



SCHOOL OF ECONOMICS AND MANAGEMENT

Funding Fever: How Venture Capital Type Shapes Post-IPO Outcomes in Biotechnology

A Quantitative Study of How Corporate and Independent Venture
Capital Shape Innovation Output and Financial Performance in Public
Biotechnology Firms

Bachelor's Programme in International Business

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Abstract

This study aims to investigate how corporate venture capital (CVC) and independent venture capital (IVC) influence innovation and financial outcomes in biotechnology firms following their initial public offering (IPO), and how factors like technological fit and failure tolerance mediate innovation outcomes. Using a sample of US-based biotechnology firms that completed IPOs between 2010 and 2020, we conduct parametric tests and regression analyses based on patent data, investor type, and industry-adjusted stock returns. Our results suggest that investor identity plays a significant role in shaping the innovative trajectories of newly public biotechnology firms. We find that CVC-backed firms produce significantly more patents in the three years following IPO compared to IVC-backed firms. However, we find no evidence that CVCs exhibit higher failure tolerance or that technological fit enhances the innovation output of CVC-backed firms. While failure tolerance is positively associated with patenting activity, it does not appear to be a distinguishing feature of CVCs, potentially due to the high-risk characteristics of the industry. Moreover, we find no significant relationship between investor type and post-IPO financial performance. These findings provide novel empirical evidence on the post-IPO effects of CVC versus IVC backing and contribute to the VC literature by highlighting the need for other mediating mechanisms explaining the difference between the two investor types in post-IPO outcomes in this industry.

Keywords: Corporate Venture Capital (CVC), Independent Venture Capital (IVC), Technological Fit, Failure Tolerance, Biotechnology, post-IPO

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Finally, we hope the reader finds this thesis both interesting and informative, and that the findings and conclusions contribute to the broader field of venture capital and innovation research.

Sincerely,

Linn Elderot, John Johansson & Samuel Schatz

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1. Introduction

1.1 Background

Biotechnology operates at the crossroads of scientific discovery, substantial returns and high uncertainty. Developing a new therapy often takes over a decade, costs nearly a billion dollars, and involves a daunting failure rate, with about 90% of drug candidates never making it through clinical trials (Evens, 2016). Given these hurdles, venture capital (VC) has become a lifeline for biotechnology start-ups. These investors provide essential funding years before any product reaches the market, taking on significant risk in exchange for a potential future payoff. In recent years, the VC landscape has evolved markedly. Especially in the healthcare industry, traditional independent venture capital (IVC) firms are now accompanied by corporate venture capitalists (CVCs), investment arms of large companies. 2010 marked a key turning point, with CVC participation increasing, and general VC and R&D activity rebounding after the global financial crisis (Rossi, Thrassou, & Vrontis, 2011). By the early 2010s, CVC accounted for approximately 15% of US biotechnology venture investments, a share that rose to 25% in the first half of 2011, highlighting CVCs as an increasingly influential source of biotechnology financing (Lefteroff, 2012).

Previous research has established that there is a notable divergence between IVC and CVC investors. IVCs typically invest with the primary goal of generating financial returns for their limited partners within the constraints of fixed fund life cycles (Gompers, 1996; Chemmanur, Loutskina & Tian, 2014; Colombo and Murtinu, 2017; Ivanov & Xie, 2010). CVCs, by contrast, operate as strategic investment arms of established corporations, additionally seeking technological synergies, market insights, and complementary innovation (Colombo & Murtinu, 2017; Ivanov & Xie, 2010). This divergence implies that start-ups gain access to markedly different resources, expertise, and investor priorities depending on which investor backing is obtained. As CVC investors play an increasingly prominent role in funding biotechnology start-ups, it becomes important to explore how the type of VC backing influences these firms' development and outcomes.

For biotechnology start-ups, an IPO is a major milestone that marks the start of a new phase, where firms face pressure to meet short-term investor expectations while simultaneously pursuing long-term innovation. The post-IPO phase remains largely underexplored in VC literature but is critically important. Analyzing outcomes during this stage helps determine how early-stage investor contributions continue to shape innovation and financial performance once the firm faces public market pressures and broader shareholder scrutiny. Research conducted by Chemmanur et al. (2014) is one of the few studies to show that CVC-backed firms outperform IVC-backed firms in both pre- and post-IPO innovation, attributing this to two key mechanisms: technological fit and failure tolerance. However, their analysis spans across multiple industries and does not assess whether these effects are stronger in specific sectors. A meta-analysis by Haslanger, Lehmann and Seitz (2022) found no significant relationship between CVC-backing and strategic or financial outcomes in the healthcare sector, underscoring the need for more industry-specific studies. Moreover, while researchers like Guo and Zhou (2014) and Ivanov and Xie (2010) suggest that CVCs contribute to long-term financial success, the causal mechanisms, particularly those related to post-IPO innovation, remain unexplored.

Extending the work of Chemmanur et al. (2014), this thesis explores whether differences in technological fit and failure tolerance between CVCs and IVCs help explain variation in innovation output. By focusing on a highly innovation-driven industry like biotechnology, where such mechanisms are expected to be especially influential, it allows us to uncover potential strategic advantages tied to investor type. We further explore whether CVC-backing influences financial performance in this sector, potentially offering a contrast to the general findings of Haslanger et al. (2022). In conclusion, this study provides new insights into how the type of VC investor influences post-IPO innovation and financial performance in a highly innovation-driven industry.

1.2 Aim and Objectives

This thesis aims to investigate if differences in innovation output and financial performance among biotechnology start-ups can be attributable to differences in the type of VC they received funding from. Furthermore, it explores whether the difference in innovation output is mediated by two mechanisms: technological fit and failure tolerance. To accomplish the given aim, the

main objectives have been divided into three parts. 1) To review and synthesize existing academic literature on the resource-based differences between CVC and IVC, with a focus on how these differences impact innovation in funded ventures. 2) To collect and analyze quantitative data on post-IPO outcomes of biotechnology firms in order to test the proposed hypotheses and examine the relationship between investor type and innovation output, as well as between investor type and financial performance. 3) To interpret the findings in light of existing literature, assess whether they support or challenge prior results and our hypotheses, and identify potential directions for future research.

1.3 Research Purpose

The purpose of this thesis is to examine how the type of VC investor influences post-IPO outcomes in the biotechnology industry, with a particular focus on innovation output and financial performance. While previous research has established that CVCs and IVCs differ in investment objectives, resource contributions, and time horizons, it remains unclear whether these differences translate into divergent outcomes once firms enter the public market. Most venture capital research focuses on innovation performance during the private stage or up to the IPO (e.g., Alvarez-Garrido & Dushnitsky, 2016; Park & Steensma, 2013; Ivanov & Xie, 2010).

This study investigates whether two mechanisms, technological fit and failure tolerance, mediate the relationship between investor type and post-IPO innovation output. In addition, it examines whether the type of VC backing directly influences financial performance post-IPO. By focusing on a recent cohort of US biotechnology firms, this thesis provides updated, sector-specific insights into the strategic value of different VC entities. It suggests that the identity of the backer may not merely determine access to funding but could fundamentally shape a firm's ability to innovate and achieve sustained financial success. Accordingly, the central research question guiding this thesis is:

How does the type of venture capital investor (CVC versus IVC) influence post-IPO innovation outcomes and financial performance in the biotechnology industry?

1.4 Delimitations

This study is subject to several delimitations that define its scope and boundaries. Firstly, the analysis is limited to firms headquartered in the US. While VC investment in biotechnology occurs throughout the world, restricting the sample to the US allows for greater consistency in regulatory, financial, and reporting environments while maintaining a sufficient sample size. Secondly, the study focuses exclusively on firms operating within the biotechnology sector. This industry was selected due to its high dependence on external capital to fund innovation cycles, coupled with disputes among previous scholars on VCs' effects on the industry.

Thirdly, the sample includes firms that conducted an IPO between 2010 and 2020. This decade was chosen to ensure a consistent IPO environment prior to the 2021 surge, while also capturing a period in which CVC activity had become sufficiently established to allow meaningful comparisons with IVCs. Fourthly, the study distinguishes between the two types of VC investors. Other investor types beyond CVC and IVC, including angel investors, family offices, and accelerators are excluded to maintain a focused and comparable analytical framework. Lastly, the analysis includes only firms that remain publicly listed during the entire three-year post-IPO observation period. While mergers and acquisitions are common modes of exit for VC investors, and may also reflect investor influence and firm success, these exit routes fall outside the scope of this study, because privately held companies differ fundamentally from publicly traded firms.

1.5 Outline of the Thesis

Chapter 2 presents a review of the relevant literature, introducing the theoretical foundations and prior empirical work that inform the study's hypotheses. Chapter 3 describes the methodological approach, including the research design, data collection, and data analysis. Additionally, this chapter outlines the study's limitations and potential sources of bias. Chapter 4 presents the statistical results of the tests. In Chapter 5 said results are analyzed in light of the theoretical framework and existing literature. Additionally, the research question and hypotheses are interpreted. Finally, Chapter 6 concludes the thesis by summarizing the main findings, presenting their contributions to literature, practical implications, and proposing topics for future research that could expand the knowledge in the field.

2. Literature Review

2.1 The Difference Between CVCs and IVCs

2.1.1 Strategic versus Financial Objectives

One of the main distinctions between CVCs and IVCs is the difference in their underlying objectives. An IVC, on the one hand, is primarily concerned with financial objectives (Gompers, 1996; Chemmanur et al. 2014; Colombo & Murtinu, 2017; Ivanov & Xie, 2010). IVCs invest on behalf of different limited partners, and are expected to generate a return on these funds over a set time period. The objective of such an organization is thus primarily financial, as the success of the portfolio is used to generate new funds and keep the IVC in business (Gompers, 1996). A CVC, on the other hand, differs in that its parent company operates in its own product or service market, and the CVC therefore pursues additional strategic goals in venture capital (Colombo & Murtinu, 2017; Ivanov & Xie, 2010). The funds are generated by the parent company, and although the venture unit does face financial pressures, the benefits are additionally reaped through strategic synergies with the start-ups (Chemmanur et al. 2014). These synergies, in research commonly referred to as strategic or technological fit (Ivanov & Xie, 2010; Chemmanur et al. 2014; Tian & Wang, 2014), provide knowledge and strategic benefits to the parent organization, which aids in long-term competitiveness of the organization. Further, studies suggest that these strategic motives are becoming increasingly prioritized for CVC organizations (Anokhin, Wincent, & Oghazi, 2016).

2.1.2 The Resource-Based View: Resources and Capabilities

The differing objectives of these two types of investors are further coupled with distinct resources and capabilities (R&Cs) in aiding start-up growth. We approach this distinction between CVCs and IVCs through the lens of the resource-based view (RBV) of the firm (Barney, 1991), which emphasizes that firms gain a competitive advantage from valuable, rare, inimitable, and non-substitutable resources and capabilities. From this perspective, the R&Cs that CVCs and IVCs provide are not only different in nature but may also have varying strategic value for the start-up's innovation and financial performance. In line with Dyer and Singh (1998), it is

suggested that interfirm relation-specific assets can be used as a source of competitive advantage for the start-ups. An interfirm relation-specific asset is a resource or capability developed by one firm that holds significant value within a specific partnership (Dyer & Singh, 1998). In a VC-to-start-up relationship this could entail assets such as technological support, market access, or specialized business expertise.

