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A New Dawn for Europe's Sustainable Innovation?

Assessing Venture Capital Performance in European Climate Technology

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Abstract

This thesis investigates venture capital investments in the European climate tech sector, focusing on the past decade. Through survival analysis, it examines three hypotheses: the relative success rate of climate tech investments compared to peer sectors, the influence of capital intensity on investment success, and the performance of corporate venture capital (CVC)-backed companies versus traditional venture capital (VC) backing.

The study finds that the climate tech sector generally underperforms, with inconsistent statistical significance across models. The impact of capital intensity on success is not clear. However, moderate capital intensity may be associated with higher success rates. Finally, limited evidence suggests a marginal advantage in success and innovation for CVC-backed companies.

These findings highlight the complexities between investment strategies and sectoral performance in the European climate tech landscape, underscoring the need for nuanced approaches in venture capital investment to navigate this sector's unique challenges and potential.

Keywords – Venture Capital, Climate Tech, Survival Analysis

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1 Introduction

The European Union estimates that meeting the objectives of the Green Deal and RepowerEU will require an annual investment of over 620 BEUR, with a significant portion expected to come from private capital (Commission, 2023). Additionally, the International Energy Agency (2023) underscores that while current technologies may satisfy demands for the 2030 emissions reduction targets, the goals for 2050 will largely depend on new technologies.

In the past decade, the European Union has been instrumental in shaping the climate investment landscape in Europe through its regulatory initiatives. These initiatives have created a stable and attractive environment for investors, and directed the flow of climate-related investments (Chandaria et al., 2023). Measures like the European Investment Bank's targeted financing and the Horizon Europe program have been crucial in supporting research and innovation, thereby reducing the risks of investing in emerging climate technologies (Lechtenfeld et al., 2023).

Surrounded by EU support and regulatory initiatives, venture capitalists (VCs) emerge as key players in bridging the gap between innovative ideas and necessary private capital, particularly in developing and implementing emergent climate technologies. However, the venture capital landscape in this sector has been challenging. The late 2000s saw a rise in VC investments in clean tech, culminating in the 'Clean Tech 1.0' bubble burst in 2011, leading to significant losses (Gaddy et al., 2016). Gaddy et al. (2016) further proposed that the sector's inherent risks and capital-intensive nature made it less attractive to VCs. Nevertheless, there has been a notable shift in the post-bubble era, with the emergence of 'Climate Tech 2.0' with a record-high investment of 37 BUSD in 2021 (Kanoff et al., 2017).

In the aftermath of the Clean Tech 1.0 bubble, the dynamics within the climate tech sector have undergone significant changes. Despite these developments, there remains a notable gap in quantitative research, particularly regarding the performance of VC investments in this evolving landscape. This thesis aims to address this gap by evaluating the investments made in the climate tech sector over the past decade. It will specifically focus on assessing the performance of these investments in an environment bolstered by solid regulatory support for sustainability and innovation.

To comprehensively evaluate these investments, the thesis will explore several sub-hypotheses. This includes examining the industry's performance in comparison to its peers, investigating how capital intensity impacts investment outcomes, and analysing the performance variations between different types of VCs. We will primarily use survival analysis to examine investment success, supplemented by a regression model to assess company innovativeness as an alternative success measure.

Our analysis of the European climate tech reveals key findings on venture capital investment success in this evolving industry. Preliminary results suggest that despite favourable regulatory changes, the climate tech sector may still pose challenges for VC success compared to other industries. It also seems that companies with a moderate level of capital intensity tend to have higher success rates. When analysing the impact of different types of backing, our research points to a complex scenario concerning corporate venture capital (CVC) versus traditional venture capital (VC) support. The results hints that CVC-backed companies may have an edge in terms of success. However, the current evidence needs to be more comprehensive to form definitive conclusions on this aspect.

The results of this study provide valuable insights regarding the dynamics of venture capital in the climate tech sector, underscoring the diverse factors that might affect the success rate. These findings not only reveal the current state of climate tech investments, but also aim to provide guidance on factors to consider when investing in this field.

2 Literature Review

The following section will present and discuss the main concepts guiding our thesis. First, we will focus on presenting VC as a funding source with its different facets before focusing on VCs as impact investors. Lastly, we will investigate climate tech investments and their characteristics.

2.1 Venture Capital

Venture capital (VC) can be defined as a form of financing provided to early-stage companies with high growth and risk potential, and it is the preferred financing for these particular companies (Giraudo et al., 2019; Metrick & Yasuda, 2010). Venture Capital is known for its crucial role in supporting innovation and developing new technologies globally (Bowonder & Mani, 2004; Taylor & Khan, 2021).

In this study, we will use the abbreviation VC to refer to both the venture capital industry and the individual venture capitalist. Metrick and Yasuda (2010) define that VC has the following five main characteristics:

1. They act as a financial intermediary since they handle and invest external investors' money.
2. Only investing in private companies hence investing in companies not traded on public exchanges.
3. Being an active owner - by adding value to the companies.
4. Their main goal is to maximize the financial returns by exiting the investments through an exit.
5. Their equity investments are used to fuel internal growth in the portfolio companies.

Understanding these characteristics of VC leads us to their basic operational structure. A VC fund is structured through a limited partnership, where the VCs are often categorized as general partners (GPs), raising funds from the investors who are categorized as limited partners (LPs), hence the first characteristic of a financial intermediary (Metrick & Yasuda, 2010). The partnership consists of agreements on such as the outline of investment strategies, the fund's lifecycle, management fees, and other formalities (Marcus et al., 2013). Traditional VC funds operate with a lifecycle of ten years, where the first five years are used to invest, called the investment period. During this period, the fund makes initial investments, specifically acquiring minority positions, in targeted companies. The fund may also make additional follow-up investments if the fund's management remains confident in the company's potential. The last five years are used to harvest the returns of the investments, preferably through IPOs and acquisitions (P. Gompers & Lerner, 2000; Metrick & Yasuda, 2010). The operations are funded through a management fee from the LPs, which usually is around 2-5% of the total committed capital of the fund annually. In addition, funds set up a structures to incentivize the GPs to strive for excess returns, which gives the VC claim on 20-30% of the excess profit when the fund returns are higher than a particular pre-agreed hurdle (Haislip, 2011). The carrot of potential profits and the limited timeframe to achieve them are the main drivers behind their focus on maximizing financial returns.

This operational involvement is particularly essential given the nature of VC investments. VCs provide more than just financial support to their portfolio companies. They also actively participate in their strategic and operational development to help them achieve growth and scale. This is done through having seats on the board, regular meetings with management teams, recruiting talent, and utilizing the VC network for partnerships and collaborations (Haislip, 2011). These systematic strategies are designed to ensure the internal growth of the companies and help them mature and grow as the VCs prepare for an exit, which will be presented later.

As a company progresses through successive funding rounds, it often attracts additional investors. Each new investor typically takes an equity stake, leading to a more populated capitalization table and consequentially, the dilution of ownership for each investor. Hence, the VC also potentially reduce their influence in the company through value-adding and monitoring activities. An increased capitalization table also increases coordination costs, by complicating decision-making (Dimov & De Clerq, 2006). Kim and Park (2021) studied how the number of investors in each funding round affects the company's performance. Their findings suggest that while additional investors bring in valuable resources, the benefits are offset by increased coordination costs, which diminish the marginal contribution each investor have on the company's performance.

VCs typically invest in early-stage, high-tech companies that have the highest information asymmetries (P. A. Gompers, 1995). However, such companies pose a significant technological investment risk. To mitigate this risk, while still benefiting from potential growth, VCs often invest through contracts such as convertible preferred stock (P. Gompers & Lerner, 2002; Kaplan & Strömberg, 2003). Additionally, VCs invest smaller amounts at different stages of a company's lifecycle, allowing them to reach predetermined milestones before making subsequent investments. This strategy is applied to the more successful portfolio companies over time (P. A. Gompers, 1995).

Strategic planning for exit is a crucial aspect of the investment process, and it starts right from the beginning. VCs aim to achieve a successful exit through an Initial Public Offering (IPO) by listing the company on a stock exchange, or by selling the company to a strategic third party through a merger or acquisition. If these exit strategies do not work out, the VCs will try to sell their shares to a third party through secondaries, or back to the founders via a buyback. In case of an unfavourable outcome, the VCs will take a write-off and attempt to liquidate the company's assets to cover the losses as much as possible (Metrick & Yasuda, 2010). The role of the investments of VCs not only impacts individual companies but also has a significant influence on the broader innovation landscape. This is evident from their pivotal role in shaping the modern entrepreneurial ecosystem.

VCs have been vital in driving innovation and success for countless companies. VC-backed firms, while representing less than 0.5% of new firms based on AUM in the US (Puri,2012), account for nearly half of the firms making a successful transition to the public market (Lerner & Nanda, 2020). As Nobel Prize winner Kenneth Arrow stated in 1995, "Venture capital has done more, I think, to improve efficiency than anything else.". Moreover, the availability of VC funding for new startups has driven the emergence of innovations across a wide range of sectors, including healthcare, IT, and new materials (Nanda et al., 2015).

2.2 Corporate Venture Capital

Having discussed traditional venture capital, we now turn to Corporate Venture Capital (CVC), an emerging form of investment that is gaining popularity due to its unique approach to investing. Unlike traditional VC, CVCs are strategic investment arms of established corporations that invest equity in companies with potential synergies to their parent company's business strategies (Chemmanur et al., 2014; Drover et al., 2017). This approach provides additional strategic resources, such as access to established networks in terms of partnerships and customers, brand recognition, and industry expertise, which can be invaluable for startups in the given sector. Moreover, CVCs prioritize strategic alignment and long-term partnerships over immediate financial returns, which contrasts with the traditional VC model that typically seeks rapid growth and quick exits. This is because CVCs are not bound by a fund structure like a traditional limited partnership, giving them more flexibility on the holding period on the investment and investment amounts, which allows them to align with their strategic objectives over time. Due to this difference in objectives, CVCs often invest in companies aligning with the parent corporation's strategic goals and potentially integrating with its operations or enhancing its product offerings. This investment approach is convenient for companies looking for more than just financial investment; it also provides support from an established corporation that can provide access to resources and expertise to help them succeed.

A prime example of CVC investments is Google Ventures' investment in Nest Labs in 2011, which helped the company fund its smart home technology and marked a crucial move for Google into the Internet of Things sector. While Google Ventures made the initial investment, it was ultimately Google, the parent company, that acquired Nest Labs in 2014. This acquisition played a key role in the development and the later launch of Google Home in 2016 (Laricchia, 2023; Rolfe & Daisuke, 2014).

2.3 Sustainability and VCs

Transitioning from the characteristics of VCs, the next section delves into the broader landscape of sustainability. Here, we examine how VCs are adapting to the evolving landscape of sustainable investing and the implications for climate tech investment. In the past, traditional VCs focused solely on maximizing their financial returns. However, there has been a shift in recent years with the rise of impact investors. Today, the impact investing market is estimated to be worth over 1 trillion USD in assets under management (Hand et al., 2022). Bozesan et al. (2020) found that, in the new landscape of sustainable investing, there is still some variation among VCs, which aligns with Schoenmaker (2019) framework for sustainable finance. Some investors are still focused on optimizing their financial returns while also considering their environmental and social impact, known as sustainable finance 1.0 (S.F. 1.0). Meanwhile, others strive to balance financial value with environmental and social impact to maximize stakeholder value (S.F. 2.0). At the end of the spectrum, some investors prioritize environmental and social impact over financial returns and border on philanthropy (S.F. 3.0). According to recent research conducted by Barber et al. (2021), despite the growing interest and investment in impact investing VCs, these funds tend to underperform traditional VC funds by a significant margin of 4.7 percentage points, when measured by internal rate of return (IRR). However, the research also reveals that these funds' LPs are willing to accept a trade-off between financial returns and environmental and social impact. LPs are willing to accept up to 3.7 percentage points of lower IRR to achieve the desired impact on society and the environment (Barber et al., 2021).

2.4 Climate Tech

Building on our understanding of the changing investment paradigms in VC, we now shift our focus to climate tech itself. This section discusses the definition, scope, history, and recent investment trends in climate tech.

Climate tech refers to technologies and services that aim to reduce global emissions and limit the adverse effects of climate change. Although different stakeholders may have differing definitions, these technologies primarily focus on addressing and reducing greenhouse gas emissions. This ranges from investing in large carbon capture plants to implementing sustainability reporting (NASDAQ, 2023). Recent data shows that capital investment in this sector is increasing, with a record high of USD 120 billion worth of investments in 2021. Additionally, the climate tech share of total venture capital and private equity market has increased from 1.46% in 2013 to 10.02% as of Q3 2023 (E. Cox et al., 2023).

It is important to note that in the past, venture capital funds have invested in climate-related projects, particularly in the subcategory of climate tech known as cleantech. This type of technology focuses solely on the energy sector and renewable energy sources like solar, hydro, and wind energy, as well as biofuels and other technologies that improve energy efficiency. Between 2006 and 2011, VC firms invested over $25 billion in cleantech companies. However, they lost more than half of their investment, and over 90% of the cleantech companies funded after 2007 failed to return the initial capital to their investors (Gaddy et al., 2016).

