Gompers (1997). Venture capital firms execute specific roles within companies, aiming to mitigate principal-agent conflict. These roles encompass certification, coaching, and monitoring, as delineated by Wright Robbie (1998). As conceptualised by Colombo & Grilli (2010), the monitoring function pertains to acquiring proprietary knowledge and active involvement in business proceedings and signalling the quality of the enterprise to the broader market. In contrast, the coaching function is associated with the expertise inherent in venture capital firms and their capacity to effect substantial alterations in the resources and competencies of their portfolio companies. As detailed by Baum & Silverman (2004), the certification role is connected to the capability of venture capital entities in identifying firms with substantial growth potential. This identification subsequently serves as a market signal communicated through the venture capital firm's endorsement.

2.1.1 Venture Capital role during IPO

In alignment with their monitoring and certification roles, venture capital funds frequently adopt concentrated equity stakes, sustain their investments past the initial public offering phase, and partake in the board memberships of their portfolio companies (Barry et al., 1990). Barry et al. (1990) were pioneers in elucidating venture capital firms' role when their investments transition into public ownership. Their scrutiny of initial public offerings from 1978 to 1987 yielded insights into the intensive monitoring services provided by venture capital. Consequently, they discerned that venture capital firms of superior quality experienced less underpricing during their IPO procedures, underscoring the value of their intensive monitoring role. The reasons for taking a company public for VC firms was researched by Gompers (1996). He finds evidence suggesting that younger venture capital firms speed up taking companies public compared to their older counterparts. The rationale behind this behaviour is to establish a reputation and consequently garner success in future fundraising efforts, a phenomenon he labels the ‘grandstanding hypothesis’. Lee & Wahal (2004) conducted a comprehensive study of the underpricing of venture capital-backed IPOs during the two-decade span from 1980 to 2000. They further substantiate the grandstanding hypothesis. Their findings indicate abnormal first day returns and a correlation wherein greater underpricing results in more significant future inflows to the venture capital fund. Jain & Kini (1995) identify the monitoring role of venture capital during the IPO process. They discern that IPOs backed by venture capital tend to experience elevated valuations and demonstrate superior operating performance. Brav & Gompers (1997) also add to the discourse, asserting that venture capital backed initial public offerings generally outpace non-VC-backed IPOs regarding equal-weighted returns. Myers & Majluf (1984) explored the role of venture capital in the valuations of initial public offerings. Their findings challenge the certification hypothesis, instead offering considerable support for the market power hypothesis. Chemmanur and Loutskina (2006) research indicates that venture capital participation amplifies the heterogeneity of investors in an IPO by attracting a more significant number of high-calibre investors.

2.2 Lock-up

Lock-up period after IPO is predetermined time during which pre-IPO shareholders are prohibited from selling their shares. US lock-up agreements are voluntary. However, the 180-day lock-up provision has been found to be standard practice. This section is going to explore the reason for such lock-ups.

2.2.1 Reasons for lock-up

The event of a company's Initial Public Offering is an process wherein the organisation seeks capital inflows from a wide-ranging public audience through share issuance in capital markets. Information asymmetry and adverse selection are intrinsic to the IPO procedure, owing to the scarcity of accessible knowledge concerning the IPO companies for retail investors (Myers & Majluf, 1984). Lock-up agreements, significant facets of the IPO process, operate as bonding mechanisms, generally curtailing the liquidation of shares in the IPO aftermarket by pre-IPO shareholders and internal stakeholders. The foundation of the signalling theory for lock-ups can be attributed to the pioneering efforts of Leland and Pyle (1977). Their influential work elucidates the consequences of financial decisions on an enterprise's value in markets characterised by information asymmetry between business founders and prospective investors. Entrepreneurs, typically risk-averse, seek to distribute risk by inviting external investors through public offerings. However, their superior knowledge of the firm's value raises credibility concerns. To address this, Leland & Pyle (1977) propound a theoretical model suggesting that increased entrepreneurial ownership signals the endorsement of more favourable projects, thereby aiding issuers in securing better IPO prices. Nonetheless, Gale and Stiglitz (1989) express scepticism about the under-diversification being a signal of firm quality. They note that entrepreneurs have the option to liquidate shares immediately in the IPO aftermarket, which can potentially undermine the signal's potency. Courteau (1995) responds to this critique by presenting the concept of lock-up agreements as a binding mechanism. In this paradigm, business founders pledge to hold their shares for periods surpassing those stipulated by regulatory mandates, serving as a testament to the firm's quality. The period during which the ownership is maintained is a supplementary signal to the retained involvement in the entrepreneurs' initiatives, dependent on the firm's information framework. Brav and Gompers (2003), however, only validate the lock-up commitment function during an IPO to offset moral hazard for poor management or insiders not to take advantage of the public and hence agree for the higher lock-up duration. They do not find any evidence to endorse the signalling mechanism's role for insiders to signal their quality. Nevertheless, Brau et al. (2005) revised this question and concluded that Brav and Gompers (2003) misinterpreted part of their evidence and showed that signalling is still the primary role of lock-up.

2.2.2 Reasons for insiders to exit investment

Espenlaub et al. (2001) propose two primary motivations driving pre-IPO shareholders to liquidate their shares around expiration: portfolio diversification and the aspiration to monetise investments. Bodnaruk et al. (2008) discovered that individual shareholders who have less diversified portfolios, particularly those with lower wealth, are more likely to sell a larger portion of their shares during an initial public offering. They also noted that companies with controlling shareholders who have less diversified holdings exhibit a higher likelihood of going public. According to the research conducted by Chen et al. (2012), while lock-up expirations do offer insiders a chance to distribute their shares for a firm's diversification, the sales conducted by high-ranking executives appear to be partly influenced by confidential information. Conversely, other insiders' sales align more with portfolio diversification strategies.

2.3 Reasons for abnormal return

2.3.1 Empirical Evidence for abnormal return around lockup expiration

Field & Hanka (2001) were among the first to analyse share price reactions before, during, and after lock-up expiration. Their findings reveal that the mean cumulative average abnormal return significantly differs from zero at the 1% level. In a broad investigation encompassing a sample of 2,529 firms, Bradley et al. (2001) uncovers statistically significant average abnormal returns on the event day and CAR within the event window. Analysing a larger sample of 2,793 US firms, Brav and Gompers (2003) observe negative daily abnormal returns and statistically significant buy-and-hold abnormal returns. Ofek (2000) similarly find negative abnormal returns surrounding IPO expiration and attributes it to downward sloping demand curves. Finally, Brau et al. (2004), in their study of 3,049 US firms, discover statistically significant cumulative average abnormal returns (within the [-4, 0] event window. Hakim et al. (2012) closely examine the effects of IPO lock-up expirations in the Middle East and North Africa region, identifying substantial responses in stock prices. This observation suggests that the impact of lock-up expiration on share prices transcends geographical boundaries. Yang & Hou, (2017) similarly notice a marked decrease in share prices accompanied by elevated trading volumes for Venture Capital Trust (VCT) IPOs listed on the London Stock Exchange. Interestingly, they report less unusual returns for VCTs that channel their investments into companies listed on the Alternative Investment Market (AIM). They hypothesise that this occurrence is due to the heightened information asymmetry within these markets. Similarly, Haggard & Xi (2017) identify significant price reactions in proximity to lock-up expiration events in their examination of the Chinese market and attribute it to market overvaluation. This supports the premise that the effect of lock-up expiration on share prices persists across diverse regulatory environments and national contexts.

In contrast, several studies have detected an absence of any significant adverse fluctuations in share prices around the time of IPO lock-up terminations. Espenlaub et al. (2001) embarked on an examination of UK IPOs, while Schultz, (2008) centered his attention on US internet stocks amidst the 2001 bubble, and Hong Kong IPOs constituted the focus of the research conducted by Goergen et al. (2010) None of this research found any substantial price changes corresponding to the impending lock-up expiration.

2.3.2 Downward sloping demand curves, heterogeneous beliefs and short sale constrain

The efficient market hypothesis (EMH) is a theory that states that financial markets are "informationally efficient", meaning that asset prices reflect all available information (Fama,1970). The EMH assumes that the demand curve for stocks is horizontal, which means there is no heterogeneity in beliefs on the stock price. Any supply or demand shocks without information do not affect the prevailing price (Xing, 2008). However, Shleifer (1986) tests this assumption by studying the effect of the inclusion of stock into the S&P 500 and finds out that the return on the day of inclusion is positively related to measures of buying by index fund and not in line with horizontal demand curves. They then propose downward demand sloping curves as the primary explanation, caused by a disagreement about the fair value of a security by two or both groups of investors. Harrison & Kreps (1978) propose a model with dogmatic heterogeneous beliefs and show that an asset price can exceed its fundamental value because of anticipation of finding a buyer willing to pay even more in the future. Morris (1996) develops a model with Bayesian learning with heterogeneous beliefs about the probability of high dividends. They show that in a world with investors exhibiting diverse beliefs about stock price and the existence of short sale constraint, the stock price can be higher than the fundamental value. Diether et al. (2002) investigate the role of analyst dispersion in explaining stock returns. They argue that analyst dispersion proxies for differences in opinion among investors. They find that stocks with high analyst dispersion have lower prices and higher future returns than stocks with low analyst dispersion.

2.3.3 Downward sloping demand curve, heterogeneous beliefs, and short sale constrain in the context of abnormal return around the lock-up period

The expiration of the lock-up period undeniably results in an amplified supply of shares readily available for trading in the secondary market. As per the foundational construct of downward-sloping demand curves, a permanent change in supply would inevitably cause a stock price reduction if the demand curve followed this pattern (Ofek, 2000). However, this basic framework does not explain why investors would consistently misjudge the number of stocks insiders sell after the lock-up period's expiration. Specifically, the IPO price on initial trading days should account for the potential price effect inferred from the event, discounted at the stock's requisite return. Consequently, on average, there should not be any significant price repercussions around the conclusion of the lock-up period (Ofek, 2000; Brav & Gompers, 2003).

Nevertheless, if assuming the existence of non-rational investors, short sale constraints and downward-slopping demand curves, it can be predicted that the price will decline on expiration dates (Hong et al., 2006). Hong et al. (2006) delineated two primary constituents causing stock prices to fall on the expiration day. The initial reason stems from the heterogeneity in the preliminary beliefs of investors and short sale constraints, engendering an optimism bias. This bias makes the market reflect prices based on the beliefs of a sanguine cohort of investors. The second constituent inducing inflation of prices prior to lock-up is the resale option effect. Their model posits that investors exhibit overconfidence, mistakenly presuming that insiders exhibit similar beliefs. Assuming that insiders' beliefs are rational—that is, they appropriately consider all available information—and that a subset of investors maintains a higher degree of optimism than insiders, an increase in insider selling activity is expected on the lock-up expiration date. This would exceed the anticipations of outside investors. Consequently, a downward adjustment in the stock price is anticipated on this date. Hence, I predict that there will be abnormal returns around the lock-up expiration date and propose the following hypothesis:

H1a: There is no abnormal return around the expiration date.

Field and Hanka (2001), Brav and Gompers (2003), Bradley et al. (2001) Ofek, (2000) all document abnormal volume surrounding lock-up expiration. The abnormal volume around lock-up return is consistent with price pressure and downward-sloping demand curves (Brav and Gompers (2003); Ofek, 2000), so I expect it to manifest in both VC and Non-VC subsamples. Therefore my null hypothesis is :

H1b: There is no abnormal volume around the expiration.

H1c: There is an negative effect of abnormal volume on abnormal return around the expiration date.

Another plausible explanation for abnormal returns around lock-up expiration is high price pressure (L. Harris & Gurel, 1986; Lynch & Mendenhall, 1997). The price pressure hypothesis relies on the fact that due to high volume, to attract liquidity providers, a temporary price drop may be necessary (Field & Hanka, 2001). If this theory is true, there should be only a temporary price decline. When heterogeneous beliefs and short sale constraints lead to downward-sloping demand curves, a permanent shift in the number of available shares can be expected. This shift is indicated by the end of the lock-up period, which signals the removal of short-sale constraints (Ofek & Richardson, 2003). As a result, there should be a permanent and positive increase in trading volume after the lock-up expiration.

2.3.4 Venture capital relation to abnormal return and abnormal volume

Venture capital participation in IPO has been popular since 1980 (Gompers & Lerner, 1999). Most VC firms will sell their shares after the lock-up agreement expires. However, some would retain their position (Gompers & Lerner, 2001). It is striking that, based on conventional theory, VC firms should be associated with less information asymmetry (Barry, 1994). Hence, there should be fewer abnormal returns, if any. However, Field and Hanka (2001) and Bradley et al. (2001) observe an association between venture capital backing and abnormal return on the expiration date, almost three times higher than standard firms. Bradley (2001) concludes that venture capital sells more than expected but does not provide any reasons for it. Firstly, in line with the grandstanding hypothesis, VC-backed companies often underpriced IPO (Cliff & Denis, 2004), and underpricing of IPO's associated with high analyst ratings (Bradley et al., 2015; Rajan & Servaes, 1997), which is associated with high information asymmetry (Anderson et al., 2005) and could influence the beliefs of part of the investors after IPO (Aggarwal et al., 2002). According to the theory of Hong et al. (2006) and Bradley et al. (2015), it would mean higher abnormal return after lock-up expiration. However, it is worth noting that Bradley et al. (2015) does not find a correlation between underpricing and five-star recommendations after the bubble of 2001. The second reason for higher abnormal return after the lock-up period for VC-backed firms is that some irrational investors misinterpret signals from the market (Hong et al., 2006), and VC capital is known for its signaling role (Wright Robbie, 1998). Moreover, VC firms were found to bring more professional investors into IPO (Chemmanur & Loutskina, 2006) which could increase dispersion in views (Hong et al., 2006). The other reason is that assuming irrational investors, this effect could be substantiated by the fact that VC capital firms are great monitors (Bernstein et al., 2016) and after a VC firm that thought to stay by overconfident part of investors leave, we see higher abnormal returns due to loss of monitoring role (Yung & Zender, 2010). Finally, the reason for greater abnormal return on the expiration date for

VC-backed companies would be high selling pressure because IPO is a way for VC to exit the company, and it will most likely automatically sell (Gompers & Lerner, 1998). If the reason for abnormal return is the premium to a market maker, I will see only a short-lived price change (Field & Hanka, 2001). If the reason is higher than expected by irrational investors sale pressure coupled with downward-sloping demand curves, I will observe a permanent decrease in stock price (Hong et al. (2006)). I propose the following hypothesis:

H2a: VC financed companies does not experience the negative abnormal return on lock-up expiration date.
H2b: VC backing has causal negative effect on cumulative abnormal return.

2.3.5 Other variables that could help to explain abnormal return

Increase in price could be signaling that the company is overvalued, which is consistent with Hong theory of resale option and overvaluation. Bradley et al. (2001) and Field and Hanks (2001) did not find evidence for the effect of change in price in their samples but reported significant results in their VC-backed subsamples. Haggard and Xi (2017) also argues that the main reason for abnormal return is overvaluation of a company.

Findings from Field and Hanka (2001), in conjunction with Bradley et al. (2001) suggest that IPOs associated with top-tier underwriters tend to decrease abnormal returns at lock-up expiry. This phenomenon is particularly pronounced in their subset of venture-capital-backed firms. On the other hand, Brav and Gompers (2003) hypothesise but do not find empirical evidence that the engagement of high-quality underwriters could potentially mitigate negative abnormal returns during the lock-up expiry period. This assertion stems from their belief that an underwriter's reputation significantly affects information asymmetry. They suggest that the enlistment of a reputable underwriter could act as an effective signal, thereby accurately conveying the inherent quality of the firm to the market. Yung & Zender, (2010) also view underwriter as reducing information asymmetry through certification.