IVCs, on the one hand, primarily contribute to business development, providing their portfolio firms with access to professionals who have deep expertise in operations and scaling businesses (Björgum & Sørheim, 2014). Moreover, IVCs secure board seats to a larger extent than their CVC counterparts, suggesting more active governance and financial oversight (Masulis & Nahata, 2009). These operational resources promote efficiency, clear exit strategies, and alignment with market expectations, which may yield higher short-term returns as compared to CVCs (Colombo & Murtinu, 2017).

CVCs, on the other hand, are often strategically motivated, using their investments to support technology development aligned with the parent firm's goals (Björgum & Sørheim, 2014). Their affiliation with its parent company grants start-ups access to specialized competencies and assets, including applied technological knowledge, manufacturing facilities, and sales, distribution and marketing channels (Maula, Autio & Murray, 2005; Katila, Rosenberger, & Eisenhardt, 2008). In addition, the intrafirm information network provides product and industry knowledge, which can inform both product development and business strategies (Ivanov & Xie, 2010). Lastly, CVCs bring credibility to its young and unproven start-ups. Backing from a well-known corporate investor signals quality strategic potential, thereby reducing information asymmetry and positively influencing market perceptions (McNally, 1997; Wang & Wan, 2014; Stuart, Hoang, & Hybels, 1999; Ivanov & Xie, 2010). Compared to IVCs, CVCs thus provide start-ups with more strategically embedded relation-specific assets, which may be less focused on short-term performance but more conducive to long-term technological and market development.

2.1.3 Investment Horizons

The investment horizons of CVCs and IVCs differ significantly. Generally, IVCs are structured as limited partnerships, wherein the IVC is the general partner investing capital provided by

limited partners, such as institutional investors, banks, etc. The partnership has a pre-specified finite life, usually 10 years, and the contractual agreement contains specific covenants, ensuring the general partner's best effort in selecting and managing the start-ups (Gompers & Lerner, 1996). Conversely, CVCs as a separate venturing unit of large corporations largely miss both of these features, suggesting that there is an insufficient amount of incentives to employ best efforts in selecting and managing start-ups (Ivanov & Xie, 2010). Furthermore, CVCs do not adopt high-powered compensation schemes to the same extent as IVCs, which potentially could exacerbate the problem, causing difficulties in recruitment and retention of talented employees and thus affecting their ability to provide value-adding services to start-ups (Gompers & Lerner, 2000).

However, while the relatively unstructured incentive schemes and lack of limited partnership structure in CVCs have been cited as weaknesses (Ivanov & Xie, 2010; Gompers and Lerner, 2000), these same features may confer advantages in contexts where long-term commitment and tolerance for uncertainty are critical. As argued by Manso (2011), tolerance for early failure and delayed success is critical to breakthrough innovation. Prior research suggests that the absence of externally imposed time pressure may enable CVCs to support longer development timelines, take on riskier bets on exploratory innovation, and remain invested through periods of volatility which an IVC would not endure (Dushnitsky & Lenox, 2005; Hellman & Puri, 2002). Tian and Wang (2014) show that IVCs who are more tolerant of early failure invest in firms that eventually produce significantly higher innovation-related productivity. Although their study examines traditional IVCs, their findings support the broader notion that investors with long-term horizons and fewer constraints may be better positioned to foster innovation in high-risk sectors.

As suggested by literature (Pisano, 2006; Guo & Zhou, 2014), the biotechnology industry may particularly benefit from investor structures that can provide long-term financing and strategic resources. Thus, we argue that the distinct organizational structure of CVCs may actually be more beneficial in this instance, as it enables strategic risk-taking and deeper innovation engagement.

2.2 Technological Fit as a Mediator

Technological fit refers to the degree of alignment between the technological focus of an investor and the strategic objectives of the start-up. In the context of CVC, this occurs when the start-up operates in an area that complements the parent company's core business (Chemmanur et al. 2014). This alignment enables strategic synergies and enhances the CVC parent's access to external innovation (Wadhwa, Phelps, & Kotha, 2016; Van de Vrande, Vanhaverbeke, & Duysters, 2011). CVCs therefore often invest in firms with similar technological expertise (Wang, Huang, & An, 2021), unlike IVCs which lack the industry specialization needed to provide such strategic support (Maula et al. 2005; Katila et al. 2008).

From a resource-based view perspective, technological fit constitutes a strategic asset (Penrose, 1959; Wernerfelt, 1984), enabling access to R&D infrastructure, joint development efforts, and in-house expertise (Alvarez-Garrido & Dushnitsky, 2013; Ivanov & Xie, 2010). These resources are especially important for innovation, which is inherently resource-intensive (Holmström, 1989). Thus, technological fit is particularly important in the biotechnology industry, where innovation is dependent on access to specialized resources and the capability to absorb highly complex, tacit scientific knowledge (Powell, Koput, Bowie, & Smith-Doerr, 2002; Toole, 2003; Zucker, Darby, & Brewer, 1998). Ribeiro, Vilha, Fallon, Mee and Rodriguez (2024) find that successful innovation in biotechnology depends not only on funding but also on access to complementary capabilities, such as advanced laboratories and specialized equipment. In fact, a lack of such assets remains one of the most significant barriers to biotechnology innovation, particularly for start-ups (Ribeiro et al. 2024). Given the high cost and specialized nature of resources in biotechnology, CVCs with a strong technological fit, commonly those operating in the same industry, are more likely to provide start-ups with access to these critical assets.

However, the benefit of these resources depends on the start-up's absorptive capacity: its ability to understand and apply external knowledge to generate innovation (Cohen & Levinthal, 1990). The complexity and tacitness of biotechnology knowledge often require close interaction and deep domain understanding, which makes knowledge transfer more difficult across organizational boundaries (Toole, 2003; Zucker et al. 1998). Mowery, Oxley and Silverman (1996) argue that strong technological fit between firms can mitigate these barriers by enhancing

the start-up's ability to absorb and apply external scientific knowledge. Tacit knowledge transfer, access to specialized assets, and networks established through the CVC relationship can have lasting effects and the benefits gained by the start-up might not vanish at the IPO. For example, a biotechnology firm that learned superior R&D processes or gained platform technologies through a CVC partnership could continue to leverage that know-how post-IPO. Based on this reasoning, we hypothesize that:

Hypothesis 1a: Biotechnology firms that exhibit technological fit with their CVC parent company are more innovative post-IPO than biotechnology firms without such fit and those backed by IVCs

2.3 Failure Tolerance as a Mediator

Failure tolerance refers to the extent to which an investor is willing to continue supporting a firm despite temporary setbacks in its innovation process (Tian & Wang, 2014). This quality is especially important in innovation-intensive sectors like biotechnology, where long R&D cycles, technical uncertainty, and repeated early-stage failures are common before a product reaches market viability (Khilji et al. 2006; Wang, 2023). The theoretical foundation for failure tolerance is grounded in Manso's (2011) work, which argues that the optimal innovation environment combines early failure tolerance with strong long-term incentives. This enables firms to explore novel R&D paths without fear of being punished for interim failure, a view supported experimentally by Ederer and Manso (2013), who found that failure tolerant structures led to more exploratory and ultimately innovative behavior.

Differences in investor objectives and incentive structures lead to different levels of failure tolerance between CVC and IVC investors, which in turn shape the start-up's innovation output. IVCs' structure as a limited partnership creates a pressure to generate timely financial returns (Gompers, 1996; Chemmanur et al. 2014). As a result, IVCs often exhibit lower tolerance for underperformance and may terminate funding early if predefined performance milestones are missed, putting ongoing innovation at risk (Tian & Wang, 2014).

In contrast, CVCs are funded by parent corporations and pursue both financial and strategic objectives, such as gaining access to emerging technologies or future markets (Colombo & Murtinu, 2017; Ivanov & Xie, 2010). Without the constraints of external fund cycles or limited partner expectations, CVCs have flexibility that allows for greater tolerance of trial-and-error processes and delayed returns, which are critical to innovation in high-risk, capital-intensive sectors like biotechnology (Manso, 2011; Pisano, 2006). Consequently, CVCs may be better equipped to support the long development timelines and uncertain innovation paths typical of the biotechnology industry, as they are less likely than IVCs to prematurely terminate promising but uncertain projects.

Failure tolerance becomes even more critical after a firm has gone public. IPOs expose firms to short-term market pressures, such as quarterly earnings expectations, which can lead to reduced R&D investment (Gentry & Shen, 2021). In short, long-term innovation is often deprioritized in favor of short-term financial performance post-IPO. The nature of the VC backing may influence how well a firm navigates this post-IPO environment. Start-ups backed by IVCs, accustomed to milestone-based incentives and short-term performance benchmarks (Tian & Wang, 2014), may be more inclined to disincentivize long-term innovation in favor of immediate financial results.

Conversely, CVC-backed firms, shaped by strategic goals and an investor with higher failure tolerance (Chemmanur et al. 2014), may be better positioned to maintain their innovation focus after going public. This distinction is further affected by the difference in investors' exit behavior. IVCs typically exit through IPOs by selling their shares to return capital to their limited partners (Ibrahim, 2012). Meanwhile, CVCs are more likely to maintain their involvement post-IPO, provided the partnership continues to align with their strategic objectives (Dai, Wang, Liao, Shao, Jiang & Zhang, 2023). This sustained investor engagement can offer biotechnology firms the continued support needed to maintain a strong focus on innovation output in the post-IPO phase. This leads to the following hypothesis:

Hypothesis 1b: Higher failure tolerance among CVC investors compared to IVCs is positively correlated with post-IPO innovation output of the biotechnology firm

2.4 Post-IPO Innovation

The majority of VC research has historically compared the innovation output of the two investor types during pre-IPO stages (e.g., Alvarez-Garrido & Dushnitsky, 2016; Park & Steensma, 2013; Ivanov & Xie, 2010). As a result, it remains unclear whether the benefits attributed to different investor types extend beyond the IPO into the publicly traded phase. One study addressing this time frame is Chemmanur et al. (2014), who find that CVC-backed firms outperform IVC-backed firms in both pre- and post-IPO innovation across a wide range of industries. While they attribute this to differences in technological fit and failure tolerance between the investors, their analysis is not industry-specific. This could disregard potentially significant differences between sectors that are fundamentally not alike.

In biotechnology, the most commercially valuable outcomes, such as FDA approvals and major licensing deals, typically occur after the IPO (McNamee, Cleary, Zhang, Salim, & Ledley, 2021). As such, sustained innovation in the post-IPO phase is particularly important for long-term success and may be influenced by the type of VC-backing the firm receives. This makes post-IPO innovation a more meaningful and timely indicator of success than pre-IPO activity, which often reflects earlier, less mature stages of development.

Building on Sections 2.2 and 2.3, this study proposes that differences in investor objectives and access to complementary resources help explain how various types of VC investors influence post-IPO innovation outcomes in the biotechnology industry. Mediators such as technological fit and failure tolerance may enable CVCs to foster greater innovation capacity. Accordingly, we hypothesize that:

Hypothesis 1c: CVC-backed biotechnology firms are more innovative post-IPO than IVC-backed biotechnology firms

2.5 Financial Performance Post-IPO

Assessing the financial performance of venture-backed firms is essential to understanding the value added by different types of VC investors. Several studies have compared the post-IPO

financial outcomes of different VC organizations (Colombo & Murtinu, 2017; Guo & Zhou, 2014; Ivanov & Xie, 2010; Guo, Jiang, & Mai, 2015), measured through stock performance, profitability accounting measures, and survival. However, these indicators can vary in relevance across industries. In the context of biotechnology, where firms often face long development timelines and have large amounts of intangible assets, traditional accounting measures can fail to capture future value.