Based on the cleantech 1.0 boom, Gaddy et al. (2016) highlighted that the venture capital model is not suited as a funding model for early-stage cleantech companies. The first key takeaway was that the VC model usually prefers a 3-5 year investment horizon, but cleantech startups required a much longer timeframe. Developing innovative cleantech solutions is inherently time-consuming due to new science and technology complexities. As a result, cleantech companies could not meet the rapid growth and return expectations set by VCs, which led to a high failure rate.

Secondly, cleantech startups faced significant capital expenditure demands, especially those in the early stages of technology development. They often needed to raise hundreds of millions of dollars for building factories and scaling operations, even when their core technologies were still in development. This contradicts the median equity ticket of VC investors, which is ranging from 1-14 MUSD, depending on stage (Lavender et al., 2023). Significant investments are needed in the cleantech industry, and these investments are much higher than what VCs usually allocate. Scaling and intensive R&D are crucial in cleantech, and they require a more extensive financial commitment. However, this high outlay has been a major hurdle for companies in this sector, as they operate in competitive markets with slim margins and face stiff competition from established lower-cost alternatives.

Recent research has shown that the traditional VC models may not be as effective in promoting innovation as they were in the past. These models have a narrow focus on technological advancements, which often overlooks the unique needs and timelines of new radical technologies (Lerner & Nanda, 2020). As mentioned, VCs tend to favour software and service companies because they rely on established technologies, leaving many climate tech innovations needing more funding. These innovations, also known as 'deep tech,' require more time to mature and typically need 25% to 40% more time between funding rounds than conventional technologies. Additionally, "deep tech" innovations carry a higher risk of failure due to their pioneering nature and the complexities of developing new solutions (Bobier et al., 2023). This creates a significant funding gap for climate tech innovations, which contradicts the urgent need for radical technological solutions to address climate-related challenges.

3 Hypotheses

Our thesis aims to investigate the successfulness of venture capitalists' investments in the European climate tech sector the last decade. This period has been marked by significant shifts in the investment landscape, with the rise in importance of climate tech investments driven by government initiatives and regulatory support. This shift aligns with the VC community's growing focus on sustainable and impact investing.

To investigate this, we have developed the following hypotheses:

Hypothesis 1: The climate tech sector experiences fewer successful exits than other sectors traditionally favoured by venture capitalists.

This hypothesis originates from observations in the literature that cleantech investments often involve longer timeframes and higher risks, potentially leading to fewer successful exits. The literature review reveals challenges such as high capital expenditure requirements and extended development cycles, which raise questions about their compatibility with traditional VC investment strategies, that typically emphasize rapid growth and quick exits.

Hypothesis 2: In the climate tech industry, capital intensity negatively impacts the likelihood of successful exits for venture capitalists.

This hypothesis explores that climate tech companies' high capital expenditure demands may challenge venture capitalists, who generally prefer investments with lower initial capital requirements and faster returns. We aim to investigate if venture capitalists have learned any lessons from the era of 'cleantech 1.0' by comparing the high capital-intensive sectors with the lower ones.

Lastly, in contrasting the VC model with the CVC model, we consider the premise that CVCs, with their access to extensive resources and strategic alignment with parent companies, might offer a more conducive environment for cleantech startups. This leads to our final hypotheses:

Hypothesis 3-1: CVC-backed startups in the climate tech sector are more likely to succeed than those backed by traditional VCs.

This hypothesis is based on the assumption that CVCs, due to their strategic focus and longer-term investment horizons, are better positioned to support the growth and success of climate tech startups, measured as preferred exits through IPOs and acquisitions.

Hypothesis 3-2: CVC-backed startups in the climate tech sector exhibit higher innovation than those supported by traditional VCs.

Hand-in-hand with 3-1, this hypothesis explores the potential of CVCs being better suited to foster innovation compared to traditional VCs.

Through these hypotheses, we aim to provide more insights on the dynamics of venture capital in the climate tech sector and contribute to the discourse on aligning VC models with the unique demands and challenges of the European climate tech sector.

4 Data gathering

The deal-by-deal financial data was obtained from Crunchbase. The database has been recognized as the primary source of venture capital information, with over 75 million users globally (Wiggers, 2022). The database gathers information from two main channels: extensive investor and contribution networks, and AI web scraping techniques. This approach ensures that the database always contains the latest updated information (Dalle et al., 2017). The contributors update their company profiles, which Crunchbase's moderators manually verify. Considering the popularity of the database, it is reasonable to assume that innovators and investors are incentivized to keep their information updated, as maintaining updated information aligns with their interest in showing good results.

In addition to using Crunchbase as our main source of information, we combine it with relevant data from other databases. We obtained industry codes on climate tech companies and investors from Orbis, a database that holds information on more than 425 million private companies. To ensure that we had the most up-to-date and comprehensive data on exits, we cross-verified our exit information with Refinitiv Eikon. Although Refinitiv Eikon had similar data on exits as Crunchbase, the cross-checking helped us uncover an additional 15 exits which were not present in Crunchbase.

4.1 Sample Bias

4.1.1 Survivorship Bias

Survivorship bias refers to the discrepancy in performance between a portfolio that includes all data points within a specific timeframe and a skewed portfolio that exclusively accounts for the observations that have persisted through to the end of that period (Rohleder et al., 2011). It is important to note that our data may have a potential survivorship bias due to the lack of incentives to announce data on failed investments for investors and entrepreneurs.

4.2 Location, Years and Funding Rounds

Our analysis of the European VC landscape post-cleantech 1.0 bust includes companies headquartered in Europe, founded after 2010, and raising in seed, Series A, B, and C funding rounds. These companies must have completed at least two funding rounds and have documented information on total capital raised. This study excludes rounds at the angel, pre-seed, and post-IPO levels.

4.3 Industries

Our study includes comparative analyses against the fintech, e-commerce, and healthcare sectors, which have been chosen due to their notable investment trends and market dynamics, providing comparative insights. The healthcare sector has demonstrated a steady increase in VC financing globally since 2015, as Lavender et al. (2023) reported, with a spike in investments catalysed by modernization efforts during the COVID-19 pandemic. Fintech has emerged as a significant draw for funding, attracting over 500 BUSD globally in the past decade, and since 2019, it has captured roughly 20% of venture capital investments (Bobier et al., 2023). E-commerce has been popular with VC investors in Europe over the last decade but dropped the recent year (Lavender et al., 2023).

Crunchbase recommends startups choose 2-5 categories but sets no limits. Meaning that some companies might have industry descriptions unsuitable for their line of business (Savin et al., 2022). Therefore, we also had to manually look at the company descriptions to see if they fit the industry profile.

4.3.1 Climate Tech

As defined by Li et al. (2022), climate technologies are distinct innovations aimed at reducing the environmental impact of both products and their production processes. Without a specific industry group for climate tech on Crunchbase, we conducted a thorough manual search through the sub-categories of each industry group. This process was focused on finding sub-categories that matched Li et al.'s definition of climate technology. Through this search, we identified 15 relevant sub-categories, leading to 711 companies fitting the criteria for climate tech.

4.3.2 E-commerce

E-commerce in modern times is defined as a transaction that uses the World Wide Web at least at one point in the transaction's lifecycle. It typically means buying and selling goods and services on the Internet, but by definition, it also includes the non-financial transactions that the customer has with the company (Bulsara & Vaghela, 2020). This is a broad definition, and using Crunchbase as a source could result in gathering data on companies in ten-fold sub-categories from all industries. To maintain a focused scope we limited our search to companies categorized under "E-Commerce" and "E-Commerce Platforms" resulting in a list of 1,202 companies.

4.3.3 Fintech

FinTech is the technology used to provide financial markets with a financial product or financial service, characterized by sophisticated technology relative to existing technology in that market (Knewtson & Rosenbaum, 2020). This definition, however, is not universally recognized. Therefore, similar to our approach with climate tech, we conducted a manual examination through Crunchbase to identify appropriate sub-categories. This process led us to select 18 sub-categories resulting in a list of 1,634 companies.

4.3.4 Healthtech

Diverse innovations, from advanced technologies such as home-use heart rate sensors and hospital medical devices to various services, including elderly care and therapeutic treatments characterize the healthtech sector. We used Crunchbase's own healthcare industry group in our data filtering. The decision was based on the observation that their classification covers the relevant sub-categories of the healthtech sector, and it gave us a list of 2,343 companies.

4.4 Funding Round Data

To ensure accurate funding data for companies, we excluded funding rounds without CVC or VC investors and those with missing information on the raised amount.

4.5 Definition of Variables

4.5.1 Investment Outcomes

For investment outcomes, a dummy variable for success and failure is included in the binominal analyses. It's important to note that the success rate can vary broadly based on how and for whom the investment is successful. In the case of this data, success is defined based on the VC investment. For VCs, a successful exit typically occurs through an IPO or M&A (P. Gompers et al., 2008; Metrick & Yasuda, 2010).

4.5.1.1 IPO

An IPO, or initial public offering, is a process through which a private company offers shares of its stock to the public for the first time. This allows the company to raise capital by allowing investors to buy shares and become part-owners of the company. While it is not guaranteed that the venture capitalist will sell their entire position through an IPO, it is still considered a success, as it is one of the preferred ways of exiting (P. Gompers et al., 2008; Metrick & Yasuda, 2010). The exit date is determined as the IPO date, which is accessible through public information.

4.5.1.2 M&A

Mergers and acquisitions are the other preferred ways of exiting for the VCs (P. Gompers et al., 2008; Metrick & Yasuda, 2010). When a company exits through M&A, the VC sells its complete position. The most common exit through M&A is a trade sale, where the entire company is sold to another. However, it's crucial to note that not all acquisitions are deemed successful. For example, an acquisition with a 2x multiple over a ten-year period may not meet the expected success criteria if the IRR falls below the standard VC hurdle rate of 8% (Metrick & Yasuda, 2010).

In our analysis, we have grouped both IPOs and M&As under a single 'Success' category. We made this decision because we didn't have access to the initial investment data on the VCs, which made it impossible to calculate precise investment returns for these companies. Instead, we use the occurrence of an IPO or M&A as a proxy for success. This approach acknowledges that while we don't know the exact returns on investment, the realization of an IPO or M&A usually indicates a positive and significant financial outcome (Metrick & Yasuda, 2010).

4.5.1.3 Active Companies

Active companies that have not received any funding in the past three years are classified as failures. This is based on the assumption that a startup's funding can be a good indicator of its health. Not receiving any funding for three years indicates that the company might be "living dead", which VCs do not consider to have the potential for further growth. This is consistent with Gaddy et al. (2016), who found that 80% of companies that returned at least the capital funded in the Series A-round had not gone more than three years without funding. For the active companies that have received funding in the last three years, we include them as marked "still active". A successful exit is typically set within a 5-7 year timeframe after first investment (Kaplan & Strömberg, 2003), with longer periods increasing the probability of a negative outcome (P. Gompers & Lerner, 2001). Therefore, non-exited active companies that have been funded for more than six years are seen as failures if they have an average time between funding of more than two years. Hence, companies with larger-than-average interval between funding rounds are classified as failures, as it indicates a lack of continuous investment and growth. The two-year threshold is based on empirical evidence of the median time between funding rounds for 8000 companies (Socias, 2017).

4.5.1.4 Write-offs

Investments that have been written off typically reflect a recognition of loss. Such investments often result in liquidation or continue operating with minimal to no revenue. They have therefore been classified as failures in our analysis.

4.5.1.5 Inactive Companies

If a company is inactive and has no information on the last active date, we classify it as a failure one year after its last funding date. This is based on our assumption that the absence of available information indicates the company's failure. In most cases, there is little to no incentive to conceal information on successful companies, further reinforcing this assumption.

Table 4.1: Investment Outcomes for Companies

The table displays an overview of how the companies in our data has been treated based on their funding history and different exits. As we see, only IPOs and M&As are treated as successes. The companies that are treated as "Active", still have an undetermined outcome. The inactive companies with no information are set as failure one year after last funding date.

Company's outcome depending on status:	**Outcomes:**
Exits:	
IPO	Success
M&A	Success
Active Companies:	
Invested $<$ 6 years and funded last 3 years	Active
Invested $<$ 6 years and not funded last 3 years	Failure
Invested $>$ 6 years and average time between rounds $>$ 2 years	Failure
Invested $>$ 6 years and average time between rounds $<$ 2 years	Active
Inactive Companies:	
Write-offs:	Failure
Inactive companies/No information	Failure

4.5.2 CVC

A CVC, or corporate venture capital, is a non-financial corporation that invests for strategic purposes, such as gaining access to innovative ideas and technologies. To explore our hypothesis that CVC-backed companies in climate tech are more successful and innovative than VC-backed, we also included data for CVC-backed companies. This is shown in the analyses through a dummy variable, CVC, that is equal to 1 if a CVC funds the company. Companies backed by both are categorized as CVC-backed in our data.

4.5.3 Strategic Investment

When evaluating whether a CVC investment is strategic, we assess the technological proximity between the CVC and the target company by analysing their respective industries. We do this by looking at the Statistical Classification of Economic Activities in the European Community, which is known as NACE. We compare the NACE code assigned to each investment under review with the NACE code of the target company. This comparison helps us determine the degree of overlap between the two, indicating their industrial and technological alignment. NACE codes are classifications that represent specific sectors and subsectors of economic activity (Eurostat, 2023). If a CVC and its target company share a NACE code or have similar ones, it suggests that they may have commonalities in their production processes and technological capabilities (Markides & Williamson, 1996). Therefore, a significant overlap in NACE codes implies that the investment might align strategically with the CVC's core business areas, indicating a closer match in their technological and industrial objectives.