Brav et al. (2000) and Bradley et al. (2001) incorporate the proportion of shares locked into their multivariate regression models, representing a key feature of their analytical approach. The underlying rationale for this choice is that the proportion of shares locked might serve as a reasonable proxy for the number of shares likely to be sold upon lock-up expiration. This supposition is premised on the idea that a higher proportion of locked shares may correspond to a more significant number of shares entering the market after the lock-up period, thus potentially influencing the stock's price behaviour. The empirical evidence offered by these studies universally underscores a significant association between the proportion of locked shares and the abnormal return observed at the time of lock-up expiration. This consistent finding corroborates the notion that the volume of shares transitioning from locked to freely tradable status can materially impact the stock's performance. I use percent of shares offered at IPO as a proxy.

Several researchers use the number of proceeds to indicate a company's size. Brav et al. (2000) pointed out that the larger the company, the more information it typically holds. As a firm grows, so does the information it contains, expanding proportionally. This indicates that the size of a company, as represented by the number of proceeds, can potentially impact information asymmetry.

Cumming et al. (2005) observed that venture capitalists modulate their investment choices following the state of liquidity in initial public offering exit markets. During periods of elevated liquidity risk, their study indicated a relative increase in the allocation of funds towards novel high-tech and early-stage ventures with significant technological risk, a strategy employed to delay the necessity of exit. Conversely, in scenarios where exit markets exhibit ample liquidity, venture capitalists display an expedited exit strategy, demonstrated by increased investment in later-stage ventures (Cumming et al., 2005; Nemlioglu & Mallick, 2020). The year is also a good proxy for market conditions. I could capture this effect by dividing my sample into different years. Also, year variable could capture the learning effect of investors.

CHAPTER 3 Data

I use the Eikon New Issue database as a primary data source for IPO data. I extract data on USA-based common or ordinary share IPOs that were issued on New York Stock Exchange (NYSE) and NASDAQ from 1st June 1990 to 1st June 2022. I extracted only IPOs that had lock-up agreements. I also extracted the following variables from this database: dummy variable for whether the IPO is backed by venture capital, IPO date, proceeds, underwriter, the high-tech industry, and lock-up length, state of headquarters, book value per share and percent shares offered. Initially, I had 4991 observations. Firstly, I modify the lock-up variable as some observations contain multiple lockups. If it is the case, I calculate the most frequent one and delete the other ones. Then I delete observations with missing values for the lock-up duration. When a company uses multiple underwriters, I use the first one. Then I delete observations with lock-ups shorter than 90 days, as I am using a 61-day prediction window. I transform the high-tech industry to a dummy variable that is one if the primary industry of the issuer is high-tech and 0 otherwise. I take natural logarithm of proceeds. I delete observations with missing data on 9-digit CUPIS. Transform it to 8-digit CUPIS. Then I match data from the Eikon database to the CRSP database to calculate abnormal returns, price change and abnormal volume. I lose observations due to missing observations or the wrong CUPIS code. Since some of the stock prices in the CRSP database are reported as negative values, I transformed all negative values into positive ones. I calculate price runup as a change in price from IPO offer price to -10 days before the expiration day. I use underwriter ranks created by Carter & Manaster (1990) and Keasler (2001) to create a dummy variable that is one if one of the underwriters is in the top three underwriters in the latter rank - (Goldman Sachs, Morgan Stanley, Dean Witter) - or got the highest score - nine - in former rank (First Boston Corp., Goldman Sachs, Merrill Lynch, Morgan Stanley and Salomon Brothers) and zero otherwise. I make California variable that is one if company has headcounters in California and zero otherwise. I am left with 3504 observations.

Ofek & Richardson (2002) note that high tech companies could experience greater information asymmetry and irrational pricing. In addition to this, Bradley et al. (2001) provides further insights specific to the high-tech sector. They note a notably larger negative abnormal return, at -3.33%, for high-tech companies supported by venture capital, as opposed to a -1.47% return for those not backed by venture capital. Therefore, I use high tech dummy as a control variable for effect of VC backing on 5-day CAR.

As shown in Table 1 VC backed is a binary variable, as denoted by the minimum and maximum values of 0 and 1, respectively. The mean value is 0.435, implying that approximately 43.5% of the IPOs are VC-backed. As indicated by the mean value of 0.237 of top underwriter dummy variable, about 23.7% of the IPOs are underwritten by top-tier underwriters. 54% of the IPOs are from high-tech industries. The lock-up length is concentrated on 180 days, the average lock-up period is 198.21 days, with a minimum of 90 days and a maximum of 1,095 days (or 3 years). This year variable records the year of the IPO, from 1990 to 2022. The mean value of 2004.6 suggests that most of the IPOs in the sample occurred around 2004. The standard deviation of 9.99 indicates a spread of 10 years around the mean. The average price change is small at 0.005, meaning 0.5% increase, but a large standard deviation of 0.36 indicates substantial variability. The range is wide, with a minimum of -0.93, indicating a price decrease of 93%, and a maximum of 4.91, signaling a significant price increase of 490%. The mean log proceeds value is 4.30, with an SD of 1.26. The mean value of shares offered on IPO is 33.17%.

Table 1: Descriptive Statistics

	mean	sd	min	max
VC	0.435	0.496	0.000	1.000
Year	2004.621	9.899	1990.000	2021.000
Price change	0.199	0.671	-0.978	9.212
High tech dummy	0.540	0.498	0.000	1.000
Lockup days	197.039	76.917	90.000	1095.000
Ln(proceeds)	4.333	1.260	0.501	9.681
Underwriter top	0.237	0.425	0.000	1.000
Abnormal volume	0.993	3.813	-1.000	71.633
California	0.265	0.441	0.000	1.000
Shares Offered as Pct. Of Shares offered	33.176	21.210	0.000	100.000
Book Value per Share	4.970	6.720	-147.489	127.264

Note: After removing missing values data contains 3504 observations for all variables except free float at IPO which contains 3069 observations. The statistics contains mean of different variables, standard deviations, minimum and maximum. VC backed is dummy that is 1 if backed by VC and 0 otherwise. Top underwriter is dummy variable that is one if company used one of the top underwriters as outlined in section 3. High tech is dummy that is one if company business is his tech as outlined by New Issue database and zero otherwise. California is a dummy that is equal to 1 if headquarter is in California and zero otherwise. Lockup length is measured in days. Shares offered is in percentage units.

First, I perform an F-test for equal variance between VC and not VC-backed groups. I reject the null hypothesis for an equal variance for all variables except for Top Underwriter; hence, to compare means, I use two tailed Welch's t-test for all variables except Top Underwriter, for which I use the student t-test. In total, 1,641 VC-backed companies and 2,141 non-VC-backed companies were observed. The proportion of VC-backed companies that used a top underwriter was 0.24, while the proportion for non-VC-backed companies was 0.234. The difference is not significant on the 5 per cent level. A significantly higher proportion of VC-backed companies are in the high-tech sector, with a value of 84%, compared to 31% for non-VC-backed companies. The difference is statistically significant on a 5 per cent level. On average, VC-backed companies have a lock-up period of about 185.53 days, while non-VC-backed companies have a more extended average lock-up period of approximately 205.88 days. The difference is statistically significant at 5 per cent level. VC-backed companies have gone public slightly later, on average, in 2005, compared to 2004 for non-VC-backed companies. The difference is statistically significant at a 5 per cent level. The price change for VC-backed companies was 26.7%, while that for non-VC-backed companies was 14.7%. The difference is statistically significant on the 5 per cent level. The average value of the natural logarithm of IPO proceeds for VC-backed companies is 4.17, while for non-VC-backed companies, it's 5.66, implying that non-VC-backed companies raised slightly more money on average. The difference is statistically significant on 5 per cent level. This data on free float is available for 1380 VC-backed companies and 1,698 non-VC-backed companies. The average percent offered at IPO is significantly higher for non-VC-backed companies 37.46% compared to VC-backed companies 27.94%. The abnormal volume was statistically significant on 5% level higher for VC backed companies 172% higher than average before event window compared to 43% higher for non-VC backed ones. The difference is statistically significant on 5 per cent level. The results are presented in Table 2. Correlation between variables can be seen in Table 2.

Table 3: Correlation matrix

	VC	**year**	**Prc. Change**	**High tech**	**Lockup days**	**Ln(proceeds)**	**Top underwriter**	**Abnormal volume**	**California**	**Shares Offered**	**Book value per share**
VC	1.00										
year	0.07	1.00									
Prc. Change	0.09	-0.03	1.00								
High tech	0.53	0.07	0.08	1.00							
Lockup days	-0.13	-0.20	-0.07	-0.07	1.00						
Ln(proceed)	-0.09	0.58	0.00	-0.11	-0.30	1.00					
Top underwriter	0.01	0.21	0.04	-0.01	-0.09	0.40	1.00				
Abnormal volume	0.17	0.04	0.05	0.12	-0.06	0.00	0.05	1.00			
California	0.27	0.07	0.05	0.26	-0.03	-0.01	0.04	0.09	1.00		
Shares Offered	-0.22	-0.13	-0.10	-0.28	0.04	0.07	-0.07	-0.10	-0.15	1.00	
Book value per share	-0.11	0.05	0.00	-0.18	-0.11	0.21	0.03	-0.04	-0.07	0.27	1.00

Note: The table represents correlation between variables

Table 2: VC vs non-VC characteristics

Variable	Number of Observations (VC : Non-VC)	VC-Backed Mean	Non-VC Backed Mean	Difference (Non-VC - VC)
Price Change	1523 : 1981	0.267	0.147	-0.120*** (0.024)
Lock-up Days	1523 : 1981	185.53	205.88	20.35*** (2.39)
High Tech	1523 : 1981	0.840	0.310	-0.530*** (0.014)
Year	1523 : 1981	2005.36	2004.06	-1.30*** (0.34)
Log Proceeds	1523 : 1981	4.21	4.43	0.22*** (0.04)
Top Underwriter	1523 : 1981	0.240	0.234	-0.006 (0.015)
California	1523 : 1981	0.399	0.161	-0.238*** (0.015)
Financials Book Value per Share	1334 : 1532	4.17	5.66	1.49*** (0.24)
Percent Offered	1380:1698	27.94	37.46	9.517*** (0.719)
Abnormal Volume Final	1523 : 1981	1.72	0.43	-1.28*** (0.13)

*Note: The statistics for two groups contains the number of observations, mean, difference of means with respective standard deviation in brackets. To check for significance two-tailed Welch t-test was used for all variables except top underwriter for which two-tailed student t-test was used. *, **, and *** mean differences obtained are statistically significant at 5%, 1%, and 0.1% significance levels respectively.*

CHAPTER 4 Methods

4.1 Abnormal return

Following Field and Hanka (2001) and Ofek (2000), I use 60 days estimation period. I will use a market model with the return of the CRSP value-weighted index as the market return. The model to estimate expected return will look the following way:

Beta estimation:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \tag{1}$$

Abnormal Return estimation:

$$AR_{it} = R_{it} - \widehat{R_{it}} = R_{it} - \left(\widehat{\alpha_i} + \widehat{\beta_i} R_{mt}\right) \tag{2}$$

I calculate AAR, which is abnormal return across companies, and CAAR, which is abnormal return across companies and time (Barber & Lyon, 1997). N represents number of companies considered, T_1 represents start of event window, T_2 represents end of event window.

Average abnormal return:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{3}$$

Cumulative abnormal return:

$$CAR_i = \sum_{t=T_1+1}^{T_2} AR_{i,t} \tag{4}$$

Cumulative average abnormal return:

$$CAAR = \frac{1}{N}\sum_{i=1}^{N} CAR_i \tag{5}$$

To test my hypothesis I use cross sectional test and crude dependent adjustment test (Brown & Warner, 1980) as parametric tests and generalized sign test as a non-parametric test. I use crude dependent adjustment test as it does not assume that abnormal reruns are independent (Brown & Warner, 1980). I use generalized sign test as it is robust to longer event windows then sign test and does not necessitate the abnormal returns to be symmetrically distributed across the cross-section for accurate specification (Cowan, 1992). The derivations of both tests for AAR, and CAAR can be found in Appendix A1.

4.2 Abnormal volume

I calculate abnormal volume following Brav and Gompers (2003). $\overline{V}_i$ represents average volume for company i, V_{it} represents volume for company i at day t, AV_{it} represents abnormal volume for company i at day t, N represents number of companies considered:

Average trading volume:

$$\overline{V}_i = \frac{1}{61}\sum_{t=-70}^{-10} V_{it} \tag{6}$$

Abnormal trading volume:

$$AV_{it} = \frac{V_{it}}{\overline{V}_i} - 1 \tag{7}$$

Average abnormal trading volume across firms:

$$AAV_t = \frac{1}{N}\sum_{i=1}^{N} AV_{it} \tag{8}$$

To test my hypothesis, I use the cross-sectional t-test. See Appendix A1 for derivations.

4.3 Propensity score matching

VC backing is not random, as not all companies can obtain VC investment, and not all companies want to be financed by VC. To estimate the effect of VC backing on abnormal return, I would like to know what would have happened If VC backed companies would not obtain VC investment.

$$E(Y_1 - Y_0|VC = 1, X) = E(Y_1|VC = 1, X) - E(Y_0|VC = 1, X) \tag{9}$$

However, I observe only abnormal returns of probably non-compatible companies that did not obtain VC.

$$E(Y_0|VC = 0, X) \tag{10}$$

Hence selection bias:

$$\begin{aligned} SB = E(Y_1|VC = 1, X) - E(Y_0|VC = 0, X) - E(Y_1|VC = 1, X) + E(Y_0|VC = 1, X) = \\ = E(Y_0|VC = 1, X) - E(Y_0|VC = 0, X) \end{aligned} \tag{11}$$

In economics research, PSM serves as a method to simulate a randomized control trial when such an experiment is not feasible or ethical. The propensity score, in this context, is the probability that a particular unit receives the treatment given a set of observed characteristics. The likelihood of receiving an intervention enables the investigator to equalize the test and control groups, given the multivariate distribution of the influencing factors (Harris & Horst, 2019; Stuart & Rubin, 2008). I use propensity score matching to try to eliminate selection bias in the effect of VC backing on abnormal returns surrounding the lock-up period. As is advisable to include a broad range of influencing factors, even if some of these factors only pertain to self-selection and other covariates, rather than having a direct correlation with the outcome of interest (Harris & Horst, 2019; Stuart & Rubin, 2008), I add additional variables to usually chosen for regression analysis in previous studies, this variables are California dummy and Book Value per Share. I use California dummy as it is pre-treatment variable and it could help to better specify logistic regressions, especially in Model 1. I use Book Value per share as additional variable using the same logic as Lee and Wahal (2004), financial variables are likely to correlate with things that could influence VC backing and Abnormal Return. King and Nielsen (2019) showed that matching by pairs could lead to biased results should you misspecify the model; hence I will use matching by five neighbors and kernel matching. Matching is done with replacement. In my analysis, I compute the disparity between the abnormal return of Venture Capital-backed IPOs and the corresponding abnormal return of non-VC-backed IPOs. This calculation effectively allows me to determine the average treatment effect on the treated, following the methodology proposed by Rosenbaum & Rubin (1985). I use bootstrapped standard errors based on 100 replications. The selection of the bandwidth occurs automatically, being set at a value equivalent to one and a half times the distance at the 90% quantile in the process of pair matching with replacement. I also use five nearest neighbor matching. It is worth mentioning that PSM method will only balance on observed covariates, so my results are not robust for unobserved omitted variables (Austin et al., 2007). Two assumptions noted by Rosenbaum and Rubin (1983) are Conditional Independence Assumption and common support assumption. When these two assumptions are satisfied, the treatment assignment is said to be strongly ignorable, and effect can be interpreted as causal (Rosenbaum & Rubin, 1983). The fulfillment of the common support condition is necessary to affirm that all features noted within the treatment group can also be identified within the control group, as corroborated by Austin et al. (2007). With respect to the average treatment effect on the treated, it is adequate to guarantee that for each treated individual involved in the study, a corresponding non-treated individual exhibiting close similarities can be found (Austin et al., 2007). The second assumption is Conditional Independence Assumption. To satisfy this assumption I would need to include all set of covariates that affect treatment assignment and outcome. Based on efficient or semi efficient market hypothesis there should not be any variables that affect being VC backed and Abnormal return around expiration date, however as discussed previously it might not hold true. I cannot check weather this assumption is satisfied and hence can interpret results only as association.