Guo & Zhou (2014) propose an industry-specific approach, constructing a composite index of R&D expenses, products, patents, alliances and product development stages three years following the IPO. They find that biotechnology firms with stronger innovation capability experience higher industry-adjusted abnormal returns and are more likely to survive long-term. Notably, they connect innovation capability to both stock performance and long-term viability, enabling a non-financial and financial analysis in an industry where accounting measures do not account for scientific milestones.

While Guo & Zhou's framework is tailored to the biotechnology industry, Guo et al. (2015) reinforce this broader insight using a large sample of Chinese IPO firms. They show that VC-backed firms outperform non-VC-backed counterparts in profitability, market recognition, and size growth post-IPO. Their use of propensity score matching to address identification concerns, strengthens the causal interpretation of these performance differences. Although their study does not distinguish corporate from independent venture capital, it suggests further empirical support to the idea that early-stage investor identity influences post-IPO outcomes.

Conversely, Colombo & Murtinu (2017) look at overall economic performance (OEP) of high-tech European firms, using a production function approach based on real sales, payroll and assets. They find that both CVC- and IVC-backing improves OEP with CVC-backed firms slightly outperforming its IVC counterpart. Short-term gains were stronger for IVCs, especially in sales, while CVCs showed more consistent long-term gains. While their results highlight CVCs contribution to output-side growth, particularly sales, the chosen method does not account for, and may underrepresent, the intangible R&D trajectories critical to biotechnology firms.

Ivanov & Xie (2010) complement these findings by addressing the impact of CVCs on IPO valuations and M&A premiums. They find that CVC-backed start-ups, especially those with strategic fit to the parent company, receive significantly higher IPO valuations than those backed solely by IVCs, in their paper referred to as “traditional VC”. Notably, they use 1 to 3 year post-IPO stock returns to control for temporary mispricings or market hype on the offer-day valuation, suggesting that they reflect real value rather than temporary overpricing. Albeit not biotechnology-specific, their evidence further supports the notion that the strategic nature of CVC engagement leads to more sustainable post-IPO success.

Taken together, these studies converge on a key insight: investor identity, markedly the distinction between CVC and IVC, appears to play a meaningful role in shaping a firm’s financial performance. The post-IPO period offers a particularly relevant setting to evaluate this, as it marks the transition from private venture backing to public-market accountability, revealing whether differences in early investor involvement have persistent effects. However, what remains contested is the extent to which this effect holds in the biotechnology industry, where empirical findings are mixed (e.g., Haslanger et al. 2022; Chemmanur et al. 2014). Given the theoretical and empirical evidence suggesting that CVCs differ from IVCs not only in strategic intent but also in the nature of support they provide, we argue that these differences affect financial performance in the public phase as well. Building on this we hypothesize that:

Hypothesis 2: CVC-backed biotechnology firms outperform IVC-backed biotechnology firms in post-IPO financial performance

3. Methodology

3.1 Research Approach

This thesis adopts a deductive research approach, formulating hypotheses grounded in established theory and prior empirical studies, which are then tested using statistical analysis (Bell, Bryman & Harley, 2019). The research is based on existing literature concerning the differences between CVC and IVC investors as well as their respective effects on innovation and financial performance in biotechnology start-ups. Drawing on this research, this thesis formulates a set of hypotheses. Given the objective of examining post-IPO outcomes across a large sample of firms, a quantitative research approach was adopted. This involves conducting statistical analysis of CVC-backed and IVC-backed biotechnology start-ups. By applying a method commonly used in related studies (e.g., Guo & Zhuo, 2014; Gompers & Lerner, 2000; Ivanov & Xie, 2010; Chemmanur et al. 2014), this approach also facilitates meaningful comparisons with previous research findings.

3.2 Research Design

This thesis investigates how the type of VC-backing influences post-IPO innovation output and financial performance in US biotechnology firms. To address this, the study adopts a comparative, cross-sectional research design, consistent with methodological standards in VC and innovation research (e.g., Chemmanur et al. 2014; Ivanov & Xie, 2010, Colombo & Murtinu, 2017). The comparative design enables a systematic analysis of differences between two groups: biotechnology firms backed by CVCs and those backed by IVCs. The analysis focuses on two key outcomes: 1) post-IPO innovation output, measured by the number of patent families filed and 2) post-IPO financial performance, measured using Buy-and-Hold Abnormal Returns (BHAR). To test the hypotheses, three different statistical tests were used; pooled-variance t-test, One-Way ANOVA and Ordinary Least Squares (OLS) multiple linear regression. These tests were used to evaluate whether investor type is associated with significant differences in innovation and financial outcomes from IPO until three years afterward. Further details regarding sample construction, data analysis, and the statistical tests used are presented in the following sections.

3.3 Data Collection Method

3.3.1 Data Sources: Pitchbook Financial Database & SEC Form S-1

To compile the dataset for this study, the financial database PitchBook was used. PitchBook is a database that provides comprehensive information on private and public companies, investors, funding rounds, IPO events, and intellectual property (IP) activity. It has been extensively used in prior academic research on venture investing (e.g., Cumming & Zhang, 2019; Lerner & Nanda, 2020; Lerner & Kaplan, 2016), making it a suitable and validated source for this thesis. Moreover, PitchBook was selected since it offers all the key variables required for this study, including: classification of investor types, IPO dates, the number of patent families filed by each start-up at given points in time, and the average duration of involvement in start-ups that ultimately went out of business. In addition to PitchBook, supplemental data from SEC Form S-1 filings was utilized in deriving lead investor within investor type, technological fit, and failure tolerance. A sample of PitchBook variables was manually cross-checked using public sources, including SEC filings, NASDAQ and USPTO. All reviewed entries matched, supporting PitchBook's reliability as a valid data source for this study.

3.3.2 Sample Selection Criteria

Using PitchBook's proprietary *Company Screener*, a filtering of firms was made using the following requirements:

1. Industry: Pharmaceuticals and biotechnology
2. Location of headquarters: United States
3. Exit type: IPO
4. IPO date: between 01-01-2010 and 12-31-2020
5. Exit status: Completed
6. Investor types: Venture Capital and Corporate Venture Capital
7. Ownership status: Publicly held

Restricting the sample to the United States allows for a consistent analysis given that all firms operate in a similar regulatory environment. Furthermore, the United States represents the world's largest biotechnology market, leading in terms of market size, business activity, and employment within the sector (Martin, Vicente, Beccari, Kellermayer, Koller, Lal, Marks, Marova, Mechler, Tapaloaga, Znidarsic-Plazl, & Dundar, 2021), enabling a sample of sufficient size with similar market and regulatory characteristics. The biotechnology firms were filtered using PitchBook's categorization "Pharmaceuticals and biotechnology". Additionally, only IPO exits are considered to ensure data coherence and availability.

Furthermore, in an attempt to isolate results from external factors, we only examine firms that went public between 2010 and 2020. In addition, only completed IPOs are included in order to avoid failed IPOs that were announced but did not materialize. The final filter, ownership status, was applied to ensure that only firms still publicly listed were retained in the sample, thereby guaranteeing the availability of post-IPO public information.

The sample was exported as a MS Excel file, allowing for additional data processing and statistical analyses to be conducted. When determining the investor type in a funded venture, we employed a manual approach to ensure sufficient accuracy by examining the principal shareholders in the companies' S-1 filing. The initial search yielded 2013 US-based pharmaceutical and biotechnology firms that went public between 2010 and 2020 and had received IVC or CVC funding.

3.3.3 Selection and Exclusion

Several exclusions were applied to ensure data quality and comparability. Firstly, firms not listed on the NASDAQ stock exchange were excluded. NASDAQ-listed firms are generally more homogenous in terms of growth orientation and disclosure requirements, reducing inconsistencies in financial and innovation-related information due to different disclosure standards between different exchanges. Secondly, firms that failed within three years post-IPO were removed in order to allow a comparable time frame across all firms. Thirdly, firms with undisclosed investor names were removed in order to pursue a method where we coherently determined the lead investor for each of the firms. Lastly, firms who had received investment

from a CVC which existed before the start-up went public were removed from the sample, since investors are not likely to impact start-up performance after they have exited.

3.4 Data Analysis

3.4.1 Dependent Variables

3.4.1.1 Financial Performance

To evaluate post-IPO stock performance, we use BHAR, a well-established approach in IPO research (Brav & Gompers, 1997; Krishnan, Ivanov, Masulis, & Singh, 2011; Jin, Xu, Wang, & Xi, 2020). BHAR is particularly suitable in this context hence it reflects the performance of a firm from the perspective of a passive investor, capturing compounded returns over a fixed holding period. Each firm's performance is compared to a benchmark, the XBI SPDR S&P Biotech ETF index (XBI), which represents the biotechnology segment of the S&P Total Market Index. BHAR therefore helps mitigate concerns of macro-level impacts by measuring excess returns instead of absolute returns. In this case, where we want to isolate firm-level performance, BHAR is thus suitable.

BHAR is calculated as the difference between the firm's raw return between the date of IPO and three years after, and the return of XBI index during the same time period. Since we only observe stock prices at the IPO date and three years post-IPO, BHAR is computed as the percentage return based on price appreciation relative to the XBI index over the same time frame.

$$BHAR_i = ((\frac{P_{i,3y}}{P_{i,IPO}} - 1) - (\frac{P_{b,3y}}{P_{b,IPO}} - 1)) \cdot 100$$

Where:

$P_{i,IPO}$ = Stock price of firm i at IPO

$P_{i,3y}$ = Stock price of firm i three years after IPO

$P_{b,IPO}$ = Benchmark index (XBI: SPDR S&P Biotech ETF) value at IPO

$P_{b,3y}$ = Benchmark index (XBI: SPDR S&P Biotech ETF) value three years after IPO

3.4.1.2 Innovation Output

Innovation output is operationalized as the number of patent families filed by a firm from its IPO year until the 3 years following. Patents are a widely recognized proxy for innovation, particularly in high-tech and R&D-intensive sectors such as biotechnology (Dong, Wei, Liu, & Xing, 2020; Chen, Lin, Lin, & Hsiao, 2020; Khilji et al. 2006). In the context of biotechnology, patents serve several strategic purposes. Firstly, they protect R&D investments by safeguarding IP rights in competitive scientific domains (Linton, Stone, & Wise, 2008). Secondly, they facilitate technology transfers between start-ups and other actors, enabling strategic alliances that are critical for commercialization (Linton et al. 2008). Thirdly, they act as observable signals of scientific progress for external stakeholders, such as investors, who often face limited visibility into the firm's internal development processes (Khilji et al. 2006).

Patent metrics have limitations, such as potential variation in quality and the risk of reflecting legal or strategic motives rather than genuine innovation (Adelman & DeAngelis, 2007). Nevertheless, they remain one of the most accessible and used indicators of innovation, particularly in the post-IPO phase, where alternative metrics are often limited. Empirical evidence further supports their validity in the biotechnology context. For instance, Linton et al. (2008) demonstrate a steady inflow of patents and a relatively diverse patent landscape in the biotechnology industry, suggesting that patents foster, rather than stifle, innovation. Similarly, Chen et al. (2020) find that exploitative knowledge acquisition, as reflected in patenting activity, correlates positively with innovation performance, especially when there is a strong technological overlap between partnering firms. Given these considerations, patent filings represent a relevant and practical measure of innovation output in this study's examination of post-IPO performance.