However, the NACE-based measure has its limitations, especially in categorizing large conglomerates like Equinor, which operate across multiple industries and cannot be easily classified into a single code. This traditional approach, as noted by Keil et al. (2008), overlooks the multifaceted nature of such corporations that are likely to hold several industry codes.

To better evaluate the strategic alignment of a venture investment, we analyse not only the NACE code of the investing CVC, but also the NACE codes of their parent companies. We focus on the first digit of the NACE code, which represents the primary industrial sector of the firm (Brønnøysundregisteret, 2023). By comparing this digit with the venture's NACE code, we can determine whether there is a match and create a dummy variable to indicate alignment.

4.5.4 Capital Intensity

We encountered a significant obstacle in obtaining comprehensive financial data on the capital intensity of early-stage climate tech companies. We attempted to gather this information from various databases but soon realized that it was not readily available.

To overcome this hurdle, we developed a method to categorize each company based on their projected investment requirements at full operational scale, which reflects the capital needed to run their systems or products fully. Our approach relied on the industry sub-categorization, company description from Crunchbase, and industry-specific capital expenditure benchmarks. We classified each sub-industry in Crunchbase as having low, medium, or high capital intensity based on these benchmarks, where the categorization is outlined in Appendix A.4.

For instance, in Crunchbase, a renewable energy company that falls under the 'battery producer' category is identified as highly capital-intensive, which is consistent with the significant investment that this sector usually requires. On the other hand, industries such as Software as a Service (SaaS) and Artificial Intelligence (AI) are considered low capital intensity due to their relatively lower capital needs. For companies that operate across multiple sub-industries, we used a weighted average approach, considering the company descriptions in Crunchbase to determine the most significant capital factors manually. For example, a solar energy producer incorporating AI in its battery technology would be primarily categorized as highly capital-intensive, mainly influenced by the investment demands of the solar energy production side.

It is important to understand the limitations of this method. Although Crunchbase's industry categories and sector-specific capital expenditure benchmarks are a practical solution when detailed financial data is unavailable, they may not accurately capture the unique capital requirements of each firm. Therefore, while our categorization is useful for estimation purposes, it should be considered a general guide rather than a precise measure of capital intensity.

4.5.5 Number of Patents Granted

Patents are a well-grounded proxy for measuring technological innovations in research (Burhan et al., 2017). The patent data were retrieved from Crunchbase's own IPqwery, which gathers information on companies' patents and trademarks (Crunchbase, 2023). We also wanted to include patent citations as a quality measure of innovation. Forward patent citations indicate patents scientific importance and, therefore, its value (EPO, 2022). However, as it was not a database that provided patent citations for large-quantity searches, we decided to not include it.

4.5.6 Total Amount Raised and Number of Funding Rounds

To control for the impact of investment dynamics on company success rates we are focusing on two variables: *Total Amount Raised* and *Number of Funding Rounds*. *Total Amount Raised* represents the accumulated total capital raised by a company, indicating its ability to attract significant investment. The *Number of Funding Rounds* indicates how often a company receives funding, highlighting its ongoing ability to demonstrate value and potential to investors. These are key indicators of a company's funding trajectory, yet they represent only a part of the broader success narrative.

4.5.7 Capitalization Table Size

The number of owners can impact a company's performance, as discussed in section 2.1. To determine how a company's success rate is affected by the size of its capitalization table, we have introduced a variable called *Cap Table Size*. This variable represents the cumulative total number of distinct investors who have invested in the company as the funding rounds progress.

5 Methodology

In this section, we introduce the methodological techniques we apply to investigate the various aspects of our different hypotheses. We applied various survival analysis techniques to test our hypotheses, aiming to analyse and gain deeper insight into the factors contributing to successful exits. We also applied a linear multiple regression to look further into the innovative success of CVCs over traditional VCs.

We start by looking at the basics of survival analysis before implementing the Kaplan-Meier estimator, which gives the analyses unbiased descriptive statistics of the data. We then move on to the Cox proportional hazards model, which allows us to take covariates determining exits into account. Lastly, we integrate the Fine-Gray competing risk model, allowing us to investigate the different exit outcomes, not just exits.

5.1 Survival Analysis

Survival analysis, also known as time-to-event analysis, is a set of methods used to analyse data where the outcome variable is the time until an event of interest occurs (Kleinbaum & Klein, 2010). These methods are traditionally used in medical research to study the length of time until a patient's death. However, in our analysis, we will apply this technique on businesses. Here, we will view the company as the patient and the exit of the VC as the event of interest. This will help us find the company's hazard and survival functions.

Survival functions indicate the probability that an event has not occurred by time t. It is denoted as:

$$S(t) = 1 - F(t) = P(T > t) \quad \text{for} \quad t \geq 0 \tag{5.1}$$

Where T is the random non-negative time until the event occurs, the function gives the probability of survival at time t. For instance, at $t = 0, S = 1$, and when $T \to \infty$, $S \to 0$. This framework suggests that the chance of a company successfully exiting immediately after the initial investment is zero but increases over time. The hazard function gives the instantaneous potential per unit time for the event to occur, given that the individual has survived up to time t (Kleinbaum & Klein, 2010). To put it simply, conditional probability refers to the likelihood of an event happening within a specific time frame, given that it has not occurred yet. In the context of a company's success, it means the probability of a company achieving a successful exit at a given time, assuming it has not already exited.

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t + \Delta t > T > t)}{\Delta t} = \frac{f(t)}{S(t)} \tag{5.2}$$

Where $f(t) = \frac{dF(t)}{dt}$ is the density function of $F(T)$. The hazard function, $h(t)$, can vary from 0, meaning a zero probability of an event occurring, to ∞ , meaning the event will certainly occur. The hazard rate can vary over time, either increasing or decreasing, or remaining constant. The cumulative hazard was estimated by the method of Peterson (1977). It is the integral of the hazard rate and measures the accumulated probability of the event occurring up to a given time t.

$$H(t) = \int_0^t h(u)\, du = -\ln S(t) \tag{5.3}$$

5.2 Censoring

Survival analysis involves monitoring observations until an event occurs or the monitoring period ends. A critical aspect of survival analysis is handling censored data, where information about the event is incomplete. The most common type of censored data is right-censoring, which occurs when the observer has not yet experienced the event by the end of the monitoring period (Kartsonaki, 2016).

In our analysis, we face the issue of active companies where we do not know their exit outcome yet. This is because we need to end our monitoring period at some point, giving them a survival time until the end of our monitoring period. For inactive companies without any information about their exit date or last active date, we assume that they were able to operate for an additional year after the last funding round (Quintero, 2017). This is valuable information despite being censored because it provides the minimum holding period. Excluding right-censored companies from our analysis could lead to biased results. This is because it not only limits our understanding of overall survival trends, but also increases the risks of underestimating actual survival times and introduces selection bias (Nunan et al., 2017).

Left censoring is less common and occurs when the event happened before the period started, making it less relevant for our analysis, as it would mean that a company exits before receiving its first initial investment, which is not feasible.

5.3 Non-parametric Analysis

5.3.1 Kaplan-Meier Estimator

Non-parametric analysis is a statistical method that does not rely on assumptions about the distribution of data or the effect of underlying parameters. This approach is flexible and can provide unbiased descriptive statistics of observations in the data. It is particularly useful for univariate analysis and comparisons, as it can provide accurate results without the need for complex models.

The Kaplan-Meier estimator for the survivor function on a given time can be shown as:

$$\hat{S}(t) = \prod_{i|t_i \leq t} \left(1 - \frac{d_i}{n_i}\right) \tag{5.4}$$

Where n_i is the number of observations where the event still has not occurred at time t_i, and d_i is the number of events at time t. $\hat{S}(t)$ is the empirical survival function of the data, in other words the product of all survival functions from $t = 0$ until t. We can derive the empirical cumulative hazard function from the Nelson (1972) and Aalen (1978) estimator, which has been proven equal to Kaplan-Meier at larger samples (Colosimo et al., 2002).

$$\hat{H}(t) = \sum_{i|t_i \leq t} \frac{d_i}{n_i} \tag{5.5}$$

As with the survivor function, n_i is the number of observations still at risk experiencing the event, d_i number of events at time t_i. $\hat{H}(t)$ is the accumulated probability of the event occurring up to time t.

This methodology provides us with a solid foundation to compare and analyse subgroups in our various analyses, such as the likelihood of successful exits across the various industries in *Hypothesis 1*, or between traditional VCs and CVCs in *Hypothesis 2*. While this approach is practical for initial comparisons, there may be more suitable options for analyses that require a deeper understanding of the underlying relationships and mechanisms. In the following parts, we will explore these alternatives in greater detail.

5.4 Semi-parametric Analysis (Multivariate Analysis)

5.4.1 The Cox Proportional Hazards Model

Semi-parametric models consist of two components: parametric and non-parametric. The Cox proportional hazards model is a type of semi-parametric, multivariate regression analysis that was introduced by D. R. Cox (1972). This model can be used to investigate how multiple covariates affect survival time simultaneously. The model examines the hazard rate, which is how the covariates influence the event rate at a specific point in time. For instance, in our analysis, we use the Cox model to understand how various factors, such as total funding amount or level of capital intensity, impact the likelihood of a successful exit. This could be particularly useful when exploring the subgroups of our hypothesis since we can isolate the effect of each covariate while controlling for others, providing us with further nuanced insights on what drives the likelihoods across our subgroups.

The Cox Proportional hazard model could be written as the following:

$$h(t|x) = h_0(t) \times e^{\beta' x} \tag{5.6}$$

Where t is time, x the vector of covariates, β the vector of coefficients and $h_0(t)$ the baseline hazard function, or the hazard function of $x = 0$ (Bender et al., 2005). It does not make any assumptions about the distribution of survival times, which means the baseline hazard is not estimated, resulting in a random shape. In other words, the non-parametric component of the model allows for a flexible and unrestricted estimation of the hazard function, which can be helpful when the underlying distribution of survival times is unknown or complex. By not assuming any specific distribution, the non-parametric component of the model can capture the actual shape of the hazard function, leading to more accurate predictions and a better understanding of the underlying survival process.

The Cox model relies on a crucial assumption called the proportional hazard assumption. This assumption states that the relative risk of an event, as measured by the hazard ratio, should remain constant over time as the different levels of covariates vary. In simpler terms, while the hazard rate for different groups may change over time, the ratio between these groups should remain consistent. This means that the effect of any covariate on the hazard is assumed to be multiplicative and constant over the entire period (Lalanne & Mesbah, 2016).

As mentioned in section 4, we use *Cap Table Size* and *Total Amount Raised* as covariates for the different Cox models in our analysis. However, including these covariates challenges the Cox model's proportional hazards assumption.

We have extended our model to incorporate time-dependent covariates for the *Cap Table Size* and *Total Amount Raised* covariates. This approach recognizes that the influence of these factors can change a company's lifecycle. For example, the effect of an increase in funding or changes in the capitalization table may evolve as a startup matures (Kim & Park, 2021). By allowing these covariates to vary with time, we can more accurately capture their dynamic impact on the hazard rate.

The impact of the variables on the hazard rate may vary across different countries due to varying economic, regulatory, and market conditions. For instance, the influence of funding amount or increasing number of investors can differ significantly between countries, leading to non-proportional hazards (Hodgson, 2022). To address this issue we adapt our model by including and stratifying the variable *Country*. Stratification allows us to account for the baseline hazard variation across different countries while still analysing the effect of other covariates within these stratified groups. Each country has its baseline hazard function, acknowledging each country's unique risk profile and market dynamics.

In addition, given multiple rounds of data for each company in our dataset, we use clustered standard errors to account for inherent correlations within companies over time, ensuring the robustness of our standard error estimates against potential intra-company variability.

By stratifying the model based on the country, extending it with time-dependent covariates and including clustered standard errors, we aim to maintain the suitability and accuracy of our analysis while addressing potential violations of the proportional hazard assumption.[1]

5.4.2 The Fine and Gray Competing Risk Model

The models we have discussed so far assume that the event of interest, such as a successful exit, will occur during or after the period we are examining. Both Kaplan-Meier and Cox models censor these outcomes, meaning they consider the time from the last observed data point until the given event occurs or the monitoring period ends. However, a critical limitation of these models is that they do not consider the possibility of companies dropping out or failing. Suppose a VC exits a company due to an unwanted event, such as liquidation. In that case, the model should account for it since this is crucial as it can hinder a successful exit later for the given company, influencing the accuracy of our success estimates. Therefore, we need to consider the concept of competing risk, which is very much present in our data.

Our data includes different potential outcomes for our monitored companies such as achieving an IPO, being acquired, or failing. Since each of these events are mutually exclusive and preclude the occurrence of the others, we are dealing with competing risk in our analysis. As already stated in section 4, IPOs and M&As will be treated equally due to limited data, but it is, however, still insightful it allows us to analyze not just the success rates, but also the failure rates of specific subgroups[2].