I first perform propensity score matching only with pretreatment variables: High tech dummy and California dummy. The second specification contains full set of variables that were previously used by in their multivariate regression, these variables potentially affect Abnormal return and do not have direct effect on being VC backed but could be correlated to variables that affect VC backing through its certification and identification function. Finally, I add additional financial variables and percent offered. I use following models for logistic regressions:

Models 1-4:

1. $VC = \beta 0 + \beta 1 * (High\,Tech\,Dummy) + \beta 2 * (California) + \varepsilon$

2. $VC = \beta 0 + \beta 1 * (High\,Tech\,Dummy) + \beta 2 * (Year) + \beta 3 * (Price\,Change) + \beta 4 * (Lockup\,Days) + \beta 5 * ln(Proceeds) + \beta 6 * (Top\,Underwriter) + \beta 7 * (Abnormal\,Volume) + \varepsilon$

3. $VC = \beta 0 + \beta 1 * (High\,Tech\,Dummy) + \beta 2 * (Year) + \beta 3 * (Price\,Change) + \beta 4 * (Lockup\,Days) + \beta 5 * ln(Proceeds) + \beta 6 * (Top\,Underwriter) + \beta 7 * (Abnormal\,Volume) + \beta 8 * (California) + \varepsilon$

4. $VC = \beta 0 + \beta 1 * (High\,Tech\,Dummy) + \beta 2 * (Year) + \beta 3 * (Price\,Change) + \beta 4 * (Lockup\,Days) + \beta 5 * ln(Proceeds) + \beta 6 * (Top\,Underwriter) + \beta 7 * (Abnormal\,Volume) + \beta 8 * (Percent\,Offered\,Of\,Shares\,Outstanding) + \beta 9 * (Book\,Value\,Per\,Share) + \varepsilon$

4.3 Regression analysis

In line with other studies, I perform a multivariate OLS regression model to test how different variables affect abnormal returns. I use 5-day CAR as a dependent variable. Brav and Gompers (2003) mention that there could be different reasons for abnormal return for VC and non-VC backed companies, so it is more suitable to study two different regressions for VC backed and not VC-backed subsamples and not include a VC dummy in equations to check for association between different variables and CAR. I also perform a regression with only pre-treatment covariates of being VC-backed, which are high-tech dummies. For multivariate ordinary least square model to be best linear unbiased estimate (BLUE) several assumptions are needed to be satisfied (Brooks, 2019). The first assumption requires the mean of error term to be zero

I satisfy this assumption by including a constant in my regression models. The second assumption requires constant variance in error term. Violation of this assumption lead to inconsistent standard errors. To make sure I do not have heteroskedasticity in residuals I perform a white test and if needed I use robust standard errors in my regressions. The third assumption requires no correlation in error term. Violation of this assumption lead to inconsistent standard errors. I cannot test for this assumption, but I perform clustered-robust standard errors on industry sectors. The fifth assumption requires errors term to adhere to a normal distribution. This condition is deemed satisfied in my model, thanks to the central limit theorem. I cannot test for Conditional Independence Assumption and Zero Conditional Mean (ZCM) assumption and there are possible reasons to believe that this assumption might be not satisfied in my regressions. Firstly, omitted confounder for VC backing and cumulative abnormal return could bias my estimate for VC dummy, assuming irrational investors any variable that can influence VC investment and type or believes of investors could bias my results. Secondly, attenuation bias is possible if VC companies were measured with error but not of a big concern as data was collected from reliable database. Thirdly, if missing data was not missing on random there could be selection bias. In regression 3, 4 and 5 VC estimate could be further biased since VC most likely influences price change, year, proceeds and lockup length and there could be omitted variable that affect them and CAR. Therefore, though I might capture indirect effect of VC backing in this models most likely they are bad controls for VC effect on CAR (Cinelli et al., 2022). I also address problem of multicollinearity by computing variance inflation factor (VIF), which should be less then 5 (Brooks, 2019). I use the following models. With separate analysis for models 3-5 without including VC dummy and instead dividing sample into VC and Non-VC backed ones.

Models 1-5:

1. $CAR = \beta 0 + \beta 1 * (Venture\ Capital) + \varepsilon$

2. $CAR = \beta 0 + \beta 1 * (Venture\ Capital) + \beta 2 * (High\ Tech\ Dummy) + \varepsilon$

3. $CAR = \beta 0 + \beta 1 * (Venture\ Capital) + \beta 2 * (High\ Tech\ Dummy) + \beta 3 * (Year) + \beta 4 * (Price\ Change) + \beta 5 * (Lockup\ Days) + \beta 6 ln(Proceeds) + \beta 7 (Top\ Underwriter) + \beta 8 * (Abnormal\ Volume) + \varepsilon$

4. $CAR = \beta 0 + \beta 1 * (Venture\ Capital) + \beta 2 * (High\ Tech\ Dummy) + \beta 3 * (Year) + \beta 4 * (Price\ Change) + \beta 5 * (Lockup\ Days) + \beta 6 ln(Proceeds) + \beta 7 (Top\ Underwriter) + \beta 8 * (Abnormal\ Volume) + \beta 9 * (Percent\ Offered\ Of\ Shares\ Outstanding) + \varepsilon$

5. $CAR = \beta 0 + \beta 1 * (Venture\ Capital) + \beta 2 * (High\ Tech\ Dummy) + \beta 3 * (1990 - 2000) + \beta 4 * (2001 - 2012) + \beta 4 * (Price\ Change) + \beta 5 * (Lockup\ Days) + \beta 6 * ln(Proceeds) + \beta 7 * (Top\ Underwriter) + \beta 8 * (Abnormal\ Volume) + \varepsilon$

CHAPTER 5 Results

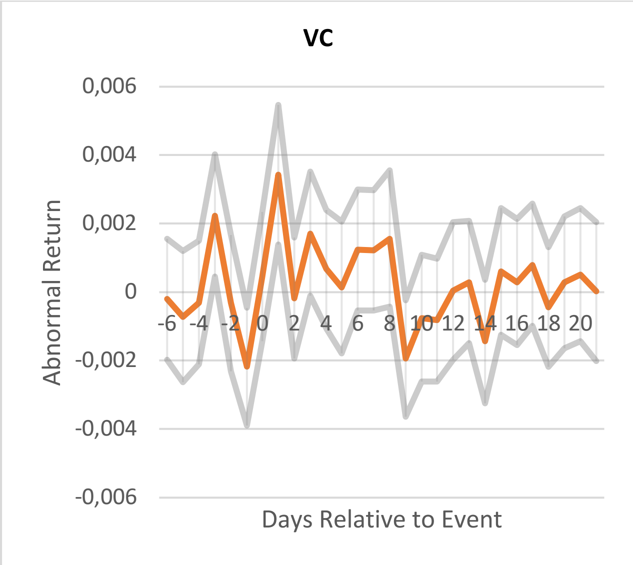
5.1 Event study

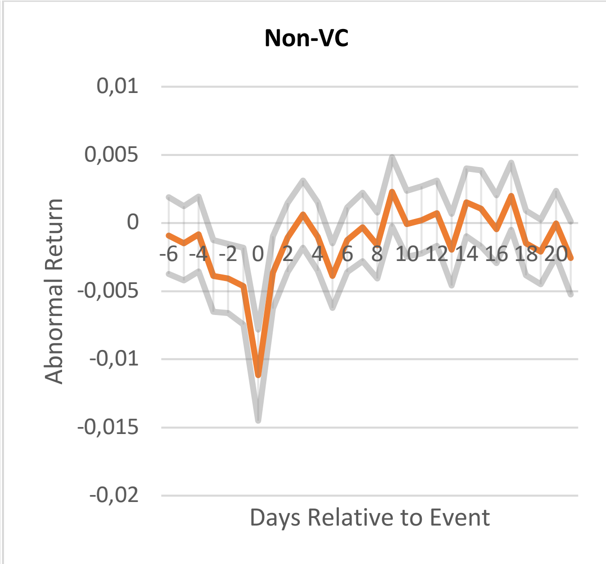
I start this section by perform an event study on mean abnormal returns and mean cumulative abnormal return. Moreover, I look at the abnormal returns during different years and high-tech or non-high-tech sectors. I report results of parametric and nonparametric tests. Finally, I perform event study on Abnormal volume.

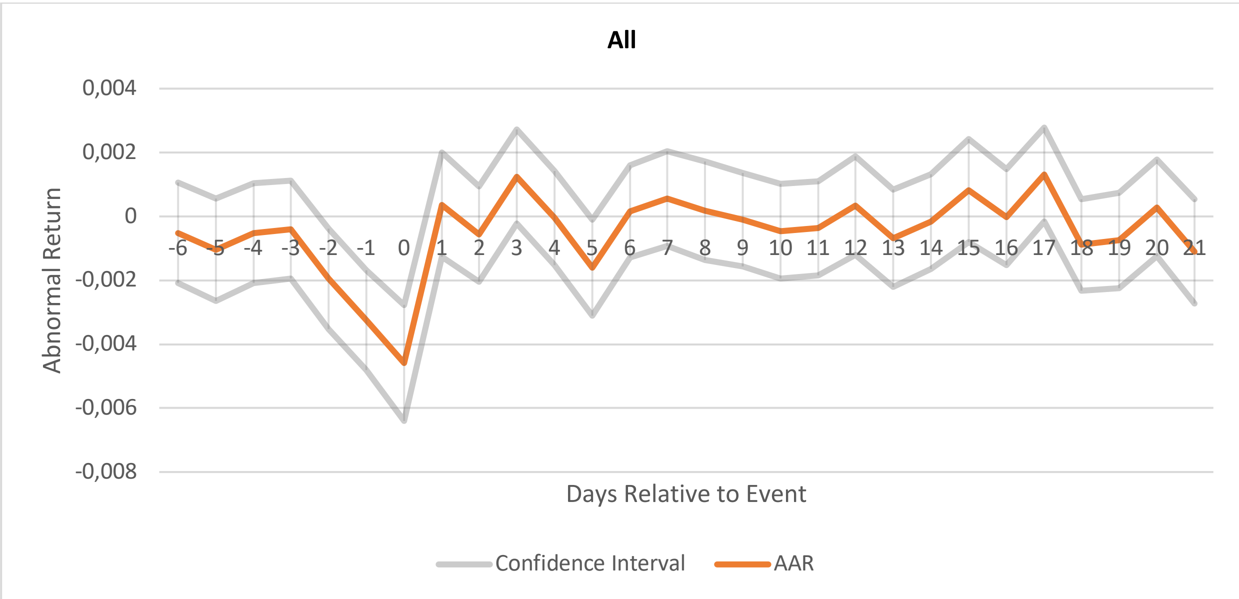
5.1.1 Abnormal return

I first perform event study on average abnormal return. The Table 4 presents the average abnormal returns (AAR) for different days before the event, along with their respective standard errors in parentheses. The AAR represents the average deviation from the expected returns surrounding the event. In the -2 day before the event, the AAR is -0.002 with a standard error of 0.0008. The coefficient is statistically significant at the 5% level, indicating a significant deviation from expected returns on this day. For the -1 day before the event, the AAR is -0.0032 with a standard error of 0.0008. The coefficient is statistically significant at the 1% level. On the event day, the AAR is -0.0046 with a standard error of 0.0009. The coefficient is statistically significant at the 1% level, indicating a significant deviation from expected returns on this day. For VC backed subsample I find significant AAR for days from -3 to 0, starting from -0.38% negative average abnormal return and ending by -1.1% negative mean abnormal return. I find small, significant on 5% level, negative abnormal return of -0.02% for non-VC backed subsample on -1 day and positive mean abnormal returns for -3 and 1 day surrounding lockup expiration date. Results for days -6 to 10 are presented in Table 4a. The generalized sign test and crude dependence adjusted test results from trading days -3 to 3 relative to the event can be seen in in Table 4b. And AAR with its 95-confidence interval for days -6 to 21 can be seen on Figures 1-3.

Figures 1-3: Average Abnormal Return







Note: These figures contain representation of AAR for VC non-VC and whole sample. The 95% confidence intervals are estimated using cross sectional t statistics. Presented for the whole sample from days -6 to 21 relative to lockup expiration date. Days relative to event can be seen on the x-axis. Abnormal return on y-axis.

Table 4a: AAR per day

Days before event	AAR	AAR (VC = 1)	AAR (VC = 0)
-6	-0.0005 (0.0008)	-0.001 (0.0014)	-0.0002 (0.0009)
-5	-0.001 (0.0008)	-0.0014 (0.0014)	-0.0007 (0.0009)
-4	-0.0005 (0.0008)	-0.0008 (0.0014)	-0.0004 (0.0009)
-3	-0.0004 (0.0008)	-0.0038** (0.0013)	0.0022* (0.0009)
-2	-0.002* (0.0008)	-0.0041** (0.0013)	-0.0003 (0.001)
-1	-0.0032*** (0.0008)	-0.0046** (0.0014)	-0.0022* (0.0009)
0	-0.0046*** (0.0009)	-0.0112*** (0.0017)	0.0005 (0.001)
1	0.0004 (0.0008)	-0.0036 (0.0014)	0.0033** (0.001)
2	-0.0006 (0.0008)	-0.001 (0.0013)	-0.0002 (0.0009)
3	0.0012 (0.0008)	0.0006 (0.0013)	0.0018 (0.0009)
4	0.0000 (0.0007)	-0.0001 (0.0013)	0.0007 (0.0009)
5	-0.0016 (0.0008)	-0.0039* (0.0012)	0.0001 (0.001)
6	0.0002 (0.0007)	-0.0012 (0.0012)	0.0013 (0.0009)
7	0.0006 (0.0008)	-0.0003 (0.0013)	0.0012 (0.0009)
8	0.0002 (0.0008)	-0.0016 (0.0012)	0.0017 (0.0010)
9	-0.0001 (0.0007)	0.0023 (0.0013)	-0.0019* (0.0009)
10	-0.0005 (0.0008)	-0.0000 (0.0012)	-0.0006 (0.0009)

*Note: The table contains AAR for full, VC backed and not backed samples for days from -6 to 10 relative to lockup expiration date. The significance presented is obtained using two-sided cross-sectional t-test. Standard error is reported in brackets. *, **, and *** represent statisticall significance at 5%, 1%, and 0.1% significance level respectively.*