3.4.1.3 Data Transformation and Outlier Treatment

In order to reduce the influence of extreme outliers without negatively affecting the sample size, as well as to reduce the heteroscedasticity and make the models more reliable, appropriate transformations were applied prior to statistical analysis. For H1a, H1b and H1c, where the

dependent variable is post-IPO innovation output, all patent data was log-transformed using $\log(\text{patent count} + 1)$ using the base 10 to adhere to best practices in statistics while maintaining interpretability (Casey and Metcalf, 2016; West, 2021). This transformation preserves zero values and reduces the influence of extremely high patent families filed. The same transformed data was used across all hypotheses involving innovation output. For H2, where the dependent variable is financial performance, the data was treated using the Inverse Hyperbolic Sine (IHS) function, which accommodates negative and zero values and closely approximates a log transformation for larger values (Norton, 2022). This improved the distributional properties of the variables, while ensuring that all observations could be retained in the analysis.

3.4.2 Independent Variables

3.4.2.1 Investor Type: CVC or IVC

The classification of investor type was made as follows: a firm was considered IVC-backed only if there were no CVCs present at the time of the IPO, meaning that all listed investors were IVCs. Conversely, a firm was classified as CVC-backed if at least one investor at the time of IPO was a CVC firm. This approach follows the definitions used by Ivanov and Xie (2010), reflecting how the literature typically distinguishes different VC-backed IPOs. In contrast to Chemmanur et al. (2014), who classify a firm as CVC-backed if it has ever received CVC funding, our method requires that a CVC remains listed as a shareholder in the IPO prospectus. This distinction is important, as investors are less likely to influence IPO outcomes if they have exited prior to the IPO event. For instance, the sample included firms which had been invested in by CVCs who had liquidated their investment before the firm went public. In this case it is not safe to assume that any post-IPO results are attributable to the CVC presence, since they were not active investors at the time of IPO.

3.4.1.2 Technological Fit

Following Chemmanur et al. (2014), technological fit is operationalized as a binary variable that equals one if the CVC parent company and the start-up share the same 2-digit SIC code and zero otherwise. This approach captures whether the two firms operate in related product markets, enabling us to proxy for domain-relevant knowledge transfer and resource complementarity. In

cases where a parent company is assigned multiple SIC codes, a match with any one of the start-up's codes is sufficient to be classified as a technological fit. Only US-based firms are required to publicly file SIC codes, meaning that parent companies that are not US-based do not necessarily file SIC codes. In this case, S&P's CompuStat was used to check "Primary Industry Classification". This was then cross-referenced against the SEC SIC list and assigned a corresponding 2-digit code. Technological fit is only assessed for CVC-backed firms, as IVC investors do not engage in specific product markets and can therefore not exhibit technological fit by our definition. This method is widely used in research, such as by Chemmanur et al. (2014), because it works well for large datasets and avoids subjective judgment. Although it does not capture every nuance, it allows for consistent comparisons and is a practical choice given the available data.

3.4.1.3 Failure Tolerance

In line with Chemmanur et al. (2014), failure tolerance is operationalized by calculating, for each lead investor, the average duration of involvement in start-ups that ultimately went out of business. First, the lead investor is identified for each firm as the one with the largest ownership stake. In cases when different investors had equal stakes, the number of board seats took precedence. Also, where the sample includes different venture arms for the same parent company, these investors are grouped together as one. For instance, *HBM Healthcare Investments* and *HBM Partners* both operate under *HBM*. The rationale is that the failure tolerance of an investor is attributable to its parent company, which implies that venture organizations of the same parent company should be considered equal. Specifically for each failed company, we compute the ratio between the number of years the investor remained involved and the total lifespan of the firm. Failure tolerance is then presented as a ratio, with each company receiving a score between 0 and 1. Consequently, if an investor has failure tolerance equal to 1, this means that they have stayed invested until failure in all of their investments that have gone bankrupt.

$$Failure\ Tolerance_i = \frac{1}{n_i} \sum_{j=1}^{n_i} \frac{Involvement_{ij}}{Lifespan_{ij}}$$

Where:

i = investor

j = start-up that went out of business

n_i = number of start-ups backed by investor i that went out of business

$Involvement_{ij}$ = number of years from investor i 's first investment in out of business start-up j to investor i 's exit.

$Lifespan_{ij}$ = number of years from investor i 's first investment in out of business start-up j to start-up j being out of business.

3.4.2 Control Variables

This thesis focuses exclusively on biotechnology firms, which ensures a high degree of comparability across firms in terms of industry characteristics, technological focus, and regulatory environment. Additionally, we include only firms that completed an IPO on the NASDAQ stock exchange. This serves as an implicit control for firm size and disclosure standards, as NASDAQ-listed biotechnology firms ensure comparability in the sample. Firm size is an important control variable because very small or micro-cap firms often behave fundamentally differently than larger, more established ones. They may lack the infrastructure, governance, or financial stability to engage in sustained innovation efforts (Shefer & Frenkel, 2005). Such differences can confound analyses of innovation output, since low patent activity may reflect operational constraints rather than investor influence. By limiting the sample to firms listed on NASDAQ, we reduce this heterogeneity and ensure that observed differences in innovation are not primarily driven by scale or firm lifecycle stage.

Lastly, the 2010-2020 time period was selected to ensure a consistent VC landscape and strengthen internal validity. CVC activity increased significantly during the 2010s, with approximately 60% of financing rounds in 2015 involving a CVC investor, compared to around 20% a decade earlier (Acha, 2017). Setting 2020 as the cut-off point also avoids the distortions of the 2021 IPO surge, ensuring sample comparability. Including firms from before 2010 would risk an overrepresentation of IVCs, while firms going public after 2020 reflect a markedly different IPO climate (Mackintosh, 2022; PwC, 2022). While we do not include further

firm-level control variables due to data limitations, this sampling strategy improves internal validity by reducing heterogeneity across firms and makes the groups more directly comparable.

3.5 Statistical Tests

To empirically evaluate our hypotheses, we employ a set of parametric statistical methods suitable for comparing group-level differences and estimating relationships between different variables. H1c and H2 are both tested using pooled-variance upper-tail t-tests for difference in means. For H1c, we compare the mean number of patent families filed by the biotechnology firm from its IPO until the 3 years following. For H2, we test whether CVC-backed firms outperform IVC-backed firms in financial performance, as measured by BHAR relative to the XBI index.

For H1a we conduct both a pooled-variance upper-tail t-test, comparing post-IPO patent families filed among CVC-backed firms with and without technological fit, and a One-Way ANOVA. The ANOVA enables us to test group-level differences across three categories: CVCs with technological fit, CVCs without technological fit, and IVC-backed firms. H1b, testing if failure tolerance is positively correlated with innovation output, is tested using multiple linear regression analysis. Here, post-IPO patent families filed is the dependent variable, and failure tolerance is included as an independent variable alongside investor type. All hypothesis tests are conducted at a 5% significance level, as it represents a widely accepted standard, balancing the risk of Type I and Type II errors (Bell, Bryman & Harley, 2019). Where applicable, assumptions of homogeneity of variance are assessed using Levene's tests since pooled-variance t-tests are contingent on both samples having equal variance. Additionally, the four key assumptions of multiple linear regression were assessed using residual plots, a normal probability plot, the Durbin-Watson test, and the variance inflation factor (VIF) to validate the appropriateness of using multiple linear regression as a statistical test.

3.6 Validity and Reliability

External validity refers to the extent to which the study's findings can be generalized beyond the specific context in which they were observed (Bryman & Bell, 2011). As this thesis focuses exclusively on US-based biotechnology firms listed on NASDAQ, generalizability to other

sectors, geographical regions, or privately held companies is inherently limited. However, this targeted scope was intentionally chosen to enhance comparability across firms and to control for variations in industry dynamics, regulatory environments, and listing standards. Additionally, prior research highlights the need for a focused study of this specific field. Lastly, the use of a relatively large and carefully selected sample helps mitigate concerns related to sampling error.

Internal validity concerns whether the observed relationships genuinely reflect underlying associations or are instead driven by uncontrolled variables or measurement error (Bryman & Bell, 2011). Although cross-sectional designs are inherently limited in establishing causality (Bryman & Bell, 2011), internal validity in this study is strengthened through a series of deliberate methodological choices. The focus on a single industry and time period reduces heterogeneity in firm characteristics and market environments.

Reliability relates to the consistency and reproducibility of results under similar conditions (Bell, Bryman, & Harley, 2019). The primary data source, PitchBook, is widely recognized as a credible and comprehensive database in VC and IPO research. The data screening process, excluding firms that failed within three years, were not listed on NASDAQ, or had undisclosed investors, was systematic and consistently applied. Variables such as investor type and innovation output were constructed using transparent, rule-based definitions, making the study replicable for future research. While alternative measures, such as more nuanced patent classifications or alternative return metrics could have been employed, the choices made align with established practices in financial and innovation research (e.g., Chemmanur et al. 2014; Guo & Zhuo, 2014) and are well-suited to the scope and aims of this thesis.

Additionally, to address concerns about selection bias and strengthen the internal validity of the analysis, we conduct a pre-investment group comparison consistent with the approach used by Bernstein, Giroud, and Twonsend (2014). Specifically, we analyze a random subsample of 60 firms, 30 CVC-backed and 30 IVC-backed, and examine their patent output during the three years preceding the first VC investment. The results show no statistically significant difference in pre-investment innovation between the two groups, suggesting that CVCs do not systematically select more innovative firms at entry. This strengthens the reliability of our

findings by mitigating the risk that post-IPO innovation differences are merely driven by selection bias rather than the type of investor involvement.

To strengthen both validity and reliability, this study relies on established proxies from prior academic research (Chemmanur et al. 2014; Chen et al. 2020; Guo & Zhuo, 2014). These choices enhance construct validity by aligning closely with how the underlying concepts are defined in theory, and they support reliability by enabling future researchers to replicate the study using the same metrics. However, as with any proxies, they simplify complex phenomena so the findings should be interpreted with this limitation in mind. The potential shortcomings of these proxies and their implications for the results are further examined in the limitations section.

3.7 Limitations

One important limitation of this thesis concerns the use of patent families filed as a proxy for innovation output. While patent families offer a more refined and internationally comparable measure than simple patent counts, as they consolidate filings across jurisdictions, they do not account for differences in patent quality, economic value, or scientific relevance. Furthermore, because PitchBook does not provide citation data or International Patent Classification (IPC) at a detailed level, it was not feasible to assess the technological significance of each patent. Consequently, some of the variation in innovation outcomes may be driven by factors unrelated to investor type or technological fit, such as differences in firms' IP strategies or scientific teams. However, this risk is partially mitigated in our study by using a large, industry-specific sample of biotechnology firms, where filing patents tends to be a central and strategic activity, increasing the likelihood that patent families reflect meaningful innovation outcomes. While we acknowledge that our measure does not capture all dimensions of innovation, it remains a widely accepted and practical proxy in previous research in high-tech and R&D-intensive sectors (Chen et al. 2020; Khilji et al. 2006).