The Fine and Gray Competing Risk Model (Fine & Gray, 1999) considers this issue by saying that observations experiencing a competing event have zero likelihood of experiencing the event of interest (Zhang, 2017). The competing risk model is a type of proportional hazard model, which we discussed earlier. It is also a semiparametric model that assumes the proportional hazard assumption holds. In the context of competing risks, this model provides partial information on different event outcomes, even though only one event is analysed for each company. For instance, if a company goes bankrupt in year X, the model allows us to take into account not only the bankruptcy event but also the period leading up to it.

[1]The assumption of proportional hazards in our Cox regression model is assessed, and the Schoenfeld Residuals are presented in Appendix A.1

[2]See Appendix A.2 for a presentation of cumulative failure rates.

The competing risk model can be expressed as:

$$\hat{h}_i(t|x_j) = h_{0,i}(t)e^{x_j^\top \beta} \tag{5.7}$$

The cause-specific hazard function for cause i, also known as the subhazard function, is defined as:

$$h_i(t) = \lim_{\delta t \to 0} \frac{P(t \leq T < t + \delta t, \epsilon = i | T \geq t \cup (T \neq t \neq \epsilon_i))}{\delta t} \tag{5.8}$$

The function represents the risk of a cause i occurring at a specific time, assuming no event has occurred at that give point in time (Stata, n.d.). The events are observed and expressed through T as the time-to-event, and δ as a cause indicator specifying the event type that occurred.

The cumulative subhazard for an event is represented through i, $\hat{H}_i$ and calculated by integrating the subhazard function from the start of monitoring until the event occurs. The *cumulative incidence function (CIF)* provides the probability of an event occurring before a given time, accounting for competing risks and represented as

$$\mathrm{CIF}_i(t) = 1 - \exp(-\hat{H}_i(t)). \tag{5.9}$$

As mentioned earlier, the competing risk model we use is semi-parametric, which means we must ensure that the proportional hazard assumptions hold. However, ensuring this is quite complex since it increases the potential for misinterpretation and errors. Therefore, we have decided not to use time-varying covariates, such as *Cap Table Size* and *Total Amount Raised*, in our Fine and Gray model application. This decision, supported by Austin et al. (2019), highlights the challenges of accurately estimating the *Cumulative Incidence Function (CIF)* and the impact of covariates on it when including internal time-varying covariates. By excluding time-dependent covariates, we prioritize the clarity and accuracy of our findings with this model, ensuring that our results remain robust and interpretable.

5.5 Ordinary Least Squares Regression (OLS)

This section will discuss an alternative measure of success for our last hypothesis using a regression model. We are examining the probability of a successful exit and whether CVCs are more innovative and successful than traditional VCs. We will measure innovativeness using the number of patents granted at the company level as a proxy.

First, we will present the details of this model. Then, we will discuss the issues and validity of using this model, particularly considering the endogeneity of self-selection biases of CVCs. Finally, we will examine how we tried to account for this bias.

5.5.1 Dependent and Independent Variables

The ordinary least squares linear regression model is a statistical method that uses a straight line to model the relationship between the outcome and the explanatory variables. The model finds the line that best fits the data and minimizes the sum of square errors (Zdaniuk, 2014). We use this model to investigate how innovation, a variable often measured using the number of patents granted (Burhan et al., 2017), depends on the type of VC backing the company. To do this, we use a dummy variable equal to 1 if the company is backed by a CVC and 0 otherwise. To simplify the modeling, we assume that a company backed by both a VC and a CVC is a CVC-backed company..

5.5.2 Control Variables and Interaction Terms

Our control variables focus on two variables that help us understand successful companies and test our hypothesis around CVC investments. The first set includes the *Total Amount Raised*, *Cap Table Size*, and *Funding Rounds* - as success metrics. The second set contains the holding period and capital intensity level, designed to help us understand the nuances of our hypothesis. We also include interaction terms between CVC involvement and these latter variables to explore how previous traits CVC-specific investment approaches impact innovation

5.5.3 Endogeneity and IV Regression

Understanding why CVCs invest in innovative companies is complex, mainly due to the potential self-selection bias among CVC investments. This bias arises because more innovative companies are more likely to attract CVC funding (Guo et al., 2015). Alternatively, CVCs may preferably invest in companies already exhibiting high innovation potential. As a result, a critical question arises: Is the innovation we observe in these firms a result of CVC involvement, or is it simply a continuation of their inherent innovation trajectory? This question creates difficulties in isolating the actual effect of CVC backing on a company's innovation, as the pre-existing innovative nature of the companies may influence the reasoning of the investment in the first place.

We have used a two-stage least squares regression approach using an instrumental variable to tackle the issue. The chosen instrument is a dummy variable that indicates strategic CVC investments. This dummy variable takes the value of '1' when the parent company of the CVC and the invested company belong to the same industry. Our methodology for categorization is based on the data-gathering approach outlined in Section 4.5.3. We have used NACE codes to determine the technological proximity and industry overlap between the corporate parent of the CVC and the target company. This methodology assumes that companies with similar NACE codes have similar production and technology functions, as Markides and Williamson (1996) suggested.

The main objective is to develop a more precise model for the decision-making process of CVC investment, considering other variables. The instrumental variable is crucial in the first stage, where the probability of CVC-backing is regressed on the dummy variable and other control variables. This stage aims to isolate the component of CVC-backing that can be attributed to strategic alignment, as indicated by industry overlap, from other factors. This isolation helps obtain an adjusted CVC-backing predictor less affected by the self-selection bias inherent in the original CVC dummy variable. In the second stage, we use the predicted values of CVC-backing obtained in the first stage. The two-stage procedure is crucial because it ensures the second-stage analysis is based on a more refined variable. This approach should provide, in theory, a more accurate assessment of the actual impact of CVC backing.

Although our chosen instrumental, *Strategic Investment*, variable has met the statistical threshold with an F-statistic value of 16.351[3], which indicates that it is not weak, there are still some concerns that need to be addressed regarding its robustness and validity, where the instruments' relevance and exogeneity are the key determinants of its validity.

Firstly, the relevancy of our instrument is hinged on the strategic alignment between the parent company and the invested company. This stems from the understanding that CVCs tend to invest in sectors similar to their parent companies. They often seek synergistic benefits, such as staying up-to-date on emerging technologies and scouting for long-term acquisition opportunities

Secondly, to be considered exogenous, our instrument must solely influence the endogenous explanatory variable (CVC-backing) and not the outcome variable (company's innovation capacity). Establishing exogeneity can be challenging as we need to differentiate the influence of inherent industry characteristics from that of CVC backing on innovation.

If the industry itself naturally leads to higher levels of innovation, attributing any observed innovative activity solely to CVC involvement could be misleading. For example, certain industries may encourage more R&D activities or have a higher rate of technological change, which could affect the innovative output of the company. Ideally, the industry alignment should influence the likelihood of CVC investment but should not have a direct causal relationship with the innovative output of the company, except through the CVC investment.

It is important to acknowledge that our instrument may not fully meet the ideal standards of exogeneity. This is due to the limitations of our dataset which makes it difficult to differentiate between industry-specific innovation drivers and the direct impact of CVC investment.

[3]The details of the regression and F-statistic calculation are provided in Table 7.4

6 Descriptive Statistics

In this section, we will discuss the descriptive statistics of our analysis. We will discuss them one by one, as they are linked to each hypothesis in our analysis.

6.1 Industry Groups

Table 6.1 displays the dataset used to analyse the first hypothesis. Upon an initial evaluation, climate tech's success rate (5.6%) is lower than that of e-commerce (14.5%), fintech (10.8%), and healthtech (7.0%). This provides preliminary support for the first hypothesis.

It is worth noting that climate tech has a higher percentage of active companies (73.4%) compared to e-commerce (49.5%), fintech (46.1%), and healthtech (48.1%). This difference suggests that many climate tech companies are still operating and have not yet reached their final exit, and might indicate a premature industry compared to the peers.

Climate tech has had 40 successful exits, a small sample size that could skew the success rate. When compared to other industries such as e-commerce (238 successful exits), fintech (176 successful exits), and healthtech (165 successful exits), the limitations of the climate tech data set become apparent.

Moreover, the average number of funding rounds in climate tech is 2.744, which is lower than that of e-commerce (3.198) and fintech (2.858) but higher than healthtech (2.575). The indication is that climate tech companies may not advance through successive rounds of funding at the same rate as those in some other industries, which could, again, reflect the sector's immaturity.

The holding period is a metric that sheds light on how long a VC is invested in a company. In the case of climate Tech, this period lasts an average of 2.201 years, which is similar to healthtech (2.037 years) but shorter than e-commerce (2.577 years) and fintech (2.730 years).

Lastly, the *Cap Table Size* metric for climate tech has a mean of 4.098, roughly the same size as both e-commerce and healthtech.

In our analysis, we acknowledge that the sample size of climate tech (N=711) is smaller than that of e-commerce (N=1,202), fintech (N=1,634), and healthtech (N=2,343). However, we have used the entire dataset to maintain the integrity of our survival analysis. This approach is crucial as omitting any data may result in incomplete insights, which is particularly important in an analysis where the timing of each company's outcome is as critical as the outcome itself.

Table 6.1: Descriptive Statistics: Industry Groups

The table displays the distribution of successes and failures among companies within industry sub-samples. In the sample, climate tech has 40 successes, 180 failures and 491 active companies. e-Commerce has 166 successes, 539 failures and 497 active companies. fintech have 176 successes, 520 failures and 938 active companies. healthtech have 185 successes, 853 failures and 1,305 active companies. It includes data on funding rounds from January 1, 2011, to October 15, 2023.

Variable	**N**	**Mean**	**Median**	**St. Dev.**	**Min**	**Max**
Industry: ***Climate tech***						
Successful Exits	711	0.056	0	0.231	0	1
Failures	711	0.267	0	0.443	0	1
Active Companies	711	0.672	0.470	0	1	
Total Amount Raised *(MUSD)*	711	23.498	3.581	153.495	0.008	3,363.718
Funding Rounds	711	1.474	1	0.886	1	7
Cap Table Size	711	4.098	3	3.572	1	28
Holding Period *(Years)*	711	2.216	1.544	1.944	0.057	12.430
Industry: ***E-commerce***						
Successful Exits	1,202	0.138	0	0.345	0	1
Failures	1,202	0.452	0	0.498	0	1
Active Companies	1,202	0.391	0.488	0	1	
Total Amount Raised *(MUSD)*	1,202	26.898	2.400	131.956	0.0003	1,830.000
Funding Rounds	1,202	1.618	1	1.143	1	11
Cap Table Size	1,202	3.993	3	3.774	1	38
Holding Period *(Years)*	1,202	2.579	1.711	2.243	0.082	11.844
Industry: ***Fintech***						
Successful Exits	1,634	0.108	0	0.310	0	1
Failures	1,634	0.320	0	0.467	0	1
Active Companies	1,634	0.571	1	0.495	0	1
Total Amount Raised *(MUSD)*	1,634	32.488	5.008	121.196	0.028	1,830.000
Funding Rounds	1,634	1.739	1	1.194	1	10
Cap Table Size	1,634	5.799	4	5.976	1	83
Holding Period *(Years)*	1,634	2.729	2.037	2.192	0.066	12.884
Industry: ***Healthtech***						
Successful Exits	2,343	0.079	0	0.270	0	1
Failures	2,343	0.368	0	0.482	0	1
Active Companies	2,343	0.552	1	0.497	0	1
Total Amount Raised *(MUSD)*	2,343	20.098	3.951	101.001	0.0005	4,241.124
Funding Rounds	2,343	1.508	1	0.841	1	6
Cap Table Size	2,343	4.098	3	3.581	1	41
Holding Period *(Years)*	2,343	2.435	1.708	2.038	0.047	12.753

6.2 Capital Intensity Level

The following table presents an analysis of three different levels of capital intensity and the distribution of company successes and failures across these segments. The success rate for all levels is around 5.6% to 5.7%. In terms of failure rates, there is a close range, with the medium segment showing a rate of 20.7% and the high capital intensity segment showing a rate of 28.9%. Across all three segments, the percentage of active companies is fairly high. In the high segment, it is 65.9%, in the medium segment, it is 72.3%, and in the low segment, it is 57.4%. This illustrates that a significant portion of companies are still in the process of navigating their paths toward success or closure.

When looking at the *Total Amount Raised*, high capital intensity firms display a broad range of funding amounts, with the largest variance at 191 MUSD compared to medium (32) and low (85), suggesting a sector with a diverse array of companies with some attracting substantial investment, while others manage with far less. The high segment also has the highest median funding at 4.2 MUSD, compared to medium (3.0) and low (3.1).

Interestingly, the low segment reports an average funding of 22 MUSD, which is higher than the medium segment's 11 MUSD. However, the two segments share a similar median funding of around 3.0 MUSD, implying a greater variance in the funding amount in the low segment. The medium segment, in contrast, might exhibit less variability in capital needs or represent a more homogeneous group of businesses.

Comparing the *Cap Table Size*, we see that the medium segment have a higher median value of unique investors at 4 compared to high and low at 3, suggesting that the they might attract a higher number of investors. The holding period is also an interesting observation. For the average it is longest for the low segment at 2.5 years compared to medium (1.9) and high (2,3). However, the median values suggest that the low segment has the shortest. The reason might be due to the low number of observations in this segment. For example, one company with a long holding period of over 12 years could skew the data.