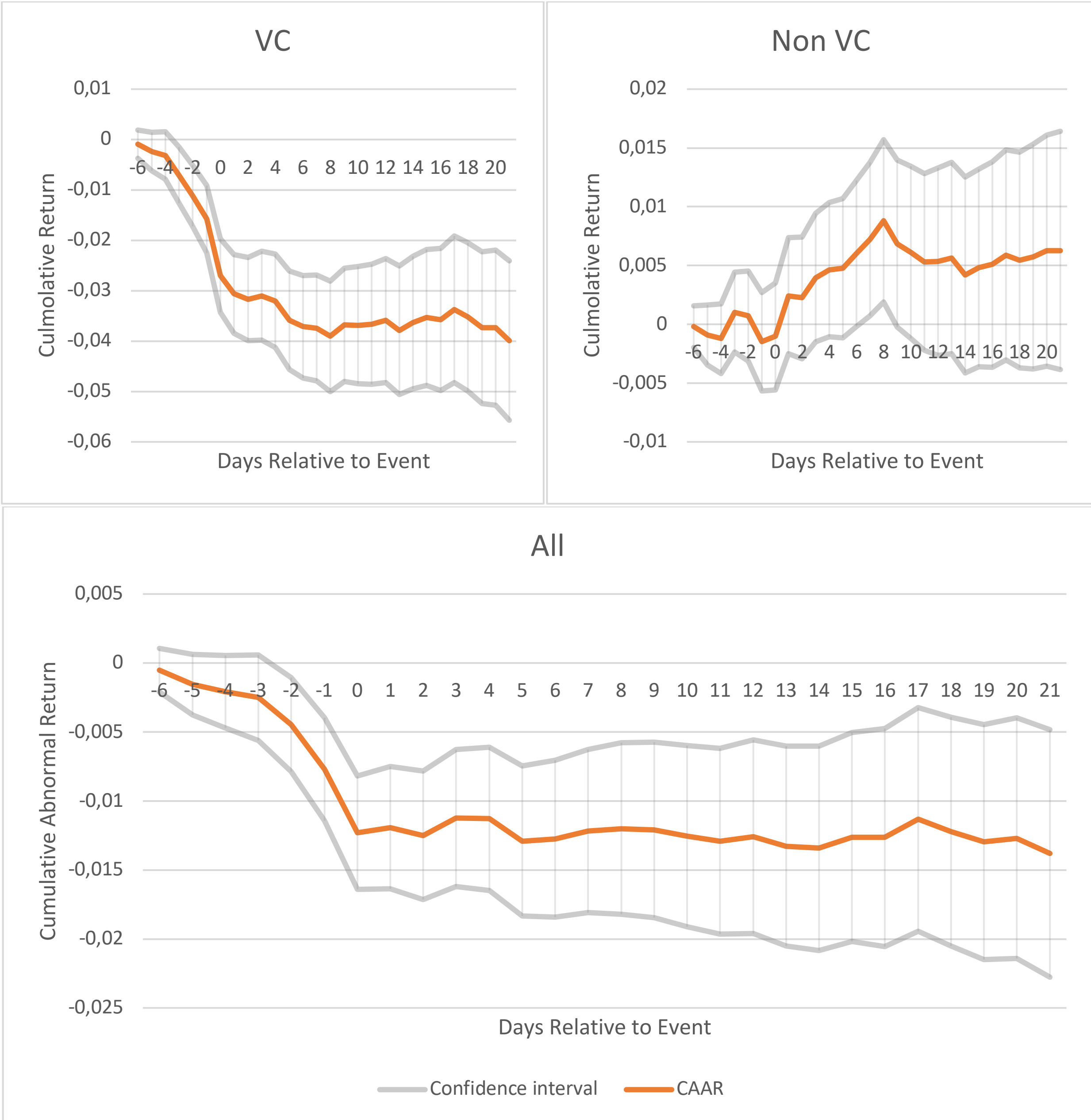
Table 4b: AAR per day

Days before event	AAR	Time series test (P-value)	Generalised sign test (P-value)	AAR (VC =1)	Time series test (P-value)	Generalised sign test (P-value)	AAR (VC = 0)	Time series test (P-value)	Generalised sign test (P-value)
-3	-0.0004	0.639	0.477	-0.0039	0.012	0.292	0.0022	0.012	0.058
-2	-0.002	0.032	0.370	-0.0041	0.003	0.143	-0.0003	0.003	0.928
-1	-0.0032	0.000	0.000	-0.0046	0.000	0.002	-0.0022	0.000	0.062
0	-0.0046	0.000	0.576	-0.0111	0.000	0.000	0.0005	0.000	0.005
1	0.0004	0.734	0.588	-0.0036	0.019	0.077	0.0033	0.019	0.022
2	-0.0006	0.511	0.343	-0.001	0.49	0.521	-0.0002	0.49	0.065
3	0.0012	0.150	0.436	0.0007	0.655	0.939	0.0018	0.655	0.261

*Note: The table contains AAR for full sample for days from -3 to 3 relative to lockup expiration date. The asterisks represent significance based on two tailed cross sectional test. *, **, and *** representing statistical significance at 5%, 1%, and 0.1% significance level respectively. The p value is reported for two-tailed crude dependence and generalised sign tests. P value of less than 0.05% indicates that I reject null hypothesis of no abnormal return on 5% level.*

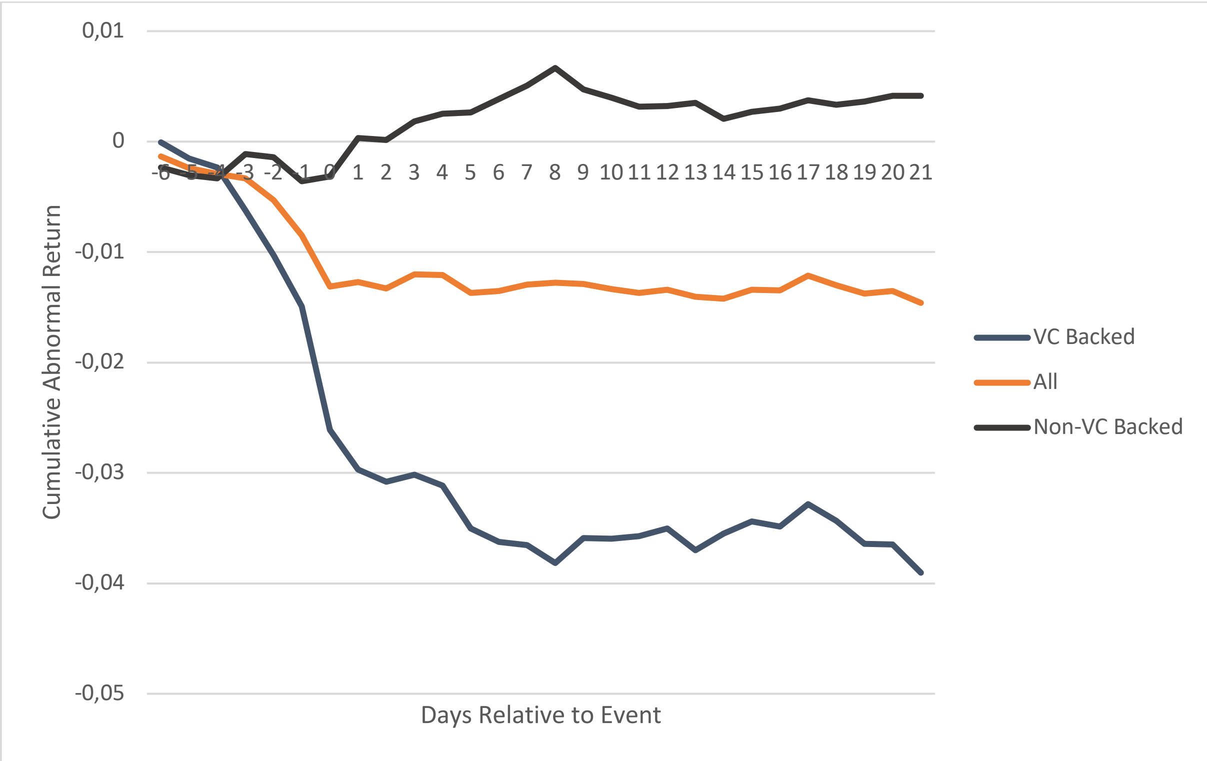
I then investigate cumulative average abnormal returns (CAAR). The Table 5 presents the results of an event study, examining the CAAR for different event windows. Here I report significance using two tailed cross-sectional test, additional tests can be seen in the table. I consider estimate statistically significant if p-value or probability of observing event as extreme under null hypothesis of no CAAR is less then 5%. The event windows are defined by different intervals, indicating the time period before and after the event. The intervals examined in this study are (-2, 2), (0, 5), (-1, 1), (-6, 10), and (-6, 21). For the (-2, 2) event window, the CAAR is -0.0099 with a standard error of 0.0018. The negative coefficient indicates a statistically significant on 5 percent negative abnormal returns during this interval. In the (0, 5) event window, the CAAR is -0.0052 with a standard error of 0.0019. Like the previous window, the negative coefficient signifies a statistically significant negative abnormal returns during this period. For the (-1, 1) event window, the CAAR is -0.0075 with a standard error of 0.0014. In the (-6, 10) event window, the CAAR is -0.0126 with a standard error of 0.0033. Lastly, the (-6, 21) event window has a CAAR of -0.0138 with a standard error of 0.0046. For the (-2, 2) event window, companies with VC funding exhibit a significant negative CAAR of -0.0245 with a standard error of 0.0031. In contrast, companies without VC funding display a relatively smaller positive CAAR of 0.0012 with a standard error of 0.0020. In the (0, 5) event window, companies with VC funding demonstrate a significant negative CAAR of -0.02 with a standard error of 0.0034. Conversely, companies without VC funding exhibit a positive but insignificant CAAR of 0.0062 with a standard error of 0.0021. For the (-1, 1) event window, companies with VC funding again show a significant negative CAAR of -0.0195 with a standard error of 0.0027. Companies without VC funding display a relatively smaller positive CAAR of 0.0017 with a standard error of 0.0015. In the (-6, 10) event window, companies with VC funding demonstrate a significant negative CAAR of -0.0368 with a standard error of 0.0059. Companies without VC funding exhibit a smaller positive but insignificant CAAR of 0.0061 with a standard error of 0.0037. Lastly, for the extended (-6, 21) event window, companies with VC funding display a significant negative CAAR of -0.0399 with a standard error of 0.008. Companies without VC funding exhibit a smaller positive CAAR of 0.0063 with a standard error of 0.0052. These results highlight the differential impact of events on abnormal returns for companies based on their VC funding status. Companies with VC funding generally experience significant negative abnormal returns during the event windows, while companies without VC funding tend to exhibit smaller positive abnormal returns or negligible effects. The results for different event windows can be seen in Table 5. The CAAR with 95 confidence interval from -6 to 21 trading day can separately for VC backed, non-VC backed and whole sample of IPOs be seen on the Figures 4-6. On Figure 7 The CAAR for VC, whole and non-VC IPOs can be seen together.

Figure 4-6: Cumulative Abnormal Return



Note: This figure represents Average Cumulative Abnormal Return and it 95% confidence interval estimated using cross sectional t statistics. Presented for the whole sample from days -6 to 21 relative to lockup expiration date. Days relative to event can be seen on the x-axis. Abnormal return on y-axis.

Figure 7: Cumulative Abnormal Return for VC and Non-VC financed companies



Note: This figure represents Average Cumulative Abnormal Return for all, VC backed and not backed companies. Presented for the whole sample from days -6 to 21 relative to lockup expiration date. Days relative to event can be seen on the x-axis. Cumulative abnormal return on y-axis.

Table 5: CAAR for different event windows

Interval	**CAAR**	**Time series test**	**Generalised sign test**	**CAAR (VC = 1)**	**Time series test**	**Generalised sign test**	**CAAR (VC = 0)**	**Time series test**	**Generalised sign test**
(-2, 2)	-0.01*** (0.0018)	0.000	0.003	- 0.025*** (0.0031)	0.000	0.000	0.001 (0.0020)	0.02	0.043
(0, 5)	-0.005*** (0.0019)	0.000	0.973	-0.02*** (0.0034)	0.000	0.000	0.006** (0.0021)	0.000	0.001
(-1, 1)	-0.008*** (0.0014)	0.000	0.003	- 0.019*** (0.0026)	0.000	0.000	0.002 (0.0015)	0.007	0.301
(-6, 10)	-0.013*** (0.0033)	0.000	0.104	- 0.037*** (0.0059)	0.000	0.000	0.006 (0.0037)	0.000	0.025
(-6, 21)	-0.014** (0.0046)	0.000	0.648	-0.04*** (0.0080)	0.000	0.085	0.006 (0.0051)	0.000	0.035

*Note: The table contains CAAR for full, VC backed and not backed samples for (-2, 2), (0, 5), (-1; 1), (-6, 10), (-6, 21). The significance presented is obtained using two-tailed cross-sectional t-test. The p value is reported for two-tailed crude dependence and generalised sign tests. P value of less than 0.05% indicates that I reject null hypothesis of no abnormal return on 5% level. Standard error is reported in brackets. *, **, and *** represent statistical significance at 5%, 1%, and 0.1% significance level respectively.*

I then investigate whether CAAR for (-2; 2) event window varies between years. For this I divide my sample into companies that went to IPO on 1990- 2000, 2001 - 2011, 2012 - 2022. I observe that CAAR in the whole sample was present only from 1990 to 2000 year and significant on 0.1% level. However, for VC backed sample I observe that there was always negative significant abnormal return. For non-VC backed sample I observe negative CAAR only from 1990 to 2000 and positive thereafter. For high tech companies I observe significant on 0.1% level negative CAAR of -0.018, however looking at VC and Non-VC backed companies reveals that negative abnormal return seems the be driven by VC backing and not by being or not being high tech company. The results are present in Table 6. I reject null Hypothesis 1a of no abnormal return. However, I note that it is driven by VC backed companies therefore I cannot reject null hypothesis of no abnormal return for non-VC backed IPOs.