A second limitation concerns the operationalization of technological fit. This study relies on a binary variable based on 2-digit SIC code matching, following established practice (e.g., Chemmanur et al. 2014). While this approach provides an objective and scalable proxy, it may overlook subtle differences in research specialization or technological platform compatibility. In

some cases, two firms may share a SIC code but operate in distinct subfields, constituting a Type I error. Conversely, another risk is the presence of false negatives, or Type II errors. These are cases where a CVC and its portfolio firm are in fact strategically or technologically aligned, but are misclassified as having no fit due to mismatched SIC codes. To minimize the risk of false negatives, this thesis adopts a deliberately inclusive approach in classifying technological fit, for example, treating a firm as having technological fit if even one of the CVC parent's SIC codes matches that of the start-up.

A third potential limitation relates to the measurement of failure tolerance. While this proxy effectively captures how long an investor remains engaged in ventures that ultimately fail, it reflects only one dimension of investor patience. Specifically, it does not account for the intensity or consistency of strategic or financial support during the investment period. An investor may formally remain involved but reduce their financial and/or strategic support as the firm underperforms, indicating some degree of failure tolerance. Nevertheless, the decision to stay invested, even passively, may signal a willingness to keep the firm within their portfolio, leaving open the possibility of re-engagement if performance improves. In contrast, a complete exit greatly reduces this chance, representing a clearer withdrawal of support. While this proxy may overstate sustained involvement in some cases, it remains a replicable measure that has been used in prior studies to distinguish the tolerance for failure between CVC and IVC investors (Tian & Wang, 2014; Chemmanur et al. 2014).

Lastly, certain assumptions and trade-offs were made in the choice of statistical methods. While the use of t-tests, One-Way ANOVA, and multiple linear regression is suitable to test the hypotheses, these models rely on assumptions about normality, no autocorrelation and no multicollinearity. While several tests were used to assess these assumptions, more advanced approaches could be used. Also, panel data methods or matching techniques such as propensity score matching, instead of pre-investment group comparisons, could be used to test mediation more directly and potentially solidify the results. However, given the scope of the thesis, the methodological choices strike a balance between analytical rigor and clarity, while allowing results to be interpreted in line with prior venture capital literature.

4. Results

Research question: *How does the type of venture capital investor (CVC versus IVC) influence post-IPO innovation outcomes and financial performance in the biotechnology industry?*

4.1 Descriptive Statistics

This section presents descriptive statistics for the main variables included in the empirical analysis: post-IPO innovation output, failure tolerance, and financial performance. Key statistics such as the mean, median, standard deviation, minimum, and maximum values are reported. Where relevant, skewness and kurtosis are included to assess the shape of the normal distributions. These descriptive patterns provide context for the hypotheses and help motivate the subsequent regression analysis. The final sample consists of 172 US-based biotechnology firms. 112 firms were backed by CVC, and 60 firms were backed solely by IVC. Of the CVC-backed firms, 69 were classified as having technological fit while the remaining 43 CVC-backed firms were classified as not having technological fit.

Table 1: Descriptive statistics for innovation output across investor types and technological fit

	n	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Full Sample	172	0.777	0.778	0.420	0.000	2.000	0.017	-0.318
IVC	60	0.680	0.650	0.450	0.000	2.000	0.469	0.178
CVC	112	0.826	0.845	0.396	0.000	1.690	-0.215	-0.349
CVC (Tech Fit)	69	0.832	0.845	0.377	0.000	1.681	-0.155	-0.258
CVC (No Tech Fit)	43	0.823	0.845	0.427	0.000	1.690	-0.279	-0.443

Table 1 presents descriptive statistics for the innovation output variable, measured as the number of patent families filed within three years post-IPO. Across the full sample of 172 firms, the mean innovation output is 0.777 with a standard deviation of 0.420, indicating that innovation output differs widely within the sample. Breaking this down by investor type, firms backed by IVC show a lower mean (0.680) compared to CVC-backed firms (0.826), aligning with theoretical expectations. Within the CVC group, there is no notable difference in means between firms with technological fit (0.832) and without (0.823), although firms with technological fit

exhibit slightly lower variability (0.377) than those without (0.427). This suggests that within the CVC-backed firms, technological fit may not influence average innovation output, since the means are nearly identical. However, the slightly lower standard deviation among firms with technological fit suggests that these firms may experience more consistent innovation outcomes.

The distributions of innovation output are moderately skewed, with the IVC group showing positive skewness (0.469), indicating a longer right tail, while the CVC group and its subgroups exhibit mild negative skewness. The positive skewness in the IVC group of 0.469 indicates that while most firms cluster around lower values, a few achieve exceptionally high innovation output, pulling the average upward. In contrast, the CVC group and its subgroups show mild negative skewness, meaning innovation output is more concentrated at higher levels, with fewer firms lagging far behind.

The kurtosis values across all groups indicate distributions that are relatively flat compared to a normal distribution, with no major concentration around the mean. This means that innovation output is broadly spread across firms. While the data show that CVC-backed firms are more innovative on average than IVC-backed ones, the similar values across the technological fit and no technological fit subgroups suggest that technological fit may not have a strong or consistent influence at this level of analysis.

Table 2: Descriptive statistics for failure tolerance scores by investor type

	n	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Full Sample	172	0.930	0.971	0.112	0.250	1.000	-2.813	9.997
IVC	60	0.915	0.955	0.125	0.250	1.000	-2.874	12.473
CVC	112	0.938	0.971	0.105	0.571	1.000	-2.733	7.112

Table 2 presents the descriptive statistics for failure tolerance. The mean failure tolerance is 0.930, with a median of 0.971 and a standard deviation of 0.112. The slightly higher mean (0.938) and lower variability (0.105) among CVC-backed firms compared to IVC-backed firms (0.915, 0.125) suggests that CVCs are more uniformly patient. The maximum is 1.000 and the minimum is 0.250 across all groups. However, the minimum failure tolerance for IVCs is 0.250,

while for CVCs it is notably higher at 0.571, again indicating greater consistency among CVC investors in terms of showing failure tolerance. These figures suggest that CVCs generally demonstrate higher and more consistent tolerance for failure, which aligns with theoretical expectations about their strategic, long-term orientation.

The distribution is strongly negatively skewed across all groups, indicating that most investors have failure tolerance scores clustered close to 1. However, there are a few with substantially lower scores pulling the tail to the left. Thus, long holding periods are likely common and short holding periods are relatively rare. Moreover, the leptokurtic distribution indicates that most investors have failure tolerances close to the mean, though there are some outliers present. Overall, this suggests that while most investors demonstrate high failure tolerance, a small subset, especially in the IVC group, exhibit substantially lower tolerance, resulting in a peaked distribution with pronounced left tails.

Table 3: Descriptive statistics for BHAR across investor types

	n	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Full Sample	172	-3.4%	-18.7%	42.3%	-59.1%	132.5%	1.394	1.342
IVC	60	-0.2%	-18.4%	47.1%	-59.1%	124.6%	1.406	0.990
CVC	112	-5.2%	-19.2%	39.6%	-58.4%	132.5%	1.342	1.470

Table 3 displays descriptive statistics for post-IPO financial performance, measured as the three-year BHAR. The full sample exhibits a slightly negative average performance (-3.4%) with a high standard deviation (42.3%), highlighting wide dispersion. Variation in returns is slightly higher for IVC-backed firms (47.1%) compared to CVC-backed firms (39.6%), indicating more dispersed outcomes. Both groups exhibit high positive skewness, indicating a long right tail and the presence of extreme positive outcomes in some cases. The kurtosis values of 0.990 for IVC and 1.470 for CVC point toward a leptokurtic distribution in both cases, suggesting more peaked distributions than a normal distribution. The higher kurtosis for CVCs suggests that CVC-backed firms tend to have more consistent BHAR performance, with fewer moderate deviations but a higher likelihood of extreme outcomes, both strongly positive and negative. In contrast, the IVC-backed firms' lower kurtosis suggests a slightly more even distribution around the mean,

with a broader range of moderately different outcomes. The minimum BHAR across all groups is approximately -59.1%, with a maximum of 132.5% for the full sample, indicating a wide range of performance outcomes.

4.2 Inferential Statistics

Table 4: Results of pooled-variance upper-tail t-tests for H1a, H1b, H1c, & H2

Hypothesis	Comparison	Dependent	t(df)	p-value	Levene's Assume Equal		
		Variable			p-value	Variances	Significance
H _{1a}	CVC (Tech Fit) vs CVC (No Tech Fit)	Innovation output	0.113 (110)	0.455	0.384	Yes	No
H _{1b}	CVC vs IVC	Failure tolerance	1.273 (170)	0.102	0.127	Yes	No
H _{1c}	CVC vs IVC	Innovation output	2.250 (170)	0.013**	0.245	Yes	Yes**
H ₂	CVC vs IVC	BHAR	-0.738 (170)	0.769	0.524	Yes	No

Note: ***p<0.01, **p<0.05, *p<0.1

Hypothesis 1a: Biotechnology firms that exhibit technological fit with their CVC parent company are more innovative post-IPO than biotechnology firms without such fit and those backed by IVCs

Table 5: Result of One-Way ANOVA for innovation output (H1a)

Source of Variation	Between Groups SS	df	Mean Square	F-value	p-value	F-crit
Between Groups	0.875	2	0.438	2.523	0.083*	3.05
Within Groups	29.308	169	0.173			

Total	30.183	171
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Note: ***p<0.01, **p<0.05, *p<0.1

A pooled-variance upper-tail t-test was conducted, yielding a p-value of 0.455. While the descriptive statistics indicated that CVC-backed firms, on average, filed more patents (0.826) post-IPO than IVC-backed firms (0.680), and that CVC firms with technological fit showed slightly lower variance than those without, these observed differences did not reach statistical significance. This suggests that the difference in mean innovation output between the two CVC groups is not statistically significant at the 5% level. In other words, technological fit did not appear to influence patent production among CVC-backed firms in this sample.

To further test for broader group-level differences, a One-Way ANOVA was conducted comparing all three groups: CVCs with technological fit, CVCs without technological fit and IVCs. The resulting p-value of 0.083 exceeded the 0.05 significance threshold, again indicating that there is no statistically significant difference at the 5% level. Albeit statistical significance is found at the 10% level, implying that the variable may still have a meaningful, though less certain, impact on the outcome. Since the t-test revealed no significant difference in innovation output between CVC-backed firms with and without technological fit, the ANOVA test comparing the means across the three groups is interpreted with caution and unlikely to offer strong additional insights. Hypothesis 1a is not supported.

Hypothesis 1b: Higher failure tolerance among CVC investors compared to IVCs is positively correlated with post-IPO innovation output of the biotechnology firm

Table 6: Result of OLS regression on innovation output (H1b)

Variables	β	Std. Error
Failure tolerance	0.833***	0.278
Investor type	0.120*	0.065
Constant	-0.076	0.259

F-value	6.792***
R ²	0.074
Adj. R ²	0.063
SER	0.407
VIF value, highest	1.010
	n=172

Note: ***p<0.01, **p<0.05, *p<0.1

Firstly, the potential difference in failure tolerance between CVCs and IVCs is examined through a pooled-variance upper-tail t-test. The results show that $p = 0.102$, indicating that there is no significant difference in failure tolerance between CVCs and IVCs at the 5% (or 10%) significance level. To test whether failure tolerance is associated with higher innovation output, a multiple linear regression and a One-Way ANOVA was conducted. Post-IPO patent output was the dependent variable, and failure tolerance and investor type were the independent variables. The overall model was statistically significant with a $p < 0.01$, indicating that the predictors jointly explain a meaningful portion of the variance in innovation output. The adjusted R² value of 0.063 suggests that 6.3% of the variance in post-IPO patent output is explained by the model.