While our survival analysis benefits from including all observations, ranging from high capital intensity (N=440) to low capital intensity (N=54), it's important to acknowledge the potential for skewing the results. The varying number of observations across segments, with high capital intensity having the most and low capital intensity the least, might influence the overall analysis.

Table 6.2: Descriptive Statistics: Capital Intensity Level

The table displays the distribution of successes and failures among the different level of capital intensity within climate tech. In the sample, the high level has 25 successes, 123 failures and 292 active companies. The medium level has 12 successes, 44 failures and 157 active companies. The low level has 3 successes, 19 failures and 32 active companies. It includes data on funding rounds from January 1, 2011, to October 15, 2023.

Variable	**N**	**Mean**	**Median**	**St. Dev.**	**Min**	**Max**
Capital Intensity Level: ***High***						
Successful Exits	440	0.057	0	0.232	0	1
Failures	440	0.280	0	0.449	0	1
Active Companies	440	0.664	1	0.473	0	1
Total Amount Raised *(MUSD)*	440	29.896	4.222	191.328	0.008	3,363.718
Funding Rounds	440	1.509	1	0.920	1	7
Cap Table Size	440	4.023	3	3.627	1	28
Holding Period *(Years)*	440	2.335	1.702	1.954	0.107	11.830
Capital Intensity Level: ***Medium***						
Successful Exits	213	0.056	0	0.231	0	1
Failures	213	0.211	0	0.409	0	1
Active Companies	213	0.732	1	0.444	0	1
Total Amount Raised *(MUSD)*	213	11.045	3.000	32.217	0.111	313.377
Funding Rounds	213	1.394	1	0.792	1	5
Cap Table Size	213	4.329	4	3.443	1	21
Holding Period *(Years)*	213	1.901	1.391	1.704	0.057	11.789
Capital Intensity Level: ***Low***						
Successful Exits	54	0.056	0	0.231	0	1
Failures	54	0.352	0	0.482	0	1
Active Companies	54	0.593	1	0.496	0	1
Total Amount Raised *(MUSD)*	54	22.014	3.082	85.229	0.150	586.987
Funding Rounds	54	1.519	1	0.966	1	6
Cap Table Size	54	3.852	3	3.718	1	18
Holding Period *(Years)*	54	2.511	1.136	2.529	0.082	12.430

6.3 CVC vs. VC

The table presents an analysis of the companies in climate tech, categorizing them based on their funding source, whether it be VC or CVC. The table shows that the CVC-backed companies have a higher success rate of 6.2%, as opposed to VC-backed companies at 5.4%. Furthermore, it is notable that the CVC-backed group constitutes a slightly larger fraction of active companies. This observation indicates that the difference in success rates could potentially be bigger in the future as these companies continue to develop and mature.

The *Total Amount Raised*, indicates a higher mean for CVC-backed companies at 45.6 MUSD, in contrast to VC-backed companies at 13.2 MUSD. The higher deviation and maximum value in the CVC-backed group suggest potential skewing by an outlier. However, the median values, standing at 7.8 MUSD for CVC-backed and 3.0 MUSD for VC-backed companies, indicate that they typically secure more funding.

The *Cap Table Size* indicate that the CVC-backed also draw a greater number of investors with a mean and median at 5 and 4, compared to the VC-backed with 3.5 and 3, respectively. As the two groups almost have the identical number of funding rounds, it shows that the CVC-backed group also attract more investors per round.

An interesting observation is the shorter average for *Holding Period* for CVC-backed companies, at 1.7 years, compared to 2.1 years for VC-backed companies. The median holding periods are closer, at 1.2 years for CVC-backed and 1.4 years for VC-backed. This finding is contrary to our initial expectations, as CVCs are typically known for their flexible investment horizons and strategic focus, which would suggest longer holding periods.

In terms of innovation, measured by the number of patents granted, there is a noticeable difference between the groups. CVC-backed companies have on average almost 0.9 more patents than VC-backed companies. The median value of 0 for both groups indicates that less than half of the companies possess granted patents. However, the deviation looks to be higher for the CVC-backed of 7.1 compared to the VC-backed at 3.8, indicating a greater heterogeneity of innovation within this group.

Table 6.3: Descriptive Statistics: CVC vs. VC

The table displays sub-samples of the climate tech industry, divided into levels of capital intensity. The table shows the number of observations and statistics of the variables used in our analysis. The number of succeses are 25 in high, 12 in medium and 3 in the low group. Number of failures are 123 in high, 44 in medium and 19 in low group. The total amount raised is shown in millions. The holding period is the number of years between the first funding round and the exit date. Our analysis is done in the period between January 1. 2011, and October 15. 2023.

Variable	**N**	**Mean**	**Median**	**St. Dev.**	**Min**	**Max**
Type: ***VC***						
Successful Exits	593	0.054	0	0.226	0	1
Failures	593	0.285	0	0.452	0	1
Active Companies	593	0.661	1	0.474	0	1
Total Amount Raised (*MUSD*)	593	13.206	2.978	45.177	0.008	586.987
Funding Rounds	593	1.373	1	0.759	1	6
Cap Table Size	593	3.518	3	2.880	1	19
Holding Period *(Years)*	593	2.053	1.440	1.821	0.057	12.430
Patents Granted	593	1.147	0	3.837	0	57
Type: ***CVC***						
Successful Exits	135	0.067	0	0.250	0	1
Failures	135	0.237	0	0.427	0	1
Active Companies	135	0.696	1	0.462	0	1
Total Amount Raised (*MUSD*)	135	45.611	7.809	290.790	0.229	3,350.000
Funding Rounds	135	1.244	1	0.539	1	3
Cap Table Size	135	5.000	4	3.421	1	20
Holding Period *(Years)*	135	1.653	1.158	1.260	0.068	6.374
Patents Granted	135	2.883	0	7.123	0	51
Strategic Investment	135	0.083	0	0.276	0	1

7 Main Results

We will now move on to the main results of our study regarding our three hypotheses. This section will present a general discussion of the similar results across our models, before exploring the findings related to each hypothesis separately.

7.1 General Findings

As outlined in Section 5, our analytical approach used several different models, including one Kaplan-Meier model, one Cox-regression model, and one Fine-Gray model for each of our proposed hypotheses, resulting in six survival models. Additionally, we developed an OLS regression to explore an alternative measurement of success in patents further for our last hypothesis. We used *Cap Table Size* and *Total Amount Raised* raised as covariates across all three Cox models and included them as control variables in the OLS regression.

Starting with the *Cap Table Size* it was observed that the control variables had a high significance level in all the Cox models. The hazard ratio ranged between 0.70 and 0.85, with the significance level being consistent at either 5% or 1% level. These findings indicate that as the capitalization table expands, the likelihood of a successful exit decreases by 15-30%, depending on the given baseline, negatively impacting the successful exit likelihood. This finding is consistent with existing literature, which argues that this may be due to inferior corporate governance with a small investor group (Dimov & De Clerq, 2006). However, it is important to interpret these results cautiously, as the variable does not consider the investors' ownership stakes, which may have been a more ideal control variable.

The *Total Amount Raised* control variable had a high level of significance across all the Cox Models. The corresponding hazard ratios were consistently above 1, ranging from 1.10 to 1.83. However, interpreting log-transformed variables is not straightforward. The hazard ratios are calculated as $HR = e^{ln(x) \times \beta}$, where β represents the coefficient and x the total money raised. For example, using the hazard ratio of 1.109 presented in Table 7.1, if a climate tech company triples its fundraising (effectively doubling the total amount raised to that point), the hazard ratio would be 1.12. This translates to a 12% increase in the likelihood of a successful exit. These observations are consistent with the literature, which suggests that more successful companies are more adept at securing additional funding (Zider, 1998).

7.2 Industry Groups

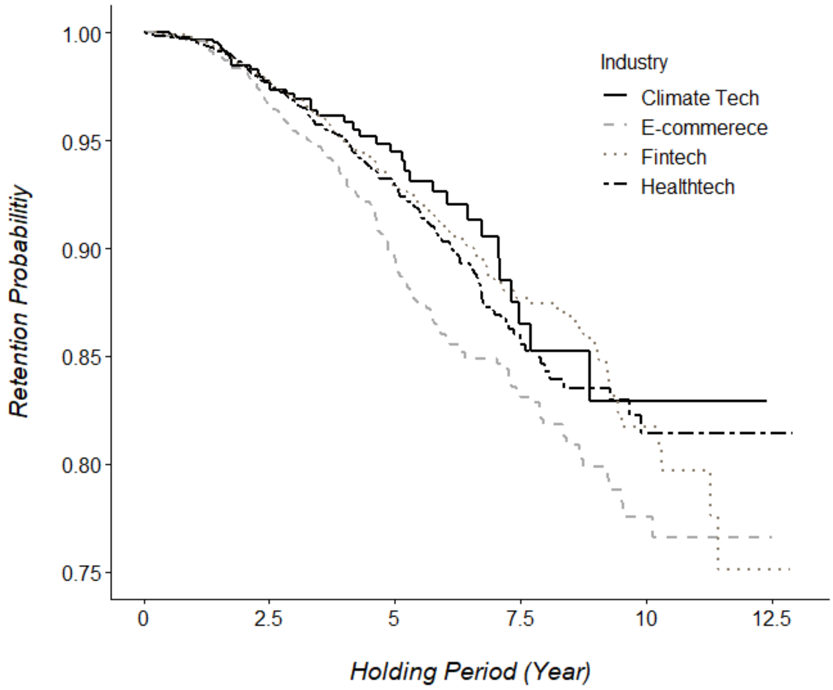

Figure 7.1: Kaplan-Meier Survival Estimate, by Industry Groups

In Hypothesis 1, we aimed to examine whether the climate tech sector experiences fewer successful exits than other sectors traditionally favoured by VCs. We began by examining the Kaplan-Meier model, presented in Figure 7.1. This model displays the retention probability[4] on the Y-axis and the holding period on the X-axis. It illustrates how climate tech companies can achieve successful exits compared to companies in peer sectors.

Based on the curves, it seems that the industries initially followed a similar pattern for the first two years. However, after this point, the e-commerce sector began to experience more exits compared to the others. Typically, we anticipate an increase in exits from year three onwards, which aligns with the usual holding period for VCs, where this expectation is confirmed as the curves become steeper. Interestingly, the curves of the peer industries steepen more than climate tech, indicating more exits.

[4]Retention probability in this context refers to the likelihood of a climate tech company remaining without a successful exit over a given time period. The Kaplan-Meier model uses this metric to illustrate the duration companies typically stay active before achieving a successful exit.

Around the 7.5-year mark, the climate tech industry intersects with the fintech sector, which might suggest that our hypothesis about climate tech requiring longer duration to success holds. However, by the 10-year mark, climate tech is overtaken again and ultimately ends up with the highest retention rate by the end of the period.

It is important to note that as holding periods lengthen, the frequency of exits decreases across all sectors. This trend is particularly pronounced in the climate tech sector, as highlighted in Section 6.1, where exits are notably lower compared to peer industries.

Table 7.1: Hazard Rates for Industry Groups

	Cox *HR*	**Fine and Gray** *HR*
E-commerce	1.428	1.248***
	(0.840,2.016)	(1.065,1.462)
Fintech	0.904	0.873*
	(0.319,1.488)	(0.744,1.024)
Healthtech	0.583*	0.1.209**
	(-0.004,1.170)	(1.039,1.406)
Cap Table Size	0.857**	
	(0.735,0.978)	
Total Amount Raised	1.109***	
	(1.049,1.169)	
E-commerce × Cap Table Size	1.058	
	(0.930,1.187)	
Fintech × Cap Table Size	1.095	
	(0.970,1.219)	
Healthtech × Cap Table Size	1.178**	
	(1.052,1.304)	
Likelihood Ratio Test[1]	57.98***	
Wald Test[2]	49.71***	
Log-Rank Test[3]	57.64***	
Concordance[4]	0.597	

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

[1] A statistical test to compare the fit of two models, assessing the improvement in fit when adding additional variables.
[2] A test to assess the significance of individual predictors in a model.
[3] A non-parametric test comparing the survival distributions of different groups.
[4] A measure of the predictive accuracy of a survival model, with 1.0 indicating perfect prediction.

When we examine the hazard ratios in Table 7.1, we observe that the Cox and Fine-Gray models provide different insights. The Cox model assesses the impact of covariates without considering competing exit possibilities, while the Fine-Gray model considers these possibilities. In both models, the hazard ratios for e-commerce are greater than 1.2, indicating that an e-commerce company is more likely to successfully exit at any given time compared to climate tech. This conclusion is strengthened by the statistically significant results of the Fine-Gray model, which are significant at the 1% level.

Looking at the fintech industry we noticed hazard ratios below 1 in both models, which suggests a lower likelihood of success than in climate tech. However, these findings do not hold statistical significance in the Cox model and are only significant at a 10% level in the Fine-Gray model.

When assessing the healthtech industry it gets more complex. According to the Cox model, the likelihood of a successful exit is lower compared to climate tech. In constrast, the Fine-Gray model suggests a higher likelihood of successful exit, with 10% and 5% significance levels, respectively. This disparity in findings might be because the models handle the underlying exit outcomes differently.