Table 6: CAAR for different types of firms

Interval	CAAR	CAAR (VC = 1)	CAAR (VC = 0)
1990- 2000	-0.019*** (0.003)	-0.031*** (0.005)	-0.009** (0.002)
2001 - 2011	-0.002 (0.003)	-0.023*** (0.005)	0.010*** (0.003)
2012 - 2022	-0.005 (0.003)	-0.018** (0.006)	0.009* (0.004)
High tech	-0.018*** (0.003)	-0.025*** (0.004)	-0.002 (0.002)
Non high tech	-0.001 (0.002)	-0.022*** (0.006)	0.003 (0.005)

*Note: The table contains 5 day (-2;2) CAAR for full, VC backed and not backed samples divided by 1990 – 2000, 2001 – 2011 and 2012 – 2022 years and High-tech non-high-tech companies. The significance presented is obtained using two-tailed cross-sectional t-test. Standard error is reported in brackets. *, **, and *** represent statistical significance at 5%, 1%, and 0.1% significance level respectively.*

5.1.2 Abnormal volume

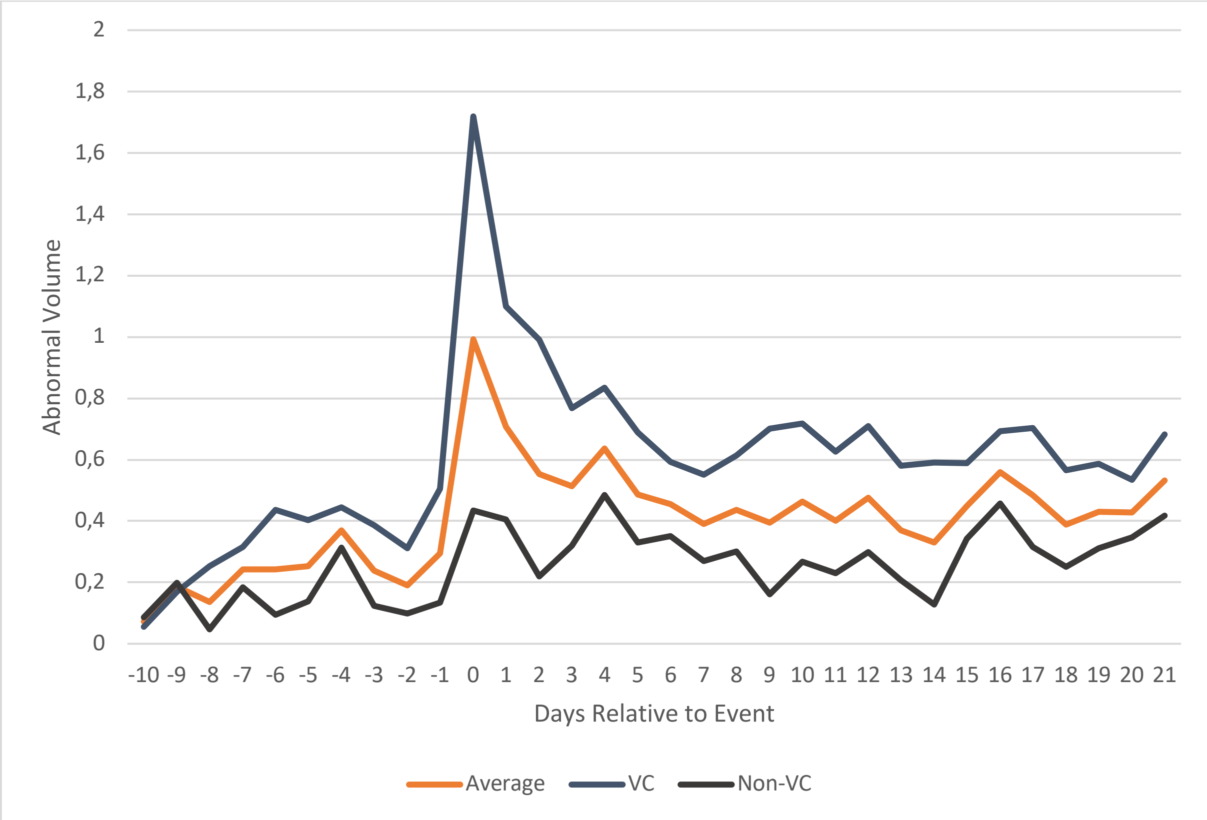
The Table 7 presents AAV for the following trading days relative to lockup expiration -2, -1, 0, 1, and 2. Figure 8 shows the AAV for an extended period, ranging from -10 to 21. The entirety of the AAV values from -2 to 2 exhibit a significant statistical relevance at a 5% confidence level. An analysis of the AAVs spread unveils a pattern. Starting at the -2-day interval, the AAV is recorded at 0.19. Advancing to the subsequent day, the -1-day interval, an increase in the AAV is observed, registering a value of 0.3. This is succeeded by a substantial increase at the 0-day interval, with the AAV reaching a peak value of 0.99. In the succeeding 1-day interval, a slight decline in the AAV is observed, dropping to 0.71. Eventually, at the 2-day interval, two days after the expiration date, the AAV exhibits a further reduction, measuring at 0.55. The data analysed in this study reveals that the average abnormal volume during the expiration date for the Venture Capitalist backed sample is approximately 4.25 times that of its non-VC backed counterpart. This is further substantiated by the data depicted in Figure 8, which demonstrates that the volume for both VC and non-VC backed samples maintains an elevated state in comparison to the 60-day average preceding the event. Interestingly, the volume for VC-backed samples is seen to be approximately twice as elevated, indicating higher relative volume of VC backed companies during and after the expiration period. The entirety of the AAV values from -2 to 2 exhibit a significant statistical relevance at a 5% confidence level. I reject null hypothesis 1b of no abnormal volume.

Table 7: Average Abnormal Volume

	AAV	**AAV (VC = 1)**	**AAV (VC = 0)**
	0.19***	0.31***	0.09*
-2	(0.04)	(0.07)	(0.04)
	0.3***	0.5***	0.12***
-1	(0.04)	(0.76)	(0.04)
	0.99***	1.72***	0.43***
0	(0.06)	(0.11)	(0.07)
	0.71***	1.1***	0.41***
1	(0.06)	(0.09)	(0.08)
	0.55***	0.99***	0.21***
2	(0.05)	(0.11)	(0.05)

*Note: The table contains AAV for full, VC backed and not backed samples for days from -2 to 2 relative to lockup expiration date. The significance presented is obtained using two-tailed cross-sectional t-test. Standard error is reported in brackets. *, **, and *** mean coefficients obtained are statistically significant at 5%, 1%, and 0.1% significance level respectively.*

Figure 8: Average Abnormal Volume

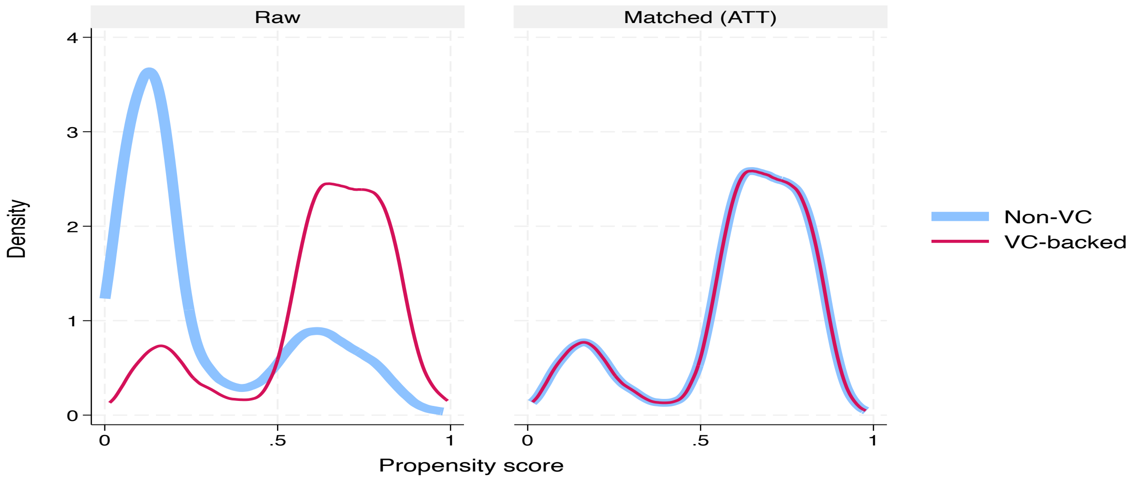


Note: This figure represents Average Abnormal Volume for all, VC backed and not backed companies. Presented for the whole sample from days -10 to 21 relative to lockup expiration date. Days relative to event can be seen on the x-axis. Abnormal Volume on y-axis.

5.2 Propensity score matching

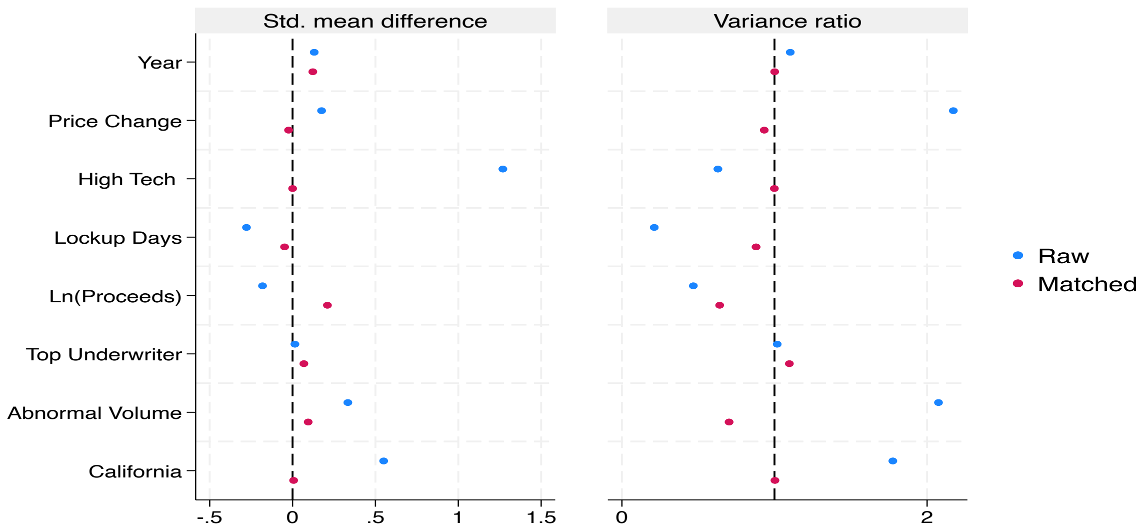
The summary statistics derived from the propensity score matching analysis highlight the differences in both raw and matched data across several covariates. In the raw data, the high-tech dummy variable demonstrated the most significant standardised difference between the treated and untreated groups, with a substantial difference of 1.269 standard deviations. Other notable differences were observed in the duration of the lockup: -0.278. Upon applying the matching process, these differences were significantly reduced, indicating a successful balancing of the covariates. Notably, in the matched dataset, the High-Tech Dummy variable had the most significant reduction, with a standardised difference of nearly zero, which is considerably lower than its counterpart in the raw data. Other variables such as year, price change, and top underwriter, exhibited minimal differences in means between the treated and untreated groups post-matching. There are also substantial deviations in the raw data of variances, particularly for high tech dummy and price change. Nevertheless, following the matching process, these ratios were reduced, though not ideally. Overall, the results in Figure 8 indicates an improved balance in the variance of the covariates between the treated and untreated groups post-matching. In conclusion, the matching process yielded improvements in balancing the covariates between the treated and untreated groups. The process reduced both the mean differences and the variance ratios across almost all covariates. Representation for balancing of model three can be seen on Figure 8 and other models on Figures 11 to 16 in Appendix A2. The distribution of propensity scores can be seen in Figure 7 for model 3, it tells that common support assumption is likely satisfied.

Figure 9: Distribution of propensity scores before and after matching



Note: The figure contains distribution of propensity scores of being VC backed for VC and non-VC financed IPOs for Kernel PSM for model 3. The left figure represents distribution before matching, the right figure presents distribution after matching. Density can be seen on the y-axis. Propensity score on x-axis.

Figure 10: Standard mean difference and variance ratio before and after matching.



Note: The figure contains standardised mean difference and variance ratio before and after matching of VC backed and non-VC backed IPOs for Kernel PSM for model 3. The left figure represents standardised mean difference before and after matching, the right figure presents variance ratio before and after matching. The closer standardised difference to 0 or variance ratio to 1 after matching the better matching process was performed. As can be seen not all variables were perfectly matched, but overall, the balance increased.

Firstly, the propensity score matching analysis was conducted using propensity-score kernel matching with 100 bootstrap replications for standard error estimation. This method estimates the counterfactual outcome for each VC backed IPO by taking a weighted average of the outcomes of all non-VC backed ones, with weights determined by a kernel function of the distance in propensity scores. The Table 8 presents the results of the propensity-score kernel matching. The treatment variable is venture capital dummy, and the covariates include year, price change, high tech dummy, lockup duration, ln(proceeds), top underwriter, and others as specified in previous chapter. The propensity score estimation model is logistic regression. The first model is constructed using high-tech and California dummy. I find that average treatment effect on treated is estimated to be -0.024. Meaning VC backed IPOs are associated with 2.4% less CAR then for the same IPOs if they were not VC backed. The point estimate is significant on 0.1%. The second model with more covariates presents slightly different results. Out of 1,523 treated observations, 1,441 were matched, and out of 1,981 control observations, 1,780 were used. The ATT of VC backing on CAR is -0.015, with a standard error of 0.006. The estimate is significant on 5% level. The third model 1444 of treated observations were matched. The ATT for is -0.018, with a standard error of 0.0058. the coefficient is significant on 1% level, reinforcing the finding of a statistically significant negative effect of VC backing on CAR. Finally in model 4 the estimated effect is -0.013. In all four analyses, the negative ATT for CAR indicates that VC backing is associated with a decrease in abnormal returns in the short term (-2 to 2 days).

Table 8: ATT estimated using Kernel matching

	Model 1	**Model 2**	**Model 3**	**Model 4**
ATT	-0.0237*** (0.0052)	-0.0148* (0.0059)	-0.0181** (0.0058)	-0.013* (0.0065)
Number of pairs	1523	1441	1444	1264

*Note: The table contains ATT of being VC financed on CAR for 5 trading days from -2 to 2 relative to expiration date . The ATT was estimated using Kernel matching with automatic bandwidth selector as discussed previously. Propensity score for all models was estimated using logistic regression. Standard errors were obtained using bootstrapping with 100 replications. Number of pairs represent number of VC backed companies out of 1523 that found match. Standard error is reported in brackets. *, **, and *** mean estimates obtained are statistically significant at 5%, 1%, and 0.1% significance level respectively.*

After Kernel Matching the results section continues with the analysis using five neighbors nearest-neighbor matching. This method matches each treated observation with the closest untreated observation based on the propensity score, which is estimated using a logistic model. The method pairs each VC-backed company with a five non-VC-backed companies that have the closest propensity scores, thereby trying to mimic a randomized experiment. This result of the first model is like the in the kernel matching analysis, which also showed a statistically significant negative effect of VC backing on CAR. The second model also found a statistically significant negative effect of VC backing on CAR, with an ATT of -0.0193 and a 95% confidence interval of -0.0325 to -0.006. This result is consistent with the kernel matching analysis on the same sample. The third and fourth Model in nearest-neighbor matching analysis found an ATT of -0.0192 and -0.0189. This result is also consistent with the kernel matching analysis using the same covariates; however, the estimates are slightly more negative. In summary, the nearest-neighbor matching analyses provide results that are consistent with the kernel matching analyses, reinforcing the conclusion that VC backing has a statistically significant negative association with CAR. The consistency of these findings across different matching methods and sets of covariates strengthens the validity of this conclusion. The results of both matching technics indicate that on average, VC-backed companies have a lower negative CAR compared to what they would have had if they were not VC-backed. This could suggest that venture capital backing has a negative effect on the CAR of the companies, after controlling for the other factors included in the propensity score model. However, I am not accepting this effect as causal and as do not accept nor reject the hypothesis of effect of VC backing on five-day cumulative abnormal return after lockup period in -2 to 2 day window. The results are presented in Table 9.