Failure tolerance was found to be positively ($\beta = 0.833$) and statistically significantly ($p < 0.01$) associated with innovation output. This supports Hypothesis 1b, indicating that greater failure tolerance tends to be associated with higher post-IPO patent activity. In contrast, investor type did not show a statistically significant effect at the 5% level ($\beta = 0.120$, $0.05 < p < 0.1$), though the direction was positive. This suggests that while investor type may exert some influence on innovation, failure tolerance appears to be the more robust predictor in this model. Nonetheless, significance at the 10% level implies that investor type should not be entirely disregarded, but rather interpreted with caution and considered as a potentially relevant factor for innovation output. Taken together, these results suggest that failure tolerance plays a meaningful role in enabling innovation in biotechnology start-ups, with investor type potentially also influencing these outcomes.

Hypothesis 1c: CVC-backed biotechnology firms are more innovative post-IPO than IVC-backed biotechnology firms

To assess whether investor type exhibits higher post-IPO innovation output, a pooled-variance upper-tail t-test was conducted comparing the mean number of patents filed by IVC-backed firms and CVC-backed firms. The test found that CVC-backed firms produced more patents on average (0.826) than IVC-backed firms (0.680), with a resulting p-value of 0.013. Since the p-value is lower than the level of significance, the null hypothesis is rejected. This demonstrates that there is a statistically significant difference in post-IPO patent output between the groups in the sample. Consequently, the results support the notion that CVCs are associated with greater post-IPO innovation than IVCs in biotechnology firms. Thus, Hypothesis 1c is supported by the data.

Hypothesis 2: CVC-backed biotechnology firms outperform IVC-backed biotechnology firms in post-IPO financial performance

To test whether CVC-backed biotechnology firms achieve superior financial performance relative to IVC-backed firms, a pooled-variance upper-tail t-test was conducted comparing their mean BHAR over a three-year post-IPO period. The test compared the mean BHAR of CVC-backed firms (-5.2%) to that of IVC-backed firms (-0.2%). The resulting p-value of 0.769 exceeds the 0.05 threshold, implying that the null hypothesis of equal means cannot be rejected. This result shows that there is no statistically significant difference in post-IPO financial performance between CVC- and IVC-backed firms in the sample. Despite an observed difference in means, the variation is not large enough to support Hypothesis 2.

4.3 Statistical Assumptions

To evaluate the validity of the parametric tests applied, Levene's tests were conducted for each hypothesis to evaluate the assumption of equal variances between groups. In all cases, the resulting p-values exceeded the 0.05 significance level, indicating that the assumption of homogeneity of variance was not violated. This supports the use of pooled-variance t-tests for group mean comparisons, thereby strengthening the reliability of the statistical inferences drawn.

To evaluate the suitability of using a linear regression model, four key assumptions were tested: linearity, independence of errors, normality of residuals, and homoscedasticity (equal variance). Linearity and homoscedasticity were assessed by plotting the standardized residuals against the fitted values (Appendix A, figure 2.1). This scatterplot displayed no funnel-shaped patterns, supporting the assumption of linearity and constant variance. Normality of residuals was examined using a normal probability plot which indicated that the residuals are approximately normally distributed, with only minor deviations at the upper-tail (Appendix A, figure 2.3). This suggests that the assumption of normality is sufficiently met.

Independence of errors was tested using the Durbin-Watson statistic, which yielded a value close to 2 ($DW = 1.919$), indicating no significant autocorrelation in the residuals. In addition to this, a Variance Inflation Factor (VIF) was done to assess to what extent a variable is inflated due to multicollinearity. The test produced a VIF of 1.010, proving that there is no issue with regard to multicollinearity. Overall, the results from these diagnostic tests suggest that the assumptions underlying our statistical models are met. This indicates that the analyses were conducted on a methodologically sound basis and that the findings presented in this thesis can be considered statistically valid.

Lastly, to examine whether selection bias may explain our results, we compare pre-investment innovation levels across CVC- and IVC-backed firms. We collected data on patent families filed three years before the first VC investment on a subsample of 60 firms (30 CVC-backed, 30 IVC-backed). This time frame was chosen to reflect a comparable window of each firm's innovation capability prior to any potential influence or signaling effects associated with external investment. Further, a Levene's test confirmed equal variance between the groups. Consequently, a pooled-variance t-test could be performed, showing no statistically significant difference in pre-investment innovation output between the two groups ($p > 0.1$). This suggests that post-IPO innovation differences are unlikely to reflect initial firm quality differences prior to investor involvement.

Table 7: Result of pooled-variance upper-tail t-test for 3 year pre-investment innovation output of CVCs versus IVCs

Comparison	Dependent Variable	t(df)	p-value	Levene's p-value	Assume Equal	
					Variances	Significance
CVC vs. IVC	Innovation output	0.862 (58)	0.196	0.340	Yes	No

Note: ***p<0.01, **p<0.05, *p<0.1

4.4 Summary of Hypotheses

Table 8: Summary of hypothesis outcomes

Hypothesis	Relationship	Result
H _{1a}	Biotechnology firms that exhibit technological fit with their CVC parent company, are more innovative post-IPO than biotechnology firms without such fit and those backed by IVCs	Not supported
H _{1b}	Higher failure tolerance among CVC investors compared to IVC investors, is positively correlated with post-IPO innovation output of the biotechnology firm	Partially supported
H _{1c}	CVC-backed biotechnology firms are more innovative post-IPO than IVC-backed biotechnology firms	Supported
H ₂	CVC-backed biotechnology firms outperform IVC-backed biotechnology firms in post-IPO financial performance	Not supported

5. Analysis and Discussion

The research purpose of this thesis was to examine how the type of VC investor influences post-IPO outcomes in the biotechnology industry, with a particular focus on innovation output and financial performance. The following section details the analysis of the results of the four hypotheses.

5.1 Hypothesis 1a: Technological Fit

The t-test indicated no significant difference in means at 0.05 level of significance ($p = 0.455$) and the One-Way ANOVA, including IVC-backed firms as an additional group, was only significant at the 10% level ($p = 0.083$). Consequently, it is concluded that biotechnology firms backed by CVCs with technological fit are not more innovative post-IPO than CVCs without such fit. However, technological fit may help explain the higher post-IPO patent output observed among CVC-backed firms compared to their IVC-backed counterparts. Nevertheless, this finding should be interpreted with caution given the level of statistical significance.

Our operationalization of technological fit with 2-digit SIC codes, in line with Chemmanur et al. (2014), might fail to capture the necessary degree of specialization within the CVC parent in the biotechnology industry. For instance, although the CVC parent may operate within the same industry, its focus might lie in a different subfield, such as dermatology, while the entrepreneurial firm specializes in oncology. While this might constitute a broad technological fit, the specific resources and expertise of the CVC parent may be of limited relevance or applicability to the venture.

However, it could also be the case that the absence of a significant mediating effect of technological fit on post-IPO innovation may reflect unique characteristics of the biotechnology industry. Previous research by Chemmanur et al. (2014) found that CVCs with technological fit significantly outperform CVCs without such fit in post-IPO innovation output compared to IVCs. Our study finds no such evidence, which could be attributed to the industry-specific characteristics. In contrast to other high-technology sectors, where knowledge sharing may yield immediate synergies, innovation in biotechnology is typically driven by deep scientific expertise

and internal R&D (Pisano, 2006). CVCs may thus lack the specialized expertise necessary for complex product development. Consequently, the knowledge flows between the CVC and start-up may be less valuable, reducing the value of a higher absorptive capacity and in turn technological fit.

Furthermore, there might be other aspects that mediate the access to the R&Cs of CVCs making technological fit a non-explanatory variable. Alvarez-Garrido and Dushnitsky (2013) claim that enhanced innovation performance is significantly influenced by the CVC's ability to leverage the complementary R&Cs of their corporate parent. We make no such distinction in our model and our results may as a consequence miss these mechanisms that explain the heterogeneity among CVCs. Distinguishing CVCs with or without technological fit may thus be irrelevant, as both of these CVC investors may have varying degrees of resource access, impacting their ability to provide the parent company's valuable resources to their portfolio firms. This, in turn, impacts the innovation output of the start-up regardless of technological fit. In conclusion, the implications of these results contribute to the broader field of investor type and innovation output. We establish that previous methods arguing that technological fit plays a vital role in innovation output (Chemmanur et al. 2014; Ivanov & Xie, 2010; Ribeiro et al. 2014), do not explain the heterogeneity among CVC investors in the biotechnology industry.

5.2 Hypothesis 1b: Failure Tolerance

The results show that firms with higher failure tolerance are significantly more innovative post-IPO at the 5% significance level. This finding supports Manso's (2011) theory that tolerance for early failure and delayed success is critical for fostering innovation, as well as Chemmanur et al. (2014), who identify failure tolerance as a key mechanism driving patenting activity. Contrary to Chemmanur et al. (2014) who additionally found a significant difference in failure tolerance between CVCs and IVCs, our sample does not. This suggests that while failure tolerance is a meaningful predictor of innovation output, the assumption that CVCs are inherently more failure tolerant does not hold in this specific sector.

This finding may appear counterintuitive given prior assumptions about CVCs having more patient capital. However, it aligns with the broader characteristics of the biotechnology industry.

Long development timelines, high technical uncertainty, and frequent early-stage failure could require a baseline level of patience from any investor active in the industry. This can help explain why observed differences in failure tolerance between CVCs and IVCs were statistically non-significant. The bar for patience and risk appetite is high for everyone by necessity. Given the potential for high returns when a product succeeds (McNamee et al. 2021), both CVC and IVC investors may be incentivized to maintain involvement through prolonged development phases, despite setbacks. This interpretation is supported by our data: 47 out of 91 lead investors (26 CVC, 21 IVC) had a failure tolerance score of 1. This pattern suggests that, in practice, high failure tolerance may be common among committed biotechnology investors regardless of type.

Another possible explanation is that IVCs' fixed fund lifecycles and pressure to deliver returns may drive them to pursue strategic exits, such as IPOs or acquisitions, rather than abandon underperforming ventures outright. This approach allows them to salvage value and formally close investments, even if the company falls short of initial expectations. By maintaining formal involvement until an exit is secured, IVCs may appear failure tolerant in the data, despite withdrawing meaningful support. Research supports this behavior, as in Gompers (1996), who shows that younger IVC firms often take companies public earlier to demonstrate track records. Consequently, reputational factors could lead IVCs to avoid terminating unsuccessful investments quickly. Instead, IVCs may keep a struggling start-up in their portfolio, but usually stop committing significant new capital while maintaining board seats to nudge the company toward a sale or merger. This behavior inflates our measurement of failure tolerance, as firms are not shut down despite poor performance. Yet the continued involvement is often motivated less by long-term support and more by managing downside risk through calculated exit strategies. Thus, IVCs may not be failure tolerant per se, rather, their prolonged presence may reflect strategic delay in exit.

5.3 Hypothesis 1c: Innovation Output

In testing H1c, the results show that start-ups backed by CVCs do indeed produce more patents post-IPO (0.83) than those backed by IVCs (0.68). However, without support for the preceding hypotheses, it is difficult to ascertain what this actually stems from. Irrespective of the

underlying mechanisms, we found that start-ups backed by CVCs produce more patents post-IPO than those invested in by IVCs.