Companies in the peer industries may be more effective in managing larger capitalization tables than climate tech companies. The interaction term for these industries suggests that as the capitalization table size increases, the peer industry companies tend to have a greater likelihood of success. That said, only the healthtech interaction is statistically significant at a 5% level.

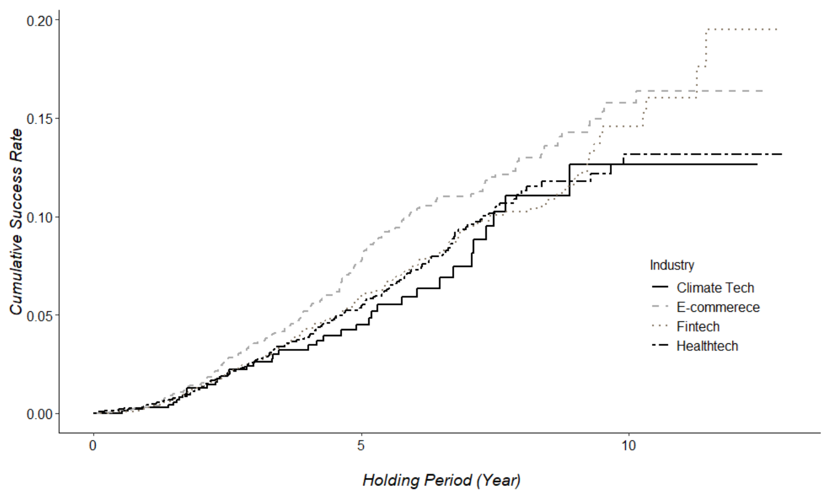

Figure 7.2: Cumulative Incidence Curve, by Industry Groups

Upon analysing the cumulative incidence curve shown in Figure 7.2, accounting for competing risks, we observe that the performance trajectory of climate tech mirrors the patterns identified by the Kaplan-Meier analysis. Initially, climate tech's exit rate is comparable to other sectors, suggesting similar success rates in the early years. This trend persists until around the third year, when a shift occurs, and the trajectories begin to diverge. At the 7.5-year mark, the path of climate tech intersects with that of fintech. However, as we approach the 10-year mark, climate tech's curve remains stagnant, indicating that it may require a longer developmental period before exit, supporting the hypothesis that climate tech companies need extended maturity periods. This culminates in the sector having the lowest cumulative success rate.

7.3 Capital Intensity Level

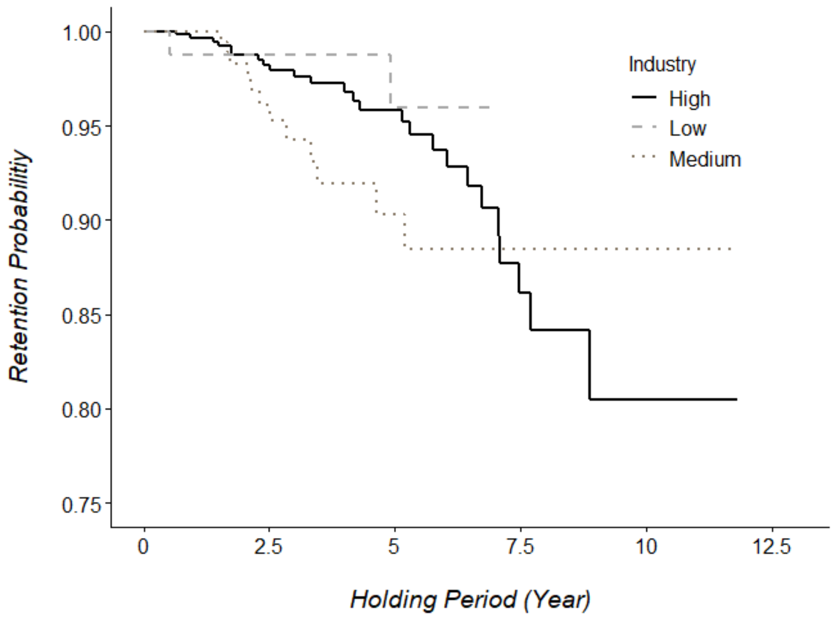

Figure 7.3: Kaplan-Meier Survival Estimate, by Capital Intensity

Hypothesis 2 investigates how capital intensity affects the likelihood of successful exits in the climate tech industry. We start off by analysing the Kaplan-Meier curves in Figure 7.3. The initial two years show little difference in retention probability between the different levels of capital intensity. However, as time progresses, the difference becomes more apparent. Companies with medium capital intensity have a steeper decline in retention probability, indicating a higher frequency of exits compared to their high capital intensity level.

On the other hand, companies with high capital intensity have a flatter curve for a longer period, possibly due to the more extensive investments and longer development cycles typically required, which may delay their exit opportunities. Companies with medium capital intensity show a moderate and steady decline in retention probability.

When analysing the impact of capital intensity on successful exits in the climate tech industry using Kaplan-Meier curves, it is crucial to consider the limited data available, as highlighted in section 6.2. In contrast to the previous section's Kaplan Meier analysis, the curves in this section are stepwise, indicating that the data points are inconsistent due to the relatively small number of exits in the climate tech industry. Due to the scarcity of data points, it is necessary to analyse the data cautiously, as each exit can significantly impact the overall trend, which may skew the results.

This limitation is relevant to the current model's analysis, as it also implicates the subsequent model evaluations within this section and our last hypothesis regarding CVC and VC investments in climate tech.

Table 7.2: Hazard Rates for Capital Intensity Level

	Cox *HR*	**Fine and Gray** *HR*
CAPEX Level: **Medium**	2.293^{**}	0.766
	(1.484,3.102)	(0.542,1.081)
CAPEX Level: **Low**	1.244	1.326
	(-0.047,3.102)	(0.816,2.155)
Cap Table Size	0.748^{***}	
	(0.599,0.898)	
Total Amount Raised	1.738^{***}	
	(1.475,2.000)	
Likelihood Ratio Test	21.42^{***}	
Wald Test	$21.72.14^{***}$	
Log-Rank Test	21.87^{***}	
Concordance	0.745	
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

When we analyse the hazard ratios for various capital intensity levels, as presented in

Table 7.2, we notice that the Cox and Fine-Gray models provide different results. The Cox model shows a hazard ratio of 2.293 for the medium capital intensity level, which means there is more than two times the probability of a successful exit compared to the high-level baseline. This result is statistically significant at the 5% level, and the 95% confidence interval lies between 1.657 and 2.438, indicating that companies with a medium level of capital intensity have a significantly higher chance of succeeding compared to the higher intensity levels. In contrast, the Fine-Gray model shows a hazard ratio below one for the medium level, which contradicts the Cox model's findings of an increased likelihood. This result is, however, not statistically significant and has ambiguous confidence intervals both above and below one.

For companies with low levels of capital intensity, the hazard ratios shown in Table 7.2 do not reach statistical significance in either the Cox or Fine-Gray models. Both models display a hazard ratio greater than one, indicating a possible association between a low level of capital intensity and the probability of successful exits. The insignificant results are likely because of the limited number of exits in the capital intensity category, as evidenced by the negative lower 95% confidence interval in the Cox model. Therefore, drawing any clear conclusions about trends or impacts is difficult.

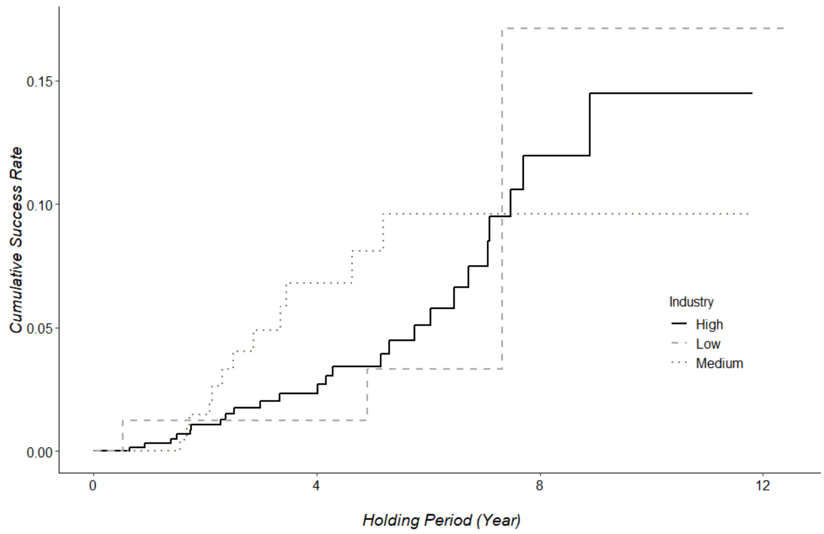

Figure 7.4: Cumulative Incidence Curve, by Industry Groups

Analyzing the cumulative incidence curve in Figure 7.4, we can observe patterns among the different capital intensity levels within the industry. Initially, all three categories - high, medium, and low - exhibit a similar likelihood of successful exits. However, the high capital intensity companies show a later but sudden increase in exit rate, which could indicate longer maturation times before becoming exit viable. In contrast, those with medium capital intensity experience more frequent exits earlier, suggesting faster routes to exit, as seen in the Kaplan-Meier curve. The curve for low capital-intensity companies is, again, affected by the few exits, but by the observed period's end, it has the highest cumulative success rate.

7.4 CVC vs. VC

We will now examine whether CVC-backed companies in the climate tech industry are more likely to succeed than those supported by traditional VC. Firstly, we will analyse exit possibilities, followed by the alternative success measure in patents granted to measure innovation success.

7.4.1 Survival Analysis

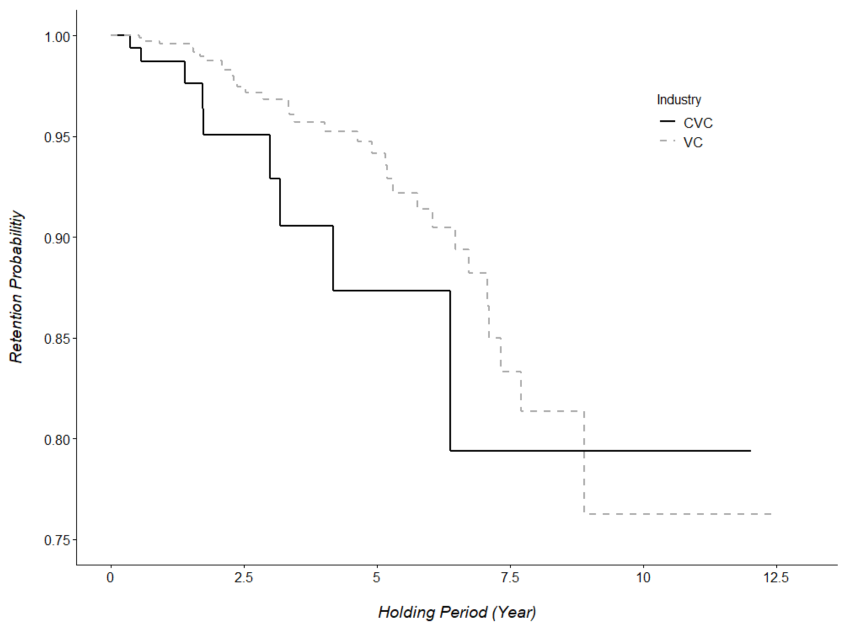

Figure 7.5: Kaplan-Meier Survival Estimate, by VC-type

When looking at the Kaplan-Meier curves within the climate tech sector for CVC and VC, in Figure 7.5, we observed that CVCs tend to initiate exits quicker in the early years. However, the trend changes as we move past the initial stage, and the VCs have a sharper retention decline. This decline is particularly noticeable after the third year and continues to around the seventh year. This suggests that VC investments may start more conservatively, but as they mature, they tend to move towards exits more aggressively than CVCs.

In the later stages, the VC curve appears to flatten out, suggesting a decrease in exit activity, possibly due to the lack of more immediate exit opportunities. On the other hand, following its initial sharp decline, the CVC curve shows a more gradual decrease, which could indicate a more measured approach to exits over an extended period.

By the end of the observed period, the CVC and VC curves intersects, with VCs showing the lowest retention probability. The pattern for CVCs indicates a preference for quicker initial exits and then a longer-term hold. Conversely, after a slower start, VCs seem to aim for a concentrated period of exit activity, reflecting the characteristic cycles of VC funds. However, it is important to note that there are limited exits from CVCs, which means that individual exits have a more significant impact on the curve than the VC curve. A larger pool of exits shapes the VC curve, and therefore may present a more consistent trend.