Table 9: ATT estimated using 5 nearest neighbour matching

	Model 1	Model 2	Model 3	Model 4
ATT	-0.0237*** (0.0055)	-0.0193* (0.0083)	-0.0192** (0.0067)	0.0189* (0.0083)
Number of pairs	1523	1523	1523	1333

*Note: The table contains ATT of being VC financed on CAR for 5 trading days from -2 to 2 relative to expiration date. The ATT was estimated using 5 nearest neighbours matching. Propensity score for all models was estimated using logistic regression. Number of pairs represent number of VC backed companies that found match out of 1523. Standard error is reported in brackets. *, **, and *** mean point estimates obtained are statistically significant at 5%, 1%, and 0.1% significance level respectively.*

5.3 Regression analysis

Firstly, I perform white tests for all my models, which indicates heteroscedasticity of residual in all of them. To also try to eliminate potential correlation in error term I perform robust clustered standard errors, clustered on industry level. Table 10 presents the estimation results of five different regression models, with cumulative abnormal returns as the dependent variable. The models were run on a dataset of 3504 observations, apart from model 4, which was limited to 3069 observations due to missing data on percent offered variable. F statistic of all models suggest that I reject null hypothesis that all point estimates are equal to zero. White test for all models indicates heteroscedasticity in residual. In all models, VC dummy is significantly and negatively associated with CAR on 0.1% level, coefficients are ranging from -0.0258 to -0.0188, indicating that holding other variables constant being VC backed is associated with from 1.88% to 2.58% lower CAR in absolute terms then non-VC backed ones. The 95% confidence intervals for first model are from -0.0314 to -0.0202 and for the third one is -0.0267 to -0.0144. Meaning that If I were to draw multiple samples and construct a confidence interval from each sample, I would expect that approximately 95% of these intervals would contain the true population parameter. Constant in Model 1 is average CAR of non-VC backed firms, it was not found to be significant. In models 2, 3, and 4, the high-tech dummy variable was included but found to be not significantly associated with CAR, suggesting that being a high-tech company is not significantly associated with abnormal returns in our sample. Year and price change variables were included in models 3 and 4. The year variable appears not to be statistically significant in these models. I also ran Model 5 with year dummies, but it did not change results. Price change is significant at the 0.1% levels in models 3 and 4 with estimated coefficients of -0.0191 and -0.0191, respectively, meaning that 1% increase in price change is associated with 0.019% decrease in CAR all else being equal. Lockup duration, a variable included in models 3 and 4, was not found to be statistically significant. Natural logarithm of proceeds included in models 3 and 4 shows a positive and significant relation to CAR at the 1% level with an estimated coefficient of 0.0069 meaning holding all other variables constant 1% increase in proceeds is associated with 0.0069% increase in CAR in absolute terms. The top underwriter variable, introduced in models 3 and 4, was not found to be statistically significant on 5 percent but was close with p value of 0.054. Abnormal volume, included in models 3 and 4, was also not statistically significant. Finally, percent of shares offered to shares outstanding was included only in model 4 but was not found to be statistically significant. The variance inflation factor scores ranged from 1.34 to 1.61, suggesting no multicollinearity concerns in our models as it is less then 5.

Table 10: Regression analysis

	Model 1	Model 2	Model 3	Model 4	Model 5
VC	-0.0258***	-0.0237***	-0.0205***	-0.0188***	-0.0205***
	(0.0028)	(0.0029)	(0.0031)	(0.0037)	(0.0031)
High-Tech		-0.0039	-0.0014	-0.0029	-0.0011
		(0.0038)	(0.0040)	(0.0044)	(0.0040)
Year			0.0003	0.0002	
			(0.0002)	(0.0003)	
Price change			-0.0191***	-0.0192***	-0.0190***
			(0.0052)	(0.0050)	(0.0053)
Lockup days			0.0000	0.0000	0.0000
			0.0000	0.0000	0.0000
Ln(proceeds)			0.0069***	0.0076***	0.0070***
			(0.0019)	(0.0019)	(0.0021)
Underwriter top			-0.0090	-0.0082	-0.0093*
			(0.0047)	(0.0046)	(0.0047)
Abnormal volume			-0.0008	-0.0012	-0.0008
			(0.0006)	(0.0008)	(0.0006)
Percent Offered				0.0000	
				(0.0001)	
1990 - 2000					-0.0016
					(0.0037)
2001 - 2011					-0.0056
					(0.0064)
Constant	0.0012	0.0024	-0.5656	-0.4942	-0.0205
	(0.0020)	(0.0021)	(0.4544)	(0.5182)	(0.0127)
Observations	3504	3504	3504	3069	3504
R^2	0.0144	0.0146	0.0386	0.0386	0.0386
Adjusted R^2	0.0141	0.0141	0.0364	0.0357	0.0361
F-statistic	83.46	43.87	15.88	25.79	14.39
White test	0.00	0.00	0.00	0.00	0.00
VIF		1.38	1.34	1.61	1.40

*Note: Model 1- 5 were developed following the methods detailed in the Methods chapter. A report of the P value from the White test signals the presence of heteroscedasticity in the error term. I implemented clustered standard errors at the industry level, which effectively handles heteroskedasticity. The F test results lead us to reject the null hypothesis that all estimated coefficients are null for every model. The Variance Inflation Factor (VIF) being less than 5 suggests that multicollinearity is not an issue. Standard errors are presented within brackets. The asterisks *, **, and *** are indicative of statistical significance at the levels of 5%, 1%, and 0.1% respectively.*

Table 11 presents four regression models predicting Cumulative Abnormal Return, this time split by whether the firms are venture capital backed. Model 3a, 4a, 5a represent firms that are not VC backed, while models 3b, 4b, 5b correspond to VC backed firms. The price change has a significant negative relationship with CAR for VC backed firms but does not have any impact for non-VC backed ones. The year was not found to be significant at 5 percent, however I found it to be significant on 10% level in all models for non-VC backed ones. I run additional model 3 using year dummies but do not find them to be statistically significant. High tech dummy was also not found to be significant in any sample. The logarithm of proceeds is significant for both VC and non-VC based firms for first model but most likely due to reduced sample size it loses significance on 5 percent level in model 2b but still significant on 10 percent, implying the IPO proceeds are associated with positive increase in CAR in VC backed and non-backed firms. Top underwriter effect was not found to be statistically significant on 5% but statistically significant on 10% for VC backed companies. The percent offered was not found to be associated with CAR. Finally abnormal volume was found to be associated with negative change in abnormal returns only in VC backed subsample.

Table 11: Regression analysis

	Model 3a (VC = 0)	Model 3b (VC = 1)	Model 4a (VC = 0)	Model 4b (VC = 1)	Model 5a (VC = 0)	Model 5b (VC = 1)
Year	0.0005	0.0000	0.0006	-0.0001		
	(0.0003)	(0.0003)	(0.0003)	(0.0004)		
Price change	-0.0022	-0.0289***	-0.0017	-0.0283***	-0.0022	-0.0290***
	(0.0056)	(0.0074)	(0.0065)	(0.0067)	(0.0058)	(0.0075)
High-tech	-0.0019	-0.0032	-0.0045	-0.0011	-0.0009	-0.0035
	(0.0049)	(0.0060)	(0.0056)	(0.0064)	(0.0050)	(0.0060)
Lockup days	0.0000	-0.0001*	0.0000	-0.0001*	0.0000	-0.0001*
	0.0000	0.0000	0.0000	0.0000	0.0000	(0.0001)
Ln(proceeds)	0.0065**	0.0094*	0.0072***	0.0089	0.0064**	0.0087*
	(0.0020)	(0.0040)	(0.0019)	(0.0045)	(0.0022)	(0.0044)
Underwriter top	-0.0070	-0.0121	-0.0046	-0.0112	-0.0072	-0.0120
	(0.0042)	(0.0092)	(0.0046)	(0.0093)	(0.0042)	(0.0089)
Abnormal volume	0.0004	-0.0016**	-0.0002	-0.0018*	0.0004	-0.0016*
	(0.0010)	(0.0006)	(0.0012)	(0.0007)	(0.0010)	(0.0006)
Percent Offered			-0.0001	0.0002		
			(0.0001)	(0.0002)		
1990 – 2000					-0.0087	-0.0037
					(0.0059)	(0.0098)
2001 – 2011					0.0007	-0.0051
					(0.0047)	(0.0060)
Constant	-1.0141	-0.0872	-1.1923	0.1319	-0.0268*	-0.0210
	(0.5140)	(0.6748)	(0.6451)	(0.6948)	(0.0127)	(0.0244)
Observations	1981	1523	1689	1380	1981	1523
R^2	0.0162	0.0462	0.0203	0.0458	0.0158	0.0464
Adjusted R^2	0.0128	0.0418	0.0156	0.0403	0.0119	0.0414
F statistic	4.80	11.52	5.59	11.59	3.97	9.21
White test	0.00	0.00	0.00	0.00	0.00	0.00
VIF	1.25	1.33	1.24	1.29	1.32	1.37

*Note: Model 3a – 5b were constructed as models 3-5 but separately for VC and non-VC backed subsamples. A report of the P value from the White test signals the presence of heteroscedasticity in the error term. I implemented clustered standard errors at the industry level, which effectively handles heteroskedasticity. The F test results lead us to reject the null hypothesis that all estimated coefficients are null for every model. The Variance Inflation Factor (VIF) being less than 5 suggests that multicollinearity isn't a pressing issue. Standard errors are referenced in the parentheses and presented within brackets. The asterisks *, **, and *** are indicative of statistical significance at the levels of 5%, 1%, and 0.1% respectively.*

CHAPTER 6 Discussion

I document existence of a negative Cumulative Average Abnormal Return for entire sample, but it is driven by VC backed companies as when examining VC backed and non-VC backed samples, I find negative abnormal return solely for venture capital financed firms. It has been observed that companies not supported by VC investments experienced less negative abnormal returns, and, from the year 2000 onwards, these non-VC backed firms displayed no abnormal returns on average. Consequently, I am compelled to reject the null hypothesis, which posits the absence of abnormal returns for both the comprehensive sample and the subset of VC-backed firms. However, there is insufficient empirical evidence to reject the null hypothesis for the non-VC backed sample.

Moreover, I identified an Average Treatment Effect and an Average Treatment effect on the Treated of being VC-backed on CAR. Empirical results suggest negative significant association of being VC backed and five-day CAR. These findings are in line with results of Field and Hanka (2001), Bradley et al. (2001) and many others. Result was robust to different specifications and types of models. However, even though potentially selection bias was reduced through Propensity Score Matching and the inclusion of a control variables within the regression analysis might help with omitted variable bias, it cannot be conclusively stated that the derived estimate is entirely unbiased. Thus, it must be interpreted as an association, and it is neither feasible to reject nor accept the hypothesis of the causal impact of being VC-backed on the Cumulative Abnormal Return and null hypothesis of no effect.

Regarding trading volumes, there were abnormal fluctuations in both VC and non-VC backed samples. However, a significant negative association between abnormal volumes was detected exclusively within the VC-backed subpopulation, consistent with findings of Bradley et al (2001). I reject null hypothesis of no abnormal volume for VC and Non-VC backed companies. I do not reject nor accept the hypothesis of the impact of volume on the Cumulative Abnormal Return, but I also cannot accept the null hypothesis of no effect. The CAAR does not dissipate post-lockup expiry and appears to persist in the negative region. This finding suggests that the probability of a liquidity premium being the rationale for the abnormal return on the expiry date is low. Instead, the data is more suggestive of downward sloping demand curves. Moreover, I noted a permanent increase in trading volume, which is consistent with the hypothesis of short sale constraint removal (Ofek & Richardson, 2003).

A potential explanation for the negative abnormal returns observed in VC-backed companies, but not in non-VC backed companies, is the potential loss of the monitoring role. However, explaining this phenomenon without factoring in irrational investors is challenging, especially considering that negative

CAAR returns have been observed for VC-backed companies over the past three decades. It remains unclear why investors would consistently misjudge the extent to which insiders will exit. One counterargument to this theory is that it fails to explain why abnormal returns were evident prior to the year 2000 for non-VC backed companies. One possible explanation is that analyst recommendation played crucial role in explaining abnormal return for non-VC backed companies, however according to research of D. Bradley et al. (2015) it ceased to exist after 2001 crisis and that could be the reason we see less abnormal return for VC and no abnormal return for non VC subsample after 2001. I did not find significant association between year variable or year dummies and CAR for VC backed sample but observed it for year variable for non-VC backed IPOs suggesting some possibility of learning effect.

Other potential explanation could be that VC investments attract different types of investors which cause overvaluation of the stock price. Interestingly, the average price appreciation from Initial Public Offering to lockup expiration date was greater for VC-backed companies and was associated with their negative abnormal return. This observation aligns with the resale option theory and the fact that insiders are rational and part of investors is irrational as proposed by Hong et al. (2006) and findings of Haggard and Xi (2017) that the main reason for abnormal returns is company overvaluation. Also, I find that proceeds are associated with less negative abnormal returns for VC backed sample and higher positive abnormal returns for non-VC backed, which is in line with hypothesis that bigger companies are associated with less information asymmetry and signal that information asymmetry could play a role in explaining abnormal returns surrounding lock-up expiration date. The fact that I find negative association between lockup duration and abnormal return could also signal role of information asymmetry, I found this association only in the VC backed subsample. I did not find a significant relationship between percent of shares offered and CAR, however most likely it is bad proxy for number of shares locked and better proxy should be found.

Overall, my finding partly corroborates that abnormal return on lock days cannot be explained by semi-efficient market hypothesis and seems to be in line with heterogeneous believes, short sale constraint and downward slopping demand curves. The factors that VC attract different types of investors and lose of monitoring role could play a role in the fact that VC companies experience higher CAAR and AAR. However, future research is needed to find concrete reasons for abnormal return and make sure the effect of VC backing is causal and not caused by something else that affect VC backing and Abnormal Return.

CHAPTER 7 Conclusion

In this study I looked at the abnormal return and volume during lockup expiration event window especially concerning VC and Non-VC backed IPO’s. Past research has found significant negative abnormal return around IPO lockup expiration date, however there is no clear consensus between reasons for abnormal return nor explanations for it and it is not clear why it is mostly VC backed companies that experience abnormal return. I try to once again connect empirical evidence with theories that could explain abnormal return and difference between in VC and Non-VC funded firms. Also, I perform propensity score matching to try to minimize selection bias and estimate ATT, which has been done in context of IPO underpricing but has not been done previously for IPO lockups. The main question that was studied is “What are the reasons for abnormal return surrounding lockup expiration date?”

To answer this question, I gathered data on US based IPOs from 1st June 1990 to 1st June 2022 using Eikon New Issue Database and CRSP database. I then calculated abnormal return around lockup expiration date for such companies using market model and abnormal volume as deviation from average volume pre-expiration of each individual stock. To examine abnormal returns, I perform standard event study coupled with propensity score matching and multivariate regressions. The results suggest that there is negative significant CAAR and AARs for VC backed companies during lockup period. It seems that CAAR is long term as I still find it significant for (-6;21). I reject the null hypothesis of absence of abnormal returns for the total sample, however, find that it is driven by VC backed firms. Therefore, I also jest the null hypothesis of absence of abnormal return for VC-backed subset but do not discard it for the non-VC-backed sample. The analysis identified a negative Average Treatment Effect and an Average Treatment effect on the Treated, in line with previous studies. While an attempt to reduce selection bias was made, I am caution against accepting the derived estimate as entirely unbiased and hence neither accept nor reject the hypothesis of effect of VC backing on abnormal return. I also observe abnormal fluctuations in trading volumes for both VC and non-VC backed firms, but with a significant negative association between it and CAR only for VC-backed firms.

I find some support that framework of heterogeneous irrational believes coupled with short sale constrained could potentially explain CAR. It seems like other factors such as loss of monitoring role, overvaluation due to the type of investors attracted by VC investment could amplify abnormal return for VC backed companies. Nevertheless, it remains unclear why investors consistently underestimate insiders exit or would invest in such companies prior to lockup expiration. More concrete evidence is required. My study faces several limitations. First, even though measures such as Propensity Score Matching were implemented to mitigate selection bias there may be confounding variables not accounted for in the analysis, which could distort the true relationship between venture capitalist backing and Cumulative Average Abnormal Return. Secondly, the study’s conclusions are based on market model using relatively low number of observations, which might distort true results. Further research should be done on what is different between venture capital and non-venture capital backed IPOs. Especially it would be interesting to examine social media and news sentiment before lockup expiration for VC and non-VC backed companies as well as further research on what type of investors participate in VC backed IPOs. Moreover, for proper identification of causal effect instrument is required, possible instruments that could be constructed by researchers is distance of founders' university to Venture Capital firm clusters and founder university degree. For policy recommendation further research is needed to establish weather this abnormal return is normal for the market, its market failure or caused by some government policies. Additional transparency about lockup sales might be required. As for regular investor this research indicates that it might be beneficial to not buy a VC backed company stocks shortly before lockup expiration.