This finding stands in contrast to Haslanger et al. (2022), who found no significant performance effects of CVC-backing in the healthcare industry. The results from our study suggest that CVC participation may actually be more influential than what is stated by Haslanger et al. (2022). One potential explanation for this divergence could reside in the time period studied in the different samples. The studies synthesized by Haslanger et al. (2022) were not conducted during the same period. As mentioned, the VC climate underwent a major transformation during the 2010s, with CVCs becoming an increasingly utilized source of financing for start-ups (Acha, 2017). We have decided to focus on a period where CVC activity has been relatively consistent, making our study increasingly focused, allowing for more applicable findings.

The result opens the door to alternative explanations that have received less attention in prior literature. For instance, the presence of a corporate investor could enhance innovation indirectly through credibility signaling and network advantages, in line with the arguments brought forth by Bjørgum and Sørheim (2014). Firstly, the involvement of a well-known CVC investor can serve as a powerful endorsement of a biotechnology firm's technological potential, signaling quality to external stakeholders. This perceived legitimacy may enhance the firm's ability to attract top scientific talent, form strategic alliances, and gain faster regulatory traction, thereby accelerating innovation outcomes without the CVC needing to be deeply involved post-IPO.

Secondly, CVCs often bring extensive industry networks through their parent corporations, including long-standing relationships with pharmaceutical companies, clinical research organizations and government bodies. Even if not formally accessed through direct collaboration, the mere presence of these networks may create spillover benefits for the portfolio firm, such as increased visibility or informal introductions to potential partners and acquirers. Thus, the lack of support for H1a and H1b, then, does not undermine the importance of investor identity. Rather, it redirects attention toward underexplored but potentially powerful drivers of innovation that go beyond direct resource-sharing or formal strategic alignment.

In conclusion, we find statistically significant evidence that investor type is associated with post-IPO patent output in the direction we hypothesized. However, we can not accurately attribute this effect to the mediators that we originally predicted to be the underlying causes of the difference. Though it was found that failure tolerance was important for innovation, the studied investor types did not exhibit differing levels, and our sample did not indicate that technological fit was conducive to innovative performance. The lack of explanatory power in our variables, coupled with the fact that overall significance was established, leads us to believe that there are other mechanisms at play. Given that this study has not successfully explained which differences account for this discrepancy in patent output, it is likely that innovation in the biotechnology sector is determined by investor traits that are outside of the scope of this study.

5.4 Hypothesis 2: Financial Performance

Despite prior research highlighting the financial benefits of CVC involvement, this study found no statistically significant difference in post-IPO financial performance between CVC- and IVC-backed biotechnology firms. One likely explanation lies in the unique nature of the biotechnology industry, where the commercial value of innovation is often delayed due to lengthy R&D timelines and regulatory hurdles (Khilji et al. 2006; Wang, 2023). Unlike sectors where innovation can be rapidly commercialized, biotechnology firms frequently wait years for critical events such as FDA approvals. As a result, the patent activity observed 3 years after the IPO may not yet be reflected in stock market performance. While Guo and Zhou (2014) found that innovation capability predicts long-term survival and abnormal returns in biotechnology, those effects may be explained by innovation metrics not captured in this analysis. That said, one could argue that even early-stage patent filings should signal future growth potential to investors and elicit some degree of market response. However, in an industry characterized by scientific uncertainty and high failure rates, such signals may be discounted until more definitive milestones are reached.

Another explanation concerns the preferences of public market investors and how they perceive different investor types. It was hypothesized that CVCs, due to their access to complementary resources and longer time horizons, would lead to superior post-IPO financial performance. Challenging Ivanov and Xie (2010), IVCs, with sharper focus on financial returns and exit

strategies, may be more appealing to public shareholders seeking short-term returns. Colombo and Murtinu (2017) support this view, as they find that IVC-backed firms often outperform in the short-run, while CVC-backed firms demonstrate more consistent long-term gains. Given the intense market pressure on newly listed biotechnology firms to show rapid progress, IVCs may steer firms toward more market-aligned milestones. Although not significant, this could explain why IVC-backed firms in this study slightly outperform CVC-backed counterparts, even though the latter are often associated with higher innovation output. Moreover, investors may view CVCs with caution, perceiving potential conflicts of interest or slower commercialization paths due to strategic rather than financial motives.

Lastly, our results may indicate that there is no significant relationship between investor type and post-IPO financial performance, nor between post-IPO patent and financial performance at all. In other words, even if CVC-backed firms produce more patents after going public, this does not necessarily lead to better financial outcomes. This indicates that, in the biotechnology sector, neither the identity of early investors nor the level of post-IPO innovation output are strong predictors of a firm's post-IPO market performance.

6. Conclusion

6.1 Research Aims & Objectives

The main aim of this study was to examine how differing R&Cs between CVC and IVC investors impact innovation output and financial performance post-IPO in US biotechnology firms. Additionally, the paper set out to investigate how the mechanisms “technological fit” and “failure tolerance” mediate the effects on innovation output imposed by the different investors. Four hypotheses were formulated to quantitatively test the effects on post-IPO outcomes. It can be concluded that CVC-backed firms produced significantly more patents post-IPO, supporting the idea that CVCs foster superior innovation output. However, while failure tolerance was found to be a significant predictor of innovation output, CVCs did not consistently exhibit higher tolerance levels. No significant impact of technological fit was observed, nor were differences found in financial performance between CVC- and IVC-backed firms three years post-IPO. These findings suggest that while CVCs may enhance innovation, the mechanisms through which this occurs remain complex and may not align with previous studies. Regardless of these nuances, the study successfully addressed its aims and objectives and contributed to the understanding of investor heterogeneity in post-IPO outcomes.

6.2 Research Contributions

This thesis makes several contributions to the literature on VC and innovation outcomes in the biotechnology sector. By focusing specifically on biotechnology, we respond to calls for more industry-specific studies that account for the unique dynamics of this innovation-intensive, high-risk sector. Since prior research has largely treated biotechnology as part of the broader healthcare industry, our study contributes by revealing differences that are not observed when examining the broader sector.

Firstly, our results provide novel empirical evidence that investor type, CVC versus IVC, has a statistically significant effect on post-IPO innovation output in biotechnology firms. While Chemmanur et al. (2014) analyzed post-IPO innovation, their study spanned multiple industries and did not isolate biotechnology-specific effects. Conversely, Alvarez-Garrido and Dushnitsky

(2016) focused on biotechnology but limited their analysis to the pre-IPO stage. By bridging this gap, our study offers a focused analysis of how venture investor type influences innovation after the IPO in biotechnology, providing new insights into the sustained impact of early-stage backing. In doing so, we challenge the findings of Haslanger et al. (2022), who concluded that CVCs have no significant effect on innovation outcomes in the healthcare sector.

Secondly, we observe a convergence in failure tolerance between CVC and IVC investors in biotechnology, contradicting earlier assumptions that CVCs are systematically more failure tolerant. This suggests that in biotechnology, IVCs may adapt their strategies to remain competitive, effectively narrowing the tolerance gap between investor types. This industry-specific nuance adds depth to the broader sentiment that organizational objectives and investment horizons shape investor effects.

Finally, we corroborate Haslanger et al. (2022) in finding no significant difference in post-IPO financial performance between CVC- and IVC-backed biotechnology firms. This implies that, in this sector, innovation advantages associated with CVCs may not necessarily translate into superior stock returns within a three-year window post-IPO. Together, these insights enrich the understanding of how VC dynamics play out in the biotechnology industry and highlight the need for sector-specific analysis when evaluating the effects of early-stage investors.

6.3 Practical Implications

The study offers several practical implications. Firstly, we have demonstrated that technological fit does not seem to be a significant predictor of post-IPO innovation in start-ups. For founders who are actively fundraising, this knowledge highlights the need to look beyond industry alignment when evaluating potential investors. We demonstrate that the sole fact that the CVC parent operates in the same industry does not imply that they possess resources that can meaningfully contribute to a firm's innovation capabilities. Rather, we argue that these positive effects might be attributable to other mechanisms, such as the relationship between the CVC and its parent company. Therefore, entrepreneurs aiming to maximize innovation should adopt a more holistic approach to investor selection, considering a broader range of factors rather than relying solely on perceived technological synergies.

Furthermore, for VC managers, this study underscores the importance of failure tolerance in R&D-intensive, high-risk industries. The results demonstrate that greater failure tolerance is positively correlated with post-IPO patent output, suggesting that patience and an acceptance of short-term setbacks are instrumental in fostering innovation. Investors should therefore be mindful that a long-term orientation and sustained support can be critical in enabling breakthrough innovation in these types of sectors. In addition, our findings show that CVCs in the biotechnology industry are not more failure tolerant than IVCs, challenging the common belief that their strategic goals make them more patient investors. Thus, entrepreneurs should not assume greater support from CVCs during clinical or regulatory setbacks, but instead carefully assess each investor, regardless of type.

Lastly, our main finding that CVC-backed firms produce more patents post-IPO has two important practical implications. Firstly, the results strengthen the case for pharmaceutical companies to maintain or expand their CVC arms, as a tool for fostering strategic insights and external innovation that persists beyond exit milestones in its portfolio firms. Secondly, policymakers aiming to boost regional biotechnology innovation ecosystems may consider incentivizing CVC investments, potentially stimulating more innovation activity, leading to more productive firms with longer-lasting innovation output.

6.4 Future Research

The findings of this study contribute to novel sector-specific insight. However, several promising directions for future research remain. Firstly, the general relationship and operationalization of technological fit in this thesis, based on matching 2-digit SIC codes between CVC parent firms and portfolio companies, offers a replicable but insignificant proxy. Although it has empirical precedent, it likely fails to capture subtler or significant dimensions of technological alignment. Future studies could explore alternative measures, such as patent classification similarity, or investigate other mechanisms, such as the CVCs proximity to the parent organization in order to yield a more precise understanding of how a CVC's resources may affect innovation output.

Secondly, while failure tolerance was significantly associated with higher post-IPO innovation output, no significant difference in failure tolerance was found between CVCs and IVCs. This result raises questions about whether industry-specific dynamics, i.e., long timelines and high failure rates in biotechnology, drive a convergence in investor patience. Future research could examine whether such convergence exists in other industries with similar characteristics or whether a combination of proxies that capture financial impatience, such as premature M&As and decreased R&D spending, provides a more precise understanding of how a CVC's resources may affect innovation output.

Thirdly, while this thesis finds that CVC-backed start-ups exhibit significantly higher post-IPO innovation output than their IVC-backed counterparts, this difference does not extend to financial performance. This raises important questions about whether increased innovation output truly translates into stronger financial returns. In an industry like biotechnology, where patents serve as observable signals of scientific progress, it is surprising that firms with more post-IPO patents do not exhibit superior financial outcomes within the observed period. Given the long commercialization timelines in biotechnology, it is possible that the financial benefits of innovation materialize beyond the three-year post-IPO window used in this study. Future research could therefore explore the long-term relationship between post-IPO patenting and financial returns using extended time horizons and longitudinal data. Panel data models or longer time frames could capture delayed effects more accurately, while qualitative methods such as investor interviews may offer additional insight into how capital markets interpret innovation signals and how investor types affect start-ups post-IPO.