Table 7.3: Hazard Rates for CVC vs VC

	Cox *HR*	**Fine and Gray** *HR*
CVC	1.589	0.865
	(0.124,3.055)	(0.595,1.256)
CAPEX Level: Medium	2.468**	0.804
	(1.657,3.279)	(0.586,1.102)
CAPEX Level: Low	1.140	1.186
	(-0.158,2.438)	(0.737,1.911)
Cap Table Size	0.704***	
	(0.516,0.892)	
Total Amount Raised	1.820***	
	(1.555,2.084)	
CVC × Cap Table Size	1.064***	
	(0.771,1.357)	
Likelihood Ratio Test	25.48***	
Wald Test	25.14***	
Log-Rank Test	25.03***	
Concordance	0.718	
Note:	*p<0.1; **p<0.05; ***p<0.01	

When we analyse the hazard ratios for CVC investments according to Table 7.3, we can see that the Cox model shows a hazard ratio of 1.589 for CVC, indicating a higher possibility of successful exits than non-CVC investments. However, this result is not statistically significant due to the wide confidence interval (0.124, 3.055), which spans below and above 1. This suggests that CVC-backed ventures might experience successful exits more frequently than VC-backed ones, but since the data is not strong enough, we cannot assert this conclusively. Additionally, in the Fine and Gray model, the hazard ratio for CVC is below 1, at 0.865, which contradicts the Cox model's result. Nevertheless, like the Cox model, this outcome is not statistically significant, with a confidence interval (0.595, 1.256) that is ambiguously above and below 1, indicating uncertainty about the comparative exit likelihood for CVC investments.

For companies with a medium level of capital intensity, the Cox model reveals a statistically significant hazard ratio of 2.468. The Fine and Gray model does not support this finding, showing a non-significant hazard ratio of 0.804. The interaction term *CVC* × *Cap Table Size* in the Cox model is significant at the 1% level, with a hazard ratio of 1.064, indicating that the effect of capitalization table size on exit likelihood is slightly more noticeable in CVC-backed companies.

Our analysis excluded an interaction term between CVC and Capital Intensity. This decision is based on the skewed distribution across the three levels of capital intensity, which is particularly evident given that only three companies that exited were both CVC-backed and categorized as low-capital intensity. This limited representation could distort any interpretive analysis of the interaction effect.

Given the mixed results obtained from the Cox and Fine-Gray models, it is difficult to make definitive statements about the effect of CVC on the probability of a successful exit. Although the Cox model revealed some statistically significant findings, this was not true for the Fine and Gray model. Moreover, the confidence intervals in both models were wide and overlapped. While the data indicates a tendency, more robust evidence is necessary to validate the trends.

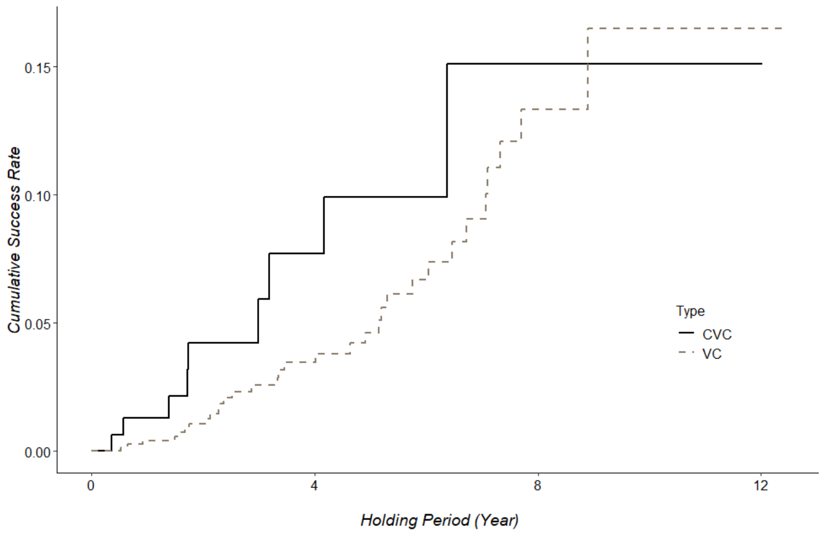

Figure 7.6: Cumulative Incidence Curve, by VC type

We will now examine the cumulative incidence curve between CVCs and VCs, presented in Figure 7.6. The VC curve shows a slower start with fewer exits in the early years of the holding period. This suggests that VC climate tech investments may take longer to mature before successful exits materialize. However, as the holding period extends, the

VC curve gradually increases the cumulative success rate, surpassing the CVC curve. On the other hand, CVC-backed companies show an immediate rise in the exit rate, which may indicate a different investment strategy, contradicting our hypothesis about longer holding periods. As holding periods prolong, the VC-backed curve continues to rise. Then, it plateaus around years 7-8, indicating a steady realization of exit opportunities over time, which aligns with the venture capital exit strategy. By the end of the observed period, VC-backed companies exhibit a higher cumulative incidence of exits despite their slower initial exit rate.

7.4.2 Patents

In the final section of our analysis, we explore the innovation level in climate tech companies backed by CVCs as opposed to those backed by VCs. We are using number of patents granted as a way to measure innovation. Given the endogeneity issues inherent in our model, as discussed in section 5.5.3, the IV regression provides a more reliable analysis than the naive OLS. Hence, we will focus our discussion on the findings obtained from the IV regression analysis.

Table 7.4: Patents Granted for Climate Tech Companies[1]

	Dependent variable:	
	Patents Granted	
	(Naive OLS)	(IV)
CVC	−0.524	−0.021
	(0.860)	(1.355)
log(Total Amount Raised)	0.480***	0.522***
	(0.140)	(0.140)
Funding Rounds	0.141	0.042
	(0.560)	(0.568)
Cap Table Size	0.082	0.137
	(0.147)	(0.164)
Holding Period	0.012	0.109
	(0.115)	(0.140)
CAPEX Level: Medium	−0.799***	−0.803*
	(0.301)	(0.424)
CAPEX Level: Low	−0.403	−1.704***
	(0.427)	(0.630)
CVC × Holding Perioid	1.007*	−0.057
	(0.513)	(0.680)
CVC × CAPEX Level: Medium	−0.077	−0.764
	(0.963)	(1.172)
CVC × CAPEX Level: Low	−0.198	5.135***
	(1.128)	(1.168)
Constant	−6.273***	−6.889***
	(1.976)	(2.033)
F-Statistics (CVC)[2]		16.351***
Wu-Hausman (CVC)[3]		1.208

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

[1] Standard errors are clustered by type of VC to account for within-group correlation and potential heteroskedasticity

[2] The reported F-statistic pertains to the strength of the instrument used in the IV model. A higher value indicates that the instrumental variable, 'Strategic Investment', is strongly correlated with the endogenous variable, providing confidence in the IV approach.

[3] The W-Hausman statistic refers to the result of the Hausman test, which compares the coefficients of the Instrumental Variable (IV) model with those of the Naive OLS to check for consistency.

The IV regression, presented in 7.4, shows a positive correlation between the Total Amount Raised and the number of patents granted, significant at a coefficient of 0.522. This implies that a 1% increase in funding is associated with a corresponding 0.522% increase in patent counts. This confirms that increased funding is a substantial driver of innovation, likely due to the money raised used in R&D, which is vital for patent development in early-stage companies (Bolívar-Ramos, 2017; Yun et al., 2021). However, this observation brings us back to the initial endogenity problem where highly innovative companies might inherently attract more funding. This interdependence makes it challenging to determine whether increased funding leads to innovation or if the inherent innovative potential of these companies drives their ability to secure more funding.

The results of the IV regression analysis show a noteworthy trend among low capital-intensity companies within the climate tech industry, revealing a significant negative coefficient of -1.704 at the 1% significance level for patent counts. This suggests that climate tech companies in less capital-intensive activities, such as climate reporting, may not emphasize patenting as a measure of innovation as much as their counterparts in more capital-intensive segments, such as biogas extraction, where patenting could be a critical component of competitive advantage.

In the IV regression analysis, the standalone CVC term displays a coefficient of -0.021, which is not statistically significant, suggesting that CVC backing alone does not show a clear effect on patents granted. This highlights that CVC-backed company, in isolation, may not be a determinant factor in driving innovation as measured by patent counts within the climate tech industry.

However, the analysis reveals some interesting insights when considering interaction terms. The interaction term for CVC with low capital intensity level is particularly significant, with a coefficient of 5.133 at the 1% significance level. This significant interaction suggests that CVC-backed companies in the low capital intensity areas of the climate tech industry tend to have a higher number of patents. This may indicate that companies backed by CVCs might have a more deliberate focus on patentable innovations within the less capital-intensive part of climate tech.

After conducting an IV regression analysis, we have concluded that there is insufficient evidence to support the claim that companies backed by CVC are more innovative than those backed by traditional VC in the climate tech industry. Although it may appear that CVC-backed companies in the low capital intensity sector are more innovative, we must be cautious in drawing this conclusion due to the small sample size of just 13 companies that are both CVC-backed and categorized as low capital intensive.

8 Conclusion and Limitations

8.1 Conclusion

Our research aims to investigate the successfulness of venture capitalists' investments in the European climate tech sector over the last decade. The investigation consisted of analysing three different hypotheses. To see if our findings are in line with what we hypothezised, this section will link the main findings from the results with each hypothesis.

The first objective of this thesis was to assess whether the recent European Union regulations and a heightened focus on impact and sustainable investments have made the European climate tech sector more attractive to venture capital firms. To address this, we proposed our initial hypothesis: The climate tech sector experiences fewer successful exits than other sectors traditionally favoured by VCs. The Cox model revealed only marginal evidence suggesting a lower success rate for climate tech than healthtech, offering minimal support for our hypothesis. However, the Fine-Gray model showed that the climate tech sector has a significantly lower success rate than all other favoured industries. This finding supports our hypothesis, indicating that despite regulatory changes and higher demand, the climate tech sector may still presents challenges for venture capital success relative to peer industries.

In light of the inherent challenges associated with the climate tech sector, such as high capital expenditures and longer investment time frames (Gaddy et al., 2016), our study aimed to examine how capital intensity influences ventures' success rates. Our hypothesis was that capital intensity negatively impacts the success rate within the climate tech sector. To test our hypothesis, The Cox model was used to compare the success rates between capital intensity levels. The results showed that medium capital intensive companies had a significantly higher success rate than their high capital intensive counterparts. However, when we applied the Fine-Gray model, we found no significant differences in success rates based on the level of capital intensity. The survival curves indicated that more capital intensive companies were actually more successful, which contradicted our hypothesis. Again acknowledging that the small number of exits might have influenced the results, making it difficult to draw clear conclusions about trends or impacts.

Lastly, we investigated whether CVC-backed companies are more likely to succeed in the climate tech sector than those backed by traditional VCs. Our aim was to identify if the strategic purpose and longer investment horizons of CVCs make them more suitable for investing in climate tech. Although the Cox and Fine-Grey models suggested higher success rates for CVCs, statistical significance could not be achieved. On the other hand, the Cox model's interaction term between *CVC* and *Cap Table Size* showed a significant positive effect on success rates. This implies that CVC-backed companies are more capable of managing larger capitalization tables. However, due to the limited number of observations and the marginal supportive evidence, we cannot make definitive conclusions about our hypothesis. Considering the trends suggested by the models favouring CVCs, a more extensive sample can generate a more comprehensive analysis and potentially confirm these preliminary observations.

Our study also explored if CVCs foster more innovation in climate tech startups than traditional VCs. Our hypothesis was that CVC-backed startups would exhibit higher innovation. However, due to endogeneity issues, we relied on the IV regression model's findings. The model demonstrated that companies with low capital expenditures had significantly fewer patents granted, regardless of whether they were CVC or VC-backed. When we looked specifically at CVC-backed companies with low levels of capital expenditures, we found that they had a strong positive coefficient. This indicates a significant difference in the number of patents between CVC-backed and VC-backed companies with low levels of capital expenditures, supporting our hypothesis that CVC-backed companies are more innovative.

In summary, our analyses present several pieces of evidence that support our hypotheses. The results indicate that the climate tech industry is comparatively less successful than other favoured industries. However, when we investigated whether the industry's capital-intensive nature was the reason behind this, the results were inconclusive. Additionally, when we analysed the difference in performance between companies funded by CVCs and VCs, we found weak evidence which partly confirms our hypothesis that CVCs are more suitable for climate tech companies. We also explored how innovation differed between companies backed by a CVC or VC, and we found some supporting evidence, which partly confirms our hypothesis.

8.2 Limitations

In the following sections of this thesis, we will take a closer look at the limitations we encountered and discuss how they have influenced our analysis and the conclusions we can draw from it.

One major challenge we faced was accessing comprehensive data on private companies. We broadened our scope to include various European companies across various industries. However, we quickly realized that the depth of available data, particularly regarding funding rounds and financial details, was less comprehensive than initially assumed. This forces us to rely on assumptions to fill these gaps. While these assumptions helped us simulate the venture capital industry's workings, they inevitably compromised the accuracy of our analysis.

Further, the lack of detailed financial data meant that we had to devise a new method to analyse our second central hypothesis about capital intensity. We classified companies into three different levels of capital intensity. While practical under our circumstances, this approach had its limitations and likely contributed to the absence of significant findings in our results. It is a method that tries to reflect reality but falls short in precision.

Regarding our regression analysis, we faced several issues. Our dependent variable was the number of patents granted, which we used as a proxy for a company's innovativeness. However, this measure has its flaws. The patent granting process can take up to four years (EPO, 2023), making it challenging to capture newer companies' innovation status accurately. Ideally, we would have liked a more comprehensive measure of innovation, such as the number of patent applications or forward patent citations, which might better indicate a company's ongoing innovation efforts.