REFERENCES

Aggarwal, R. K., Krigman, L., & Womack, K. L. (2002). Strategic IPO underpricing, information momentum, and lockup expiration selling. *Journal of Financial Economics*, *66*(1), 105–137. https://doi.org/10.1016/S0304-405X(02)00152-6

Anderson, E. W., Ghysels, E., & Juergens, J. L. (2005). Do Heterogeneous Beliefs Matter for Asset Pricing? *The Review of Financial Studies*, *18*(3), 875–924. https://doi.org/10.1093/rfs/hhi026

Austin, P. C. (2011). An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. *Multivariate Behavioral Research*, *46*(3), 399–424. https://doi.org/10.1080/00273171.2011.568786

Barber, B. M., & Lyon, J. D. (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics*, *43*(3), 341–372. https://doi.org/10.1016/S0304-405X(96)00890-2

Barry, C. B. (1994). New Directions in Research on Venture Capital Finance. *Financial Management*, *23*(3), 3–15. https://doi.org/10.2307/3665617

Barry, C. B., Muscarella, C. J., Peavy, J. W., & Vetsuypens, M. R. (1990). The role of venture capital in the creation of public companies: Evidence from the going-public process. *Journal of Financial Economics*, *27*(2), 447–471. https://doi.org/10.1016/0304-405X(90)90064-7

Baum, J. A. C., & Silverman, B. S. (2004). Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. *Journal of Business Venturing*, *19*(3), 411–436. https://doi.org/10.1016/S0883-9026(03)00038-7

Bernstein, S., Giroud, X., & Townsend, R. R. (2016). The Impact of Venture Capital Monitoring. *The Journal of Finance*, *71*(4), 1591–1622. https://doi.org/10.1111/jofi.12370

Bodnaruk, A., Kandel, E., Massa, M., & Simonov, A. (2008). Shareholder Diversification and the Decision to Go Public. *The Review of Financial Studies*, *21*(6), 2779–2824. https://doi.org/10.1093/rfs/hhm036

Bradley, D. J., Jordan, B. D., Yi, H.-C., & Roten, I. C. (2001). Venture Capital and Ipo Lockup Expiration: An Empirical Analysis. *Journal of Financial Research*, *24*(4), 465–493. https://doi.org/10.1111/j.1475-6803.2001.tb00826.x

Bradley, D., Kim, I., & Krigman, L. (2015). Top VC IPO underpricing. *Journal of Corporate Finance*, *31*, 186–202. https://doi.org/10.1016/j.jcorpfin.2015.01.016

Brau, J. C., Carter, D. A., Christophe, S. E., & Key, K. G. (2004). Market reaction to the expiration of IPO lockup provisions. *Managerial Finance*, *30*(1), 75–91. https://doi.org/10.1108/03074350410768859

Brau, J. C., Lambson, V. E., & McQueen, G. (2005). Lockups Revisited. *Journal of Financial and Quantitative Analysis*, *40*(3), 519–530. https://doi.org/10.1017/S002210900000185X

Brav, A., Geczy, C., & Gompers, P. A. (2000). Is the abnormal return following equity issuances anomalous? *Journal of Financial Economics*, *56*(2), 209–249. https://doi.org/10.1016/S0304-405X(00)00040-4

Brav, A., & Gompers, P. A. (1997). Myth or Reality? The Long-Run Underperformance of Initial Public Offerings: Evidence from Venture and Nonventure Capital-Backed Companies. *The Journal of Finance*, *52*(5), 1791–1821. https://doi.org/10.1111/j.1540-6261.1997.tb02742.x

Brav, A., & Gompers, P. A. (2003). The Role of Lockups in Initial Public Offerings. *The Review of Financial Studies*, *16*(1), 1–29. https://doi.org/10.1093/rfs/16.1.0001

Brooks, C. (2019). *Introductory Econometrics for Finance*. Cambridge University Press.

Brown, S. J., & Warner, J. B. (1980). Measuring security price performance. *Journal of Financial Economics*, *8*(3), 205–258. https://doi.org/10.1016/0304-405X(80)90002-1

Carter, R., & Manaster, S. (1990). Initial Public Offerings and Underwriter Reputation. *The Journal of Finance*, *45*(4), 1045–1067. https://doi.org/10.2307/2328714

Chemmanur, T. J., & Loutskina, E. (2006). The Role of Venture Capital Backing in Initial Public Offerings: Certification, Screening, or Market Power? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.604882

Chen, H.-C., Chen, S.-S., & Huang, C.-W. (2012). Why Do Insiders Sell Shares Following IPO Lockups? *Financial Management*, *41*(4), 813–847. https://doi.org/10.1111/j.1755-053X.2012.01217.x

Cinelli, C., Forney, A., & Pearl, J. (2022). A Crash Course in Good and Bad Controls. *Sociological Methods & Research*, 00491241221099552. https://doi.org/10.1177/00491241221099552

Cliff, M. T., & Denis, D. J. (2004). Do Initial Public Offering Firms Purchase Analyst Coverage with Underpricing? *The Journal of Finance*, *59*(6), 2871–2901. https://doi.org/10.1111/j.1540-6261.2004.00719.x

Colombo, M. G., & Grilli, L. (2010). On growth drivers of high-tech start-ups: Exploring the role of founders' human capital and venture capital. *Journal of Business Venturing*, *25*(6), 610–626. https://doi.org/10.1016/j.jbusvent.2009.01.005

Courteau, L. (1995). Under-Diversification and Retention Commitments in IPOs. *The Journal of Financial and Quantitative Analysis*, *30*(4), 487–517. https://doi.org/10.2307/2331274

Cowan, A. R. (1992). Nonparametric event study tests. *Review of Quantitative Finance and Accounting*, *2*(4), 343–358. https://doi.org/10.1007/BF00939016

Cumming, D., Fleming, G., & Schwienbacher, A. (2005). Liquidity Risk and Venture Capital Finance. *Financial Management*, *34*(4), 77–105. https://doi.org/10.1111/j.1755-053X.2005.tb00119.x

Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of Opinion and the Cross Section of Stock Returns. *The Journal of Finance*, *57*(5), 2113–2141. https://doi.org/10.1111/0022-1082.00490

Espenlaub, S., Goergen, M., & Khurshed, A. (2001). PO Lock-in Agreements in the UK. *Journal of Business Finance & Accounting*, *28*(9–10), 1235–1278. https://doi.org/10.1111/1468-5957.00414

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Field, L. C., & Hanka, G. (2001). The Expiration of IPO Share Lockups. *The Journal of Finance*, *56*(2), 471–500. https://doi.org/10.1111/0022-1082.00334

Goergen, M., Mazouz, K., & Yin, S. (2010). Price, volume and spread effects associated with the expiry of lock-in agreements: Evidence from the Hong Kong IPO market. *Pacific-Basin Finance Journal*, *18*(5), 442–459. https://doi.org/10.1016/j.pacfin.2010.05.001

Gompers, P. A. (1996). Grandstanding in the venture capital industry. *Journal of Financial Economics*, *42*(1), 133–156. https://doi.org/10.1016/0304-405X(96)00874-4

Gompers, P. A., & Lerner, J. (1999). *What Drives Venture Capital Fundraising?* (Working Paper No. 6906). National Bureau of Economic Research. https://doi.org/10.3386/w6906

Gompers, P., & Lerner, J. (1998). Venture Capital Distributions: Short-Run and Long-Run Reactions. *The Journal of Finance*, *53*(6), 2161–2183. https://doi.org/10.1111/0022-1082.00086

Gompers, P., & Lerner, J. (2001). The Venture Capital Revolution. *Journal of Economic Perspectives*, *15*(2), 145–168. https://doi.org/10.1257/jep.15.2.145

Haggard, K. S., & Xi, Y. (2017). IPO overvaluation and returns prior to lockup expiration. *Managerial Finance*, *43*(12), 1392–1410. https://doi.org/10.1108/MF-05-2017-0172

Hakim, T., Lypny, G., & Bhabra, H. S. (2012). IPO lockup expiration in the Middle East and North Africa. *Journal of Multinational Financial Management*, *22*(5), 252–262. https://doi.org/10.1016/j.mulfin.2012.06.005

Harris, H., & Horst, S. (2019). A Brief Guide to Decisions at Each Step of the Propensity Score Matching Process. *Practical Assessment, Research, and Evaluation*, *21*(1). https://doi.org/10.7275/yq7r-4820

Harris, L., & Gurel, E. (1986). Price and Volume Effects Associated with Changes in the S&P 500 List: New Evidence for the Existence of Price Pressures. *The Journal of Finance*, *41*(4), 815–829. https://doi.org/10.1111/j.1540-6261.1986.tb04550.x

Harrison, J. M., & Kreps, D. M. (1978). Speculative Investor Behavior in a Stock Market with Heterogeneous Expectations. *The Quarterly Journal of Economics*, *92*(2), 323–336. https://doi.org/10.2307/1884166

Hong, H., Scheinkman, J., & Xiong, W. (2006). Asset Float and Speculative Bubbles. *The Journal of Finance*, *61*(3), 1073–1117. https://doi.org/10.1111/j.1540-6261.2006.00867.x

Jain, B. A., & Kini, O. (1995). Venture capitalist participation and the post-issue operating performance of IPO firms. *Managerial and Decision Economics*, *16*(6), 593–606. https://doi.org/10.1002/mde.4090160603

Keasler, T. R. (2001). Underwriter Lock-up Releases, Initial Public Offerings and After-market Performance. *Financial Review*, *36*(2), 1–20. https://doi.org/10.1111/j.1540-6288.2001.tb00008.x

King, G., & Nielsen, R. (2019). Why Propensity Scores Should Not Be Used for Matching. *Political Analysis*, *27*(4), 435–454. https://doi.org/10.1017/pan.2019.11

Lee, P. M., & Wahal, S. (2004). Grandstanding, certification and the underpricing of venture capital backed IPOs. *Journal of Financial Economics*, *73*(2), 375–407. https://doi.org/10.1016/j.jfineco.2003.09.003

Leland, H. E., & Pyle, D. H. (1977). Informational Asymmetries, Financial Structure, and Financial Intermediation. *The Journal of Finance*, *32*(2), 371–387. https://doi.org/10.2307/2326770

Lynch, A. W., & Mendenhall, R. R. (1997). New Evidence on Stock Price Effects Associated with Changes in the S&P 500 Index. *The Journal of Business*, *70*(3), 351–383. https://doi.org/10.1086/209722

Morris, S. (1996). Speculative Investor Behavior and Learning*. *The Quarterly Journal of Economics*, *111*(4), 1111–1133. https://doi.org/10.2307/2946709

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*(2), 187–221. https://doi.org/10.1016/0304-405X(84)90023-0

Nemlioglu, I., & Mallick, S. K. (2020). Do innovation-intensive firms mitigate their valuation uncertainty during bad times? *Journal of Economic Behavior & Organization*, *177*, 913–940. https://doi.org/10.1016/j.jebo.2020.06.004

Ofek, E. (2000). *The IPO Lock-Up Period: Implications for Market Efficiency and Downward Sloping Demand Curves* (SSRN Scholarly Paper No. 1298279). https://papers.ssrn.com/abstract=1298279

Ofek, E., & Richardson, M. (2002). The Valuation and Market Rationality of Internet Stock Prices. *Oxford Review of Economic Policy*, *18*(3), 265–287. https://doi.org/10.1093/oxrep/18.3.265

Ofek, E., & Richardson, M. (2003). DotCom Mania: The Rise and Fall of Internet Stock Prices. *The Journal of Finance*, *58*(3), 1113–1137. https://doi.org/10.1111/1540-6261.00560

Rajan, R., & Servaes, H. (1997). Analyst Following of Initial Public Offerings. *The Journal of Finance*, *52*(2), 507–529. https://doi.org/10.1111/j.1540-6261.1997.tb04811.x

ROSENBAUM, P. R., & RUBIN, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *The American Statistician*, *39*(1), 33–38. https://doi.org/10.2307/2683903

Schultz, P. (2008). Downward-Sloping Demand Curves, the Supply of Shares, and the Collapse of Internet Stock Prices. *The Journal of Finance*, *63*(1), 351–378. https://doi.org/10.1111/j.1540-6261.2008.01318.x

Shleifer, A. (1986). Do Demand Curves for Stocks Slope Down? *The Journal of Finance*, *41*(3), 579–590. https://doi.org/10.2307/2328486

Stuart, E. A., & Rubin, D. B. (2008). Best Practices in Quasi–Experimental Designs: Matching Methods for Causal Inference. In J. Osborne, *Best Practices in Quantitative Methods* (pp. 155–176). SAGE Publications, Inc. https://doi.org/10.4135/9781412995627.d14

Wright Robbie, K., Mike. (1998). Venture Capital and Private Equity: A Review and Synthesis. *Journal of Business Finance & Accounting*, *25*(5–6), 521–570. https://doi.org/10.1111/1468-5957.00201

Xing, X. (2008). Do demand curves for stocks slope down?: Evidence from aggregate data. *The Quarterly Review of Economics and Finance*, *48*(3), 641–651. https://doi.org/10.1016/j.qref.2006.03.001

Yang, T., & Hou, W. (2017). Venture capital trusts and the expiration of IPO lock-up provisions. *The European Journal of Finance*, *23*(3), 211–242. https://doi.org/10.1080/1351847X.2016.1169199

Yung, C., & Zender, J. F. (2010). Moral hazard, asymmetric information and IPO lockups. *Journal of Corporate Finance*, *16*(3), 320–332. https://doi.org/10.1016/j.jcorpfin.2009.12.004

APPENDIX A1: Tests for event study

This section I show tests that I used during my analysis. Throughout this section I us following notation:

N: Number of firms

w: Number of firms with positive AR/CAR during event

K: Number of days in the event window

t: Number of drading day relative to event day

i: Company i out of N

p: fraction of positive AR across companies and time during estimation window

T_0: Start of estimation window day

T_1: End of estimation window day

Cross-sectional test for AAR:

$$t = \sqrt{N}\frac{AAR_t}{S_{AAR,t}} \quad \text{with} \quad S^2_{AAR,t} = \frac{1}{N-1}\sum_{i=1}^{N}\left(AR_{i,t} - AAR_t\right)^2 \tag{11}$$

$$t \sim t(N-1)$$

Cross-sectional test for CAAR:

$$t = \sqrt{N}\frac{CAAR}{S_{CAAR}} \quad \text{with} \quad S^2_{CAAR} = \frac{1}{N-1}\sum_{i=1}^{N}(CAR_i - CAAR)^2 \tag{12}$$

$$t \sim t(N-1)$$

Cross-sectional test for AAV:

$$t = \sqrt{N}\frac{AAV_t}{S_{AAV,t}} \quad \text{with} \quad S^2_{AAV,t} = \frac{1}{N-1}\sum_{i=1}^{N}\left(AV_{i,t} - AAV_t\right)^2 \tag{13}$$

$$t \sim t(N-1)$$

Crude dependence test for AAR:

$$t = \frac{AAR_t}{S_{AAR}} \quad \text{with} \quad S_{AAR}^2 = \frac{1}{M-1}\sum_{t=T_0}^{T_1}\left(AAR_t - \frac{1}{M}\sum_{t=T_0}^{T_1} AAR_t\right)^2 \tag{14}$$

$$t \sim t(M-1)$$

Crude dependence test for CAAR:

$$t = \sqrt{K} * \frac{CAAR}{S_{AAR}} \quad \text{with} \quad S_{AAR}^2 = \frac{1}{M-1}\sum_{t=T_0}^{T_1}\left(AAR_t - \frac{1}{M}\sum_{t=T_0}^{T_1} AAR_t\right)^2 \tag{15}$$

$$t \sim t(M-1)$$

Adjusted sign-test for CAAR and AAR:

$$\hat{p} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{M}\sum_{t=T_0}^{T_1} S_{i,t} \quad \text{where} \quad S_{i,t} = \begin{cases} 1 \; if \; AR_{i,t} > 0 \\ 0 \; otherwise \end{cases} \tag{16}$$