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Appendix A: Figures

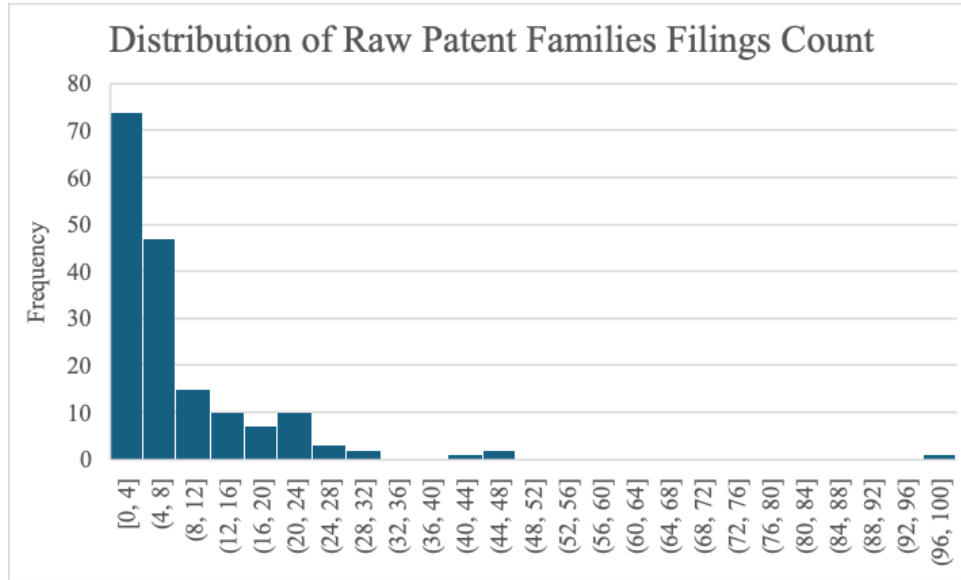


Figure 1.1: Histogram of Raw Patent Families Count

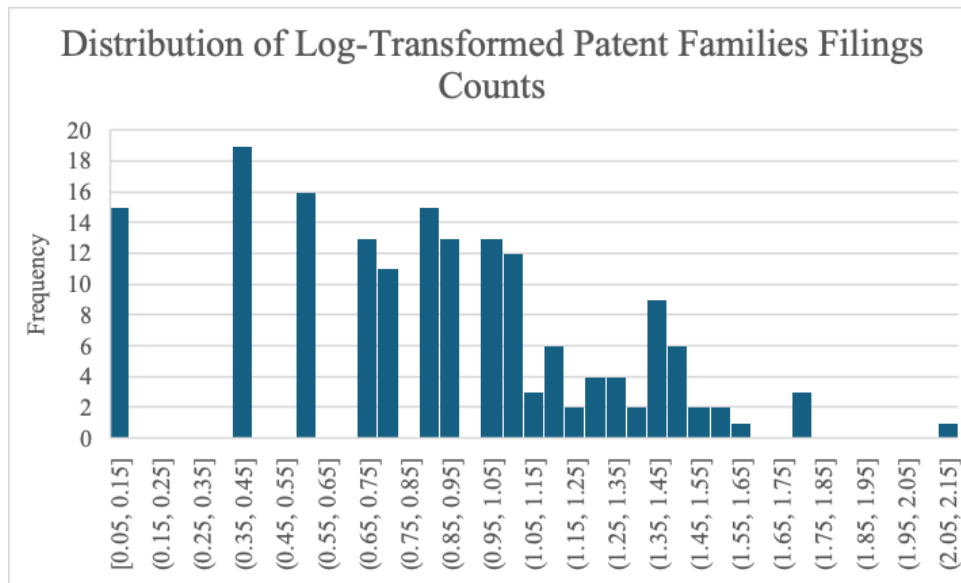


Figure 1.2: Histogram of Log-Transformed Patent Families Counts

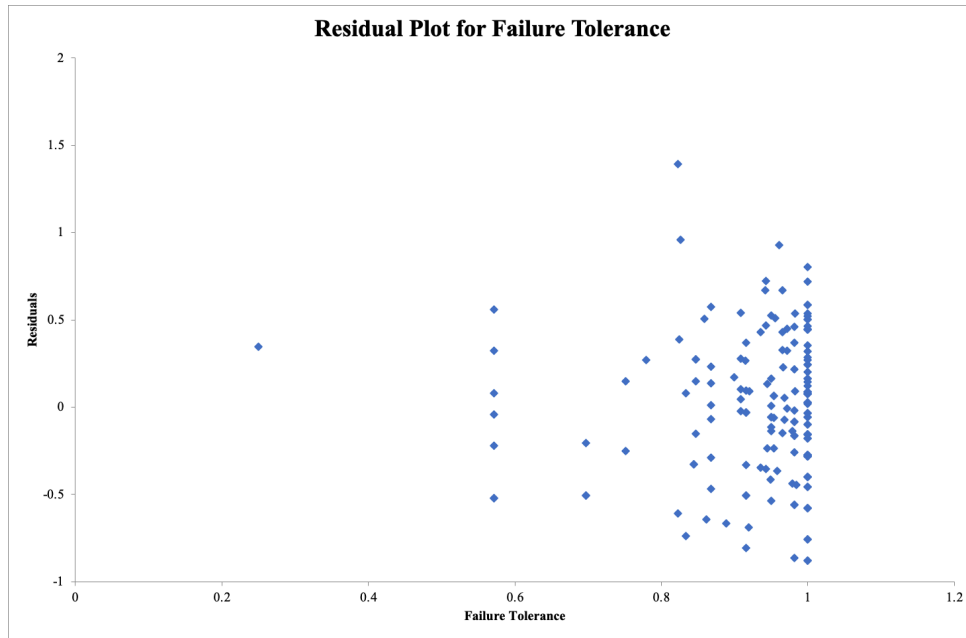


Figure 2.1: Residual Plot for Failure Tolerance

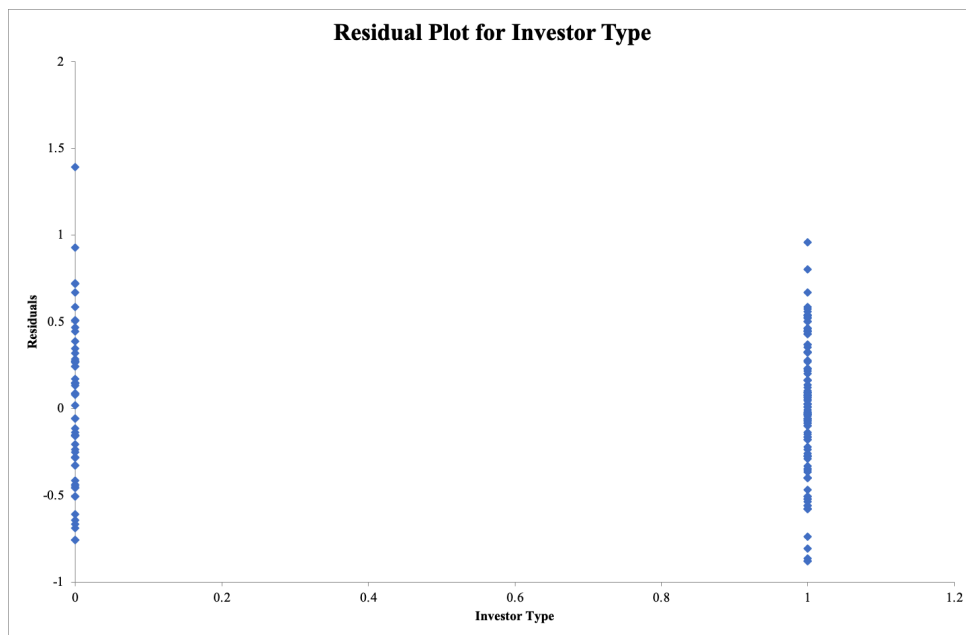


Figure 2.2: Residual Plot for Investor Type

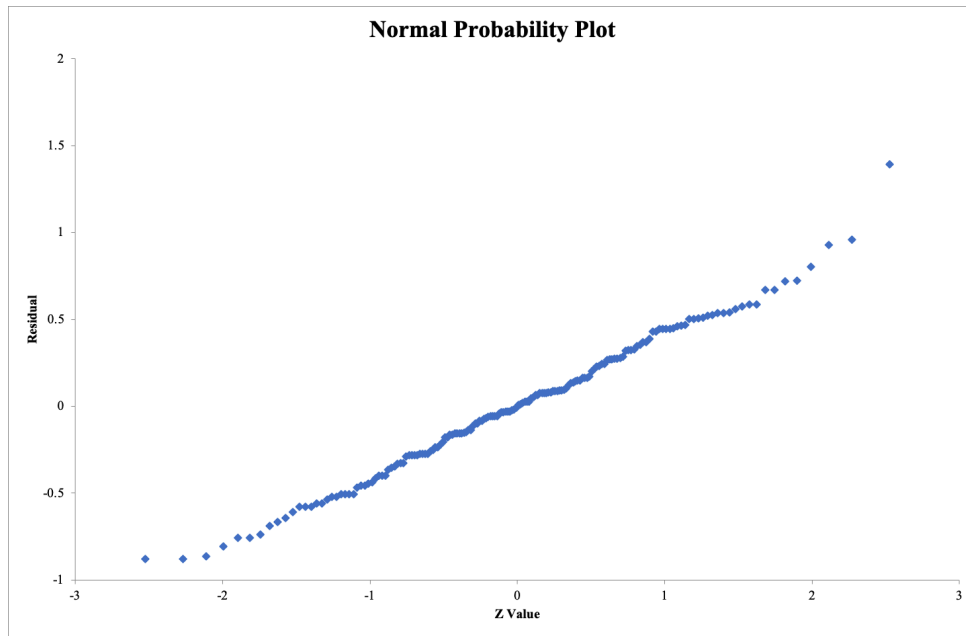


Figure 2.3: Normal Probability Plot for Patent Output

Appendix B: AI Usage Statement

In producing this thesis, the authors have employed ChatGPT 4o for three use cases. Firstly, it was used to rephrase certain sections of text to improve readability, and to ensure adequate clarity. Secondly, it has been prompted to suggest synonyms to specific words to avoid excessive repetitions. In addition to this, ChatGPT has been used to remove grammatical errors not caught by Google docs. These use cases were applied for more or less all sections of the text. See below for example prompts for each of the three use cases:

Example 1: Rephrase and increase clarity in sentences/minor portions of text:

- Can you rephrase this sentence; “Technological fit is assessed for CVC-backed firms, however not for IVCs, as they do not operate in specific product markets and can therefore not show technological fit according to our definition.”, to improve readability and clarity. Please provide a short list of potential suggestions.

Example 2: Synonym suggestions

- “Give me a list of synonyms for the word indicates.”

Example 3: Remove grammatical errors not caught by Google docs.

- I have written the following sentence; “Additionally, prior research highlight the need for a focused study of this specific field.”. When I read it I believe that there is a grammatical error, that “highlight” should be “highlights”. However, Google docs spell check did not mark anything wrong about the sentence. Could you double check if there is a grammatical error in the sentence I have provided?

Appendix C: Authorship Statement

This bachelor's thesis was written by Linn Elderot, John Johansson and Samuel Schatz, all of whom contributed equally to the project. The authors assume full responsibility for the content of the thesis and have all approved of the final product prior to submission.