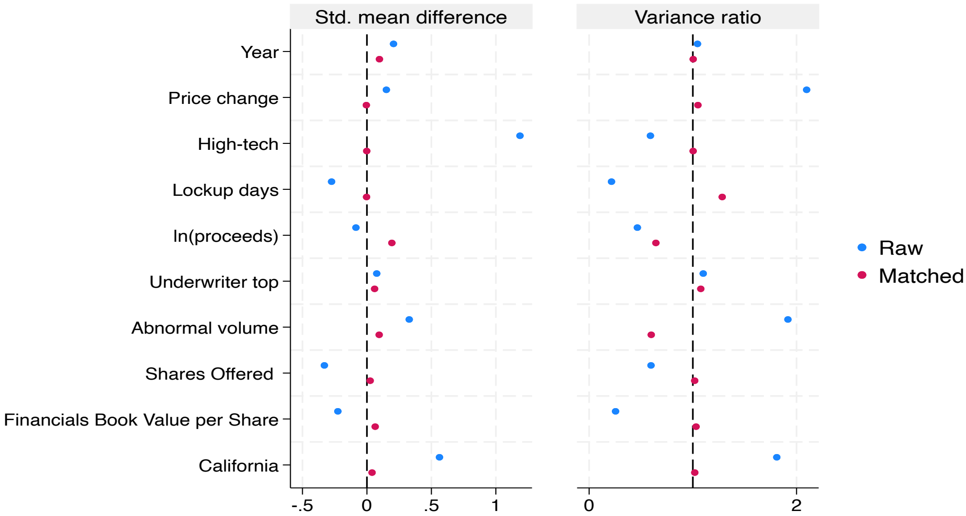
$$z = \frac{w - N \cdot \hat{p}}{\sqrt{N \cdot \hat{p}(1-\hat{p})}} \tag{17}$$

$$z \sim N(0,1)$$

APPENDIX A2: Propensity score matching

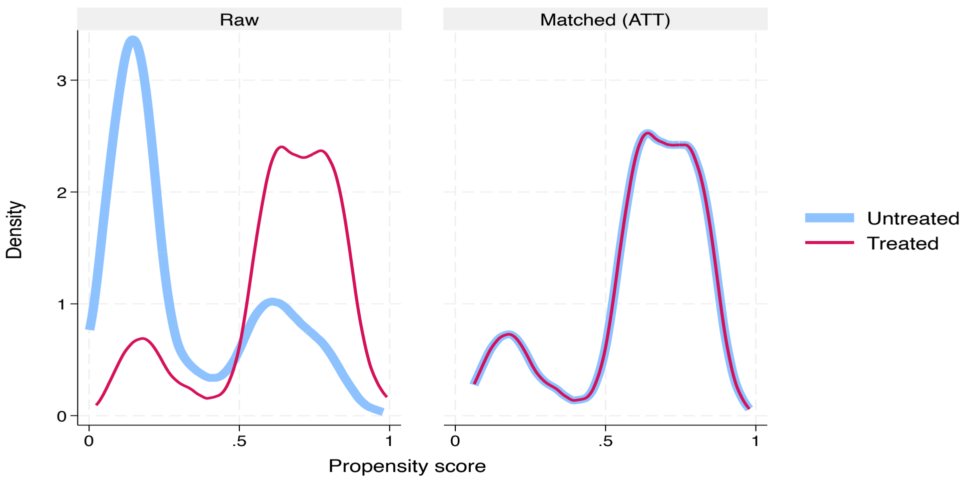
Here I present balancing figures for propensity score matching using Kernel Method. Standardised mean difference is calculated as mean difference divided but standard deviation. Variance ratio is ration of variance between VC and non-VC backed IPOs. As can be seen in Figure 11 the mean difference for model 4 was reduced for almost all variables except ln(proceeds), the year difference was reduced but not ideally. For the variance ratios, they were reduced in model 4 for all variables, though not ideally for lockup days, proceeds and abnormal volume. As can be seen in figure 12, the common support assumption seems at least weakly satisfied.

Figure 11: Standard mean difference and variance ratio before and after matching for Model 4



Note: The figure contains standardised mean difference and variance ratio before and after matching of VC backed and non-VC backed IPOs for Kernel PSM for model 4. The left figure represents standardised mean difference before and after matching, the right figure presents variance ratio before and after matching. The closer standardised difference to 0 or variance ratio to 1 after matching more balanced treated and untreaded groups become.

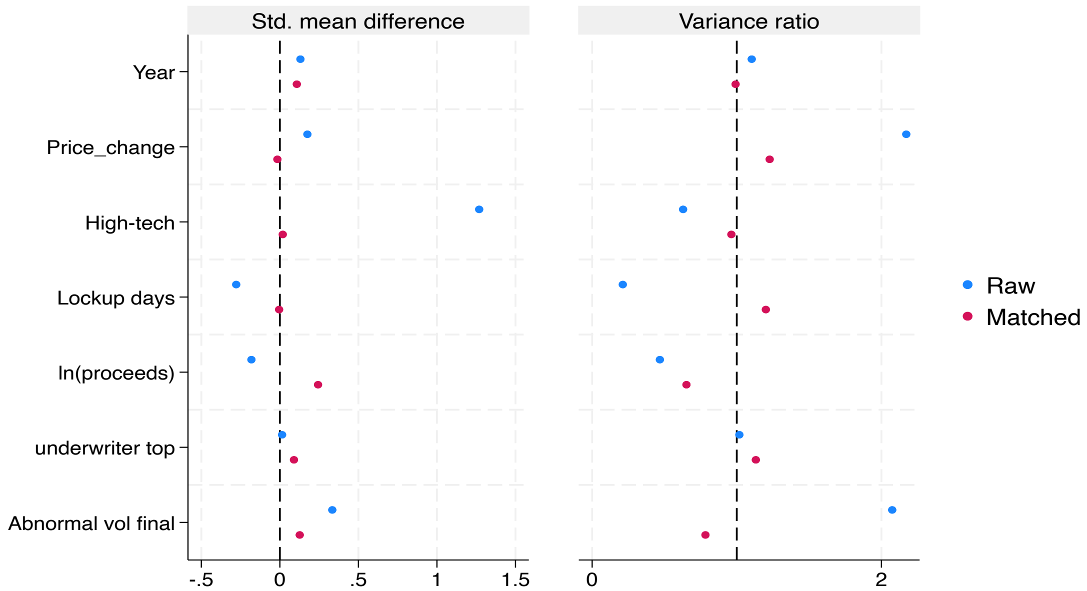
Figure 12: Distribution of propensity scores before and after matching for Model 4



Note: The figure contains distribution of propensity scores of being VC backed for VC and non-VC financed IPOs for Kernel PSM for model 4. The left figure represents distribution before matching, the right figure presents distribution after matching. Density can be seen on the y-axis. Propensity score on x-axis.

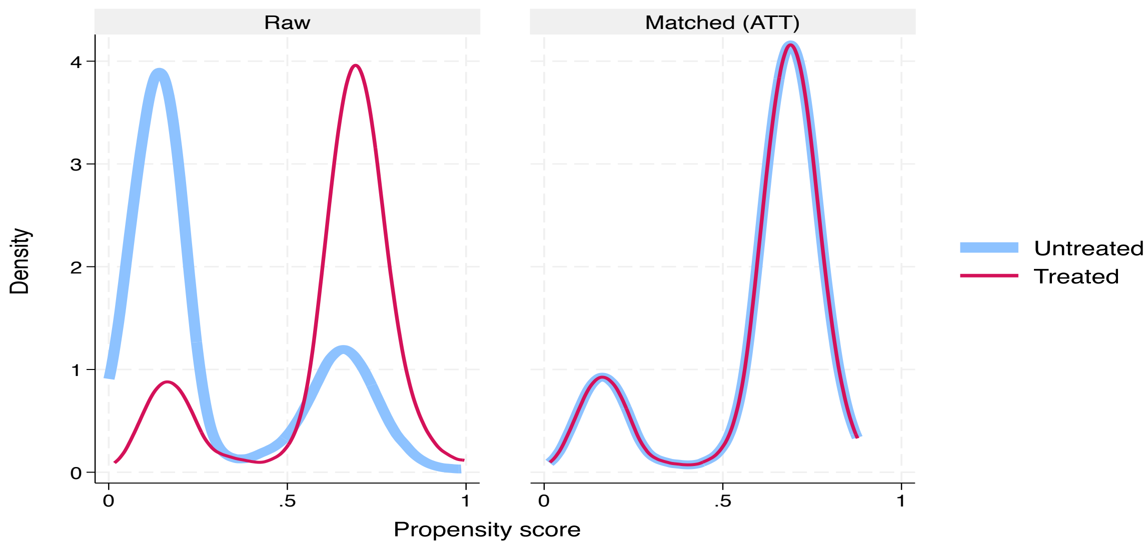
Regarding model 2, as seen in Figure 13 standardised mean difference was reduced for all variables except log of proceeds. Variance was reduced for all variables except top underwriter but remained close to zero. As seen on Figure 14 the common support assumption is weakly satisfied.

Figure 13: Standard mean difference and variance ratio before and after matching for Model 2



Note: The figure contains standardised mean difference and variance ratio before and after matching of VC backed and non-VC backed IPOs for Kernel PSM for model 2. The left figure represents standardised mean difference before and after matching, the right figure presents variance ratio before and after matching. The closer standardised difference to 0 or variance ratio to 1 after matching more balanced treated and untreaded groups become.

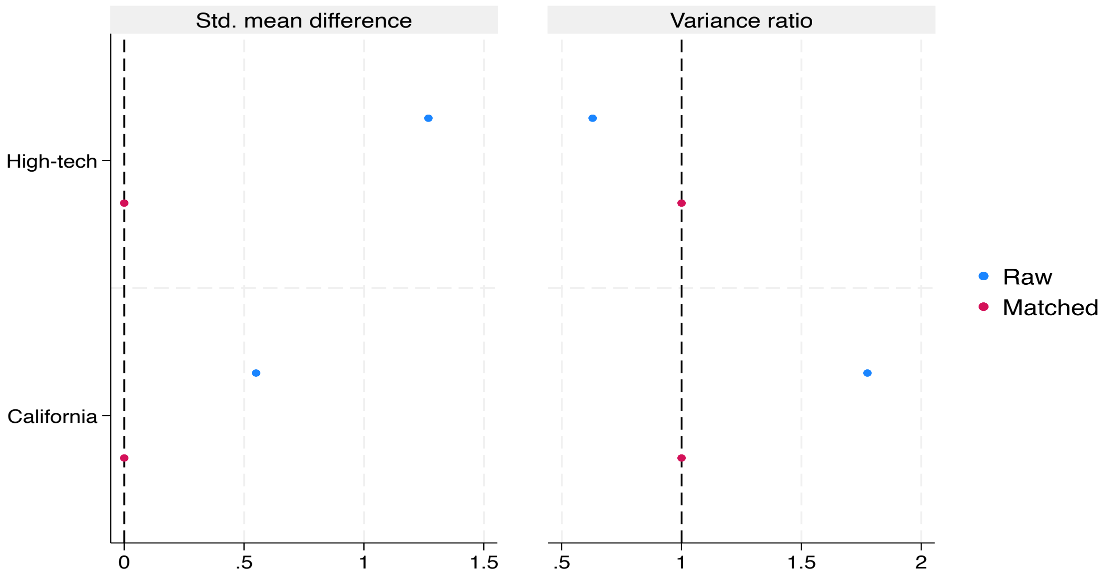
Figure 14: Distribution of propensity scores before and after matching for Model 2



Note: The figure contains distribution of propensity scores of being VC backed for VC and non-VC financed IPOs for Kernel PSM for model 2. The left figure represents distribution before matching, the right figure presents distribution after matching. Density can be seen on the y-axis. Propensity score on x-axis.

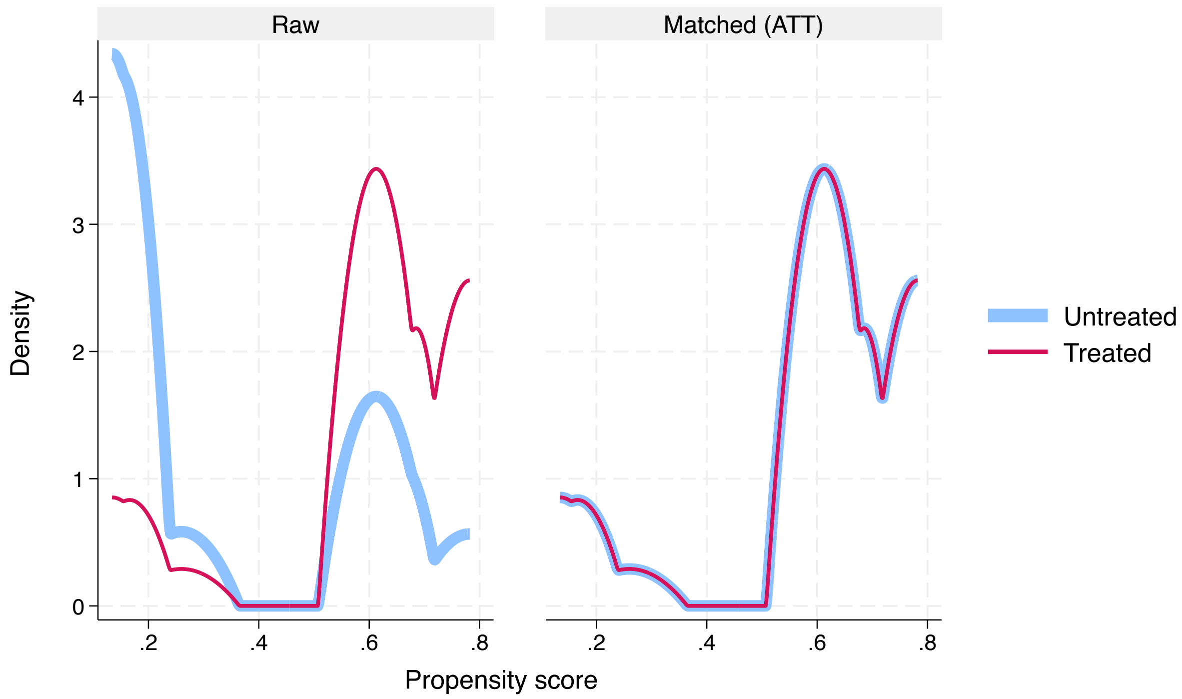
In Model 1, I got perfect balance in high-tech and California variable standardised mean difference and variance ratio. The results are present in Figure 15 and 16.

Figure 15: Standard mean difference and variance ratio before and after matching for Model 1



Note: The figure contains standardised mean difference and variance ratio before and after matching of VC backed and non-VC backed IPOs for Kernel PSM for model 1. The left figure represents standardised mean difference before and after matching, the right figure presents variance ratio before and after matching. The closer standardised difference to 0 or variance ratio to 1 after matching more balanced treated and untreaded groups become.

Figure 16: Distribution of propensity scores before and after matching for Model 1



Note: The figure contains distribution of propensity scores of being VC backed for VC and non-VC financed IPOs for Kernel PSM for model 1. The left figure represents distribution before matching, the right figure presents distribution after matching. Density can be seen on the y-axis. Propensity score on x-axis.