We also encountered endogeneity in our measure of innovation, which we attempted to address with an instrumental variable. However, the instrument's weak exogeneity is a limitation. We could have identified a stronger instrument if we had more extensive data on the companies and their investors. Again, this highlights the theme of limited data affecting the robustness of our analysis.

Another considerable limitation is the timing of our analysis in the context of the booming climate tech industry. Our descriptive statistics show that this sector has many active companies but few exits, even with our assumptions. This suggests that our analysis is premature, as the companies in this sector might not yet be ready for an analysis of this kind.

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Appendices

A Appendix

A.1 Schoenfeld Residuals

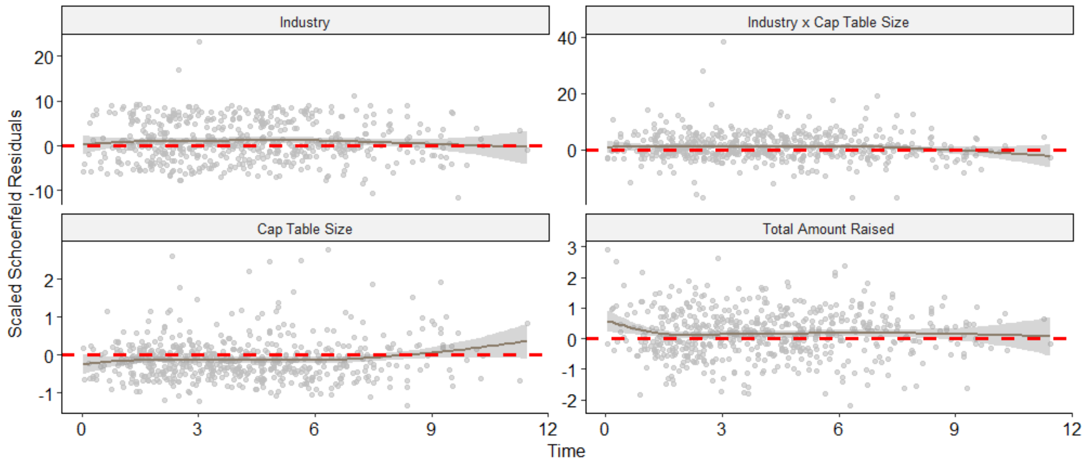

Figure A.1: Cox-model: Hypothesis 1

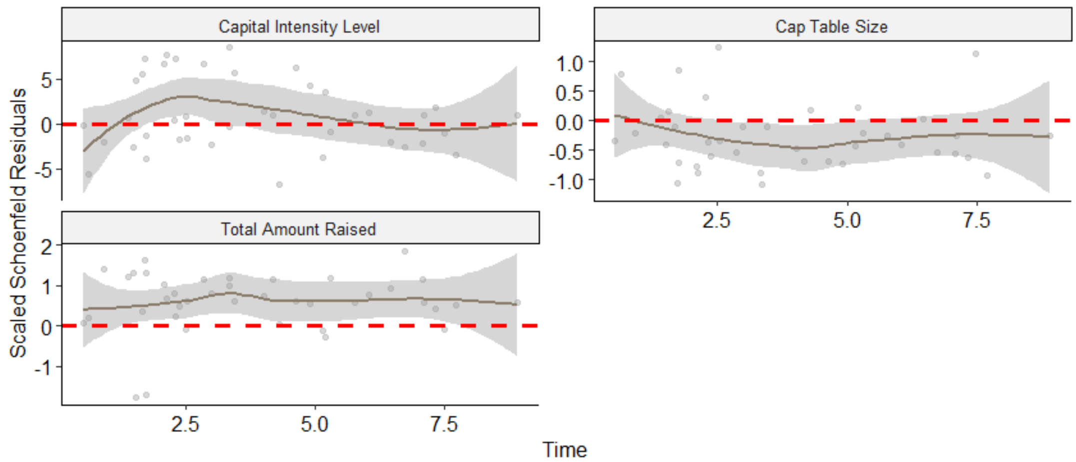

Figure A.2: Cox-model: Hypothesis 2

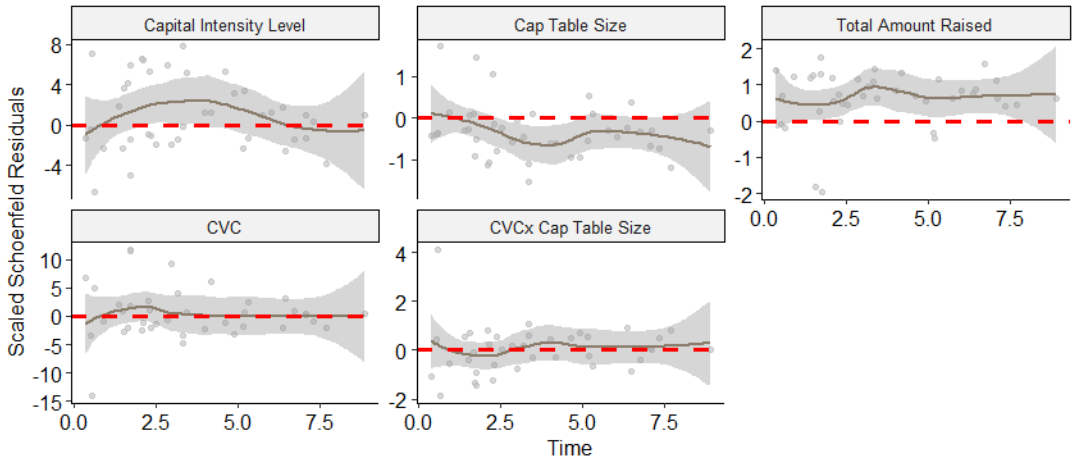

Figure A.3: Cox-model: Hypothesis 3

A.2 Cumulative Incidence Functions

The figures shows CIFs for each hypothesis, showing the likelihood of failure over time, with competing risks considered.

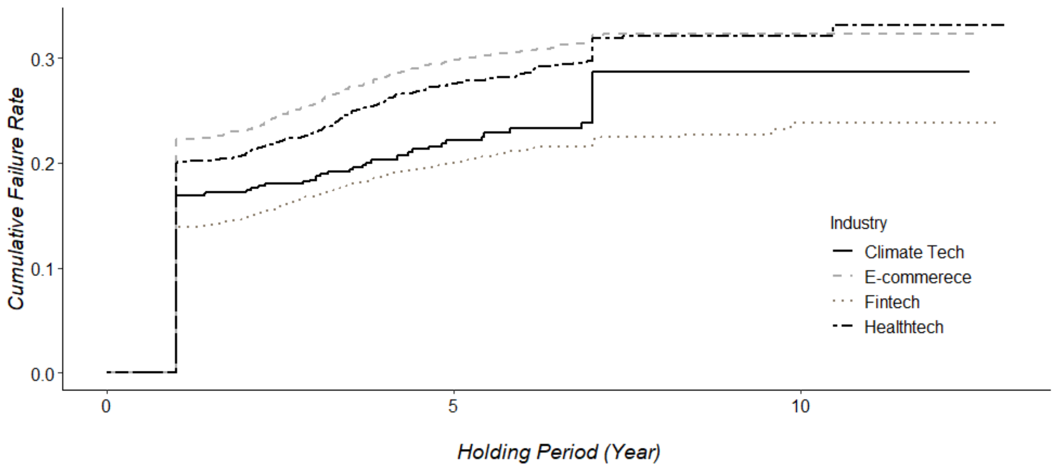

Figure A.4: CIF: Hypothesis 1

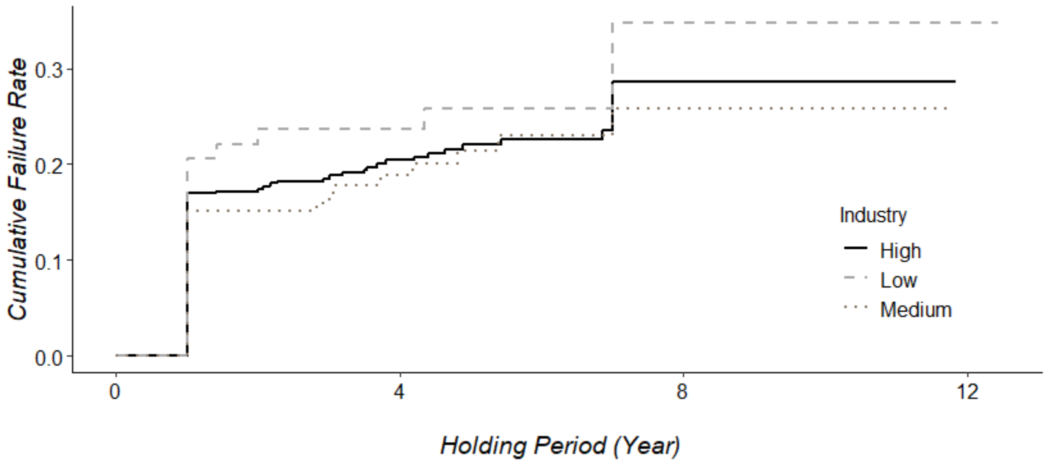

Figure A.5: CIF: Hypothesis 2

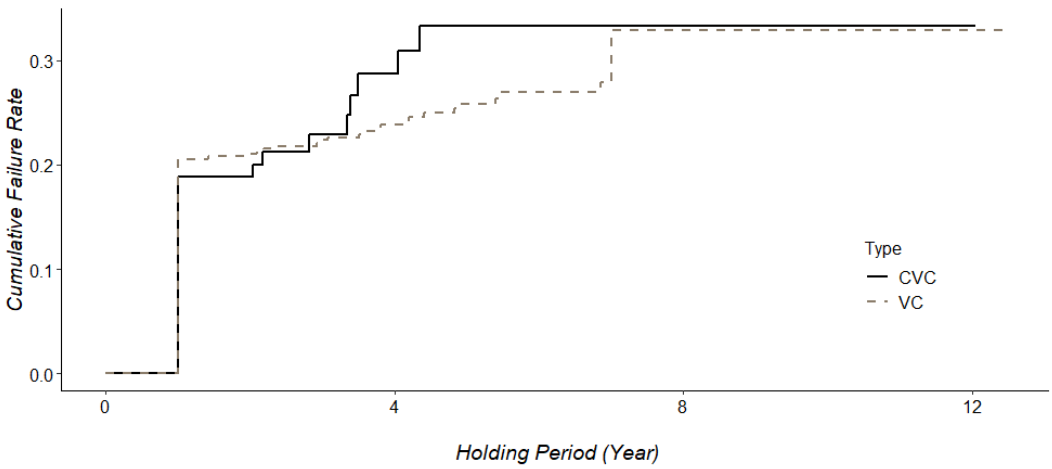

Figure A.6: CIF: Hypothesis 3

A.3 Correlation Matrix

Table A.1: Correlation Matrix: OLS Variables

	Total Amount Raised	CVC	Cap Table Size	Holding Period	Funding Rounds
Total Amount Raised	1	0.121	0.350	0.070	0.121
CVC	0.121	1	0.220	-0.089	-0.065
Cap Table Size	0.350	0.220	1	0.268	0.508
Holding Period	0.070	-0.089	0.268	1	0.650
Funding Rounds	0.121	-0.065	0.508	0.650	1

A.4 Capital Intensity Categorization

The table below displays the industry groups retrieved from Crunchbase (Crunchbase, 2023). Each industry group is classified based on its level of capital intensity, measured as the capital investment required per system at scale. The numbers are retrieved from (Stern, 2023). The whole market has on average 190 million in capital expenditures. Therefore, for instance, Farming with its 189 million on average, was set to medium.

Table A.2: Capital Intensity in Industries

Industry group	**Definition**	**Examples of sub-industries**	**Capital-intensity**
Administrative services	Companies that are primarily engaged in providing a range administrative services for others on a contract or fee basis.	Archiving Service, Call Center, Human Resources, Office Administration, Project Management	Low
Agriculture and Farming	Companies that encompass all aspects of food production.	Agriculture, AgTech, Animal Feed, Aquaculture, Farming, Forestry	Medium
Apps	Companies that build applications.	Apps, Consumer Applications, Mobile Apps, Reading Apps	Low
Artificial Intelligence	Companies that concern themselves with the simulation of human intelligence in machines.	Artificial Intelligence, Intelligent Systems, Machine Learning	Low
Biotechnology	The broad area of biology involving living systems and organisms to develop or make products, or any technological application that uses biological systems, living organisms, or derivatives thereof, to make or modify products or processes for specific use.	Bioinformatics, Biometrics, Biopharma, Biotechnology, Genetics, Life Science, Neuroscience	Medium

Commerce and Shopping	Companies involved in the buying and selling of goods by consumers and/or businesses.	E-Commerce, Gift Card, Online Auctions, Retail Technology	Medium
Consumer Electronics	Companies that produce electronic equipment intended for everyday use, typically in private homes.	Drones, Electronics, Mobile Devices, Nintendo, Smart Home, Wearables	Low
Consumer Goods	Companies that relate to items purchased by individuals and households rather than by manufacturers and industries.	Comics, Cosmetics, Flowers, Furniture, Jewelry, Toys	Low
Data and Analytics	Companies that analyze raw data in order to make conclusions about that information.	Analytics, Big Data, Data Management, Database	Low
Design	Companies that influence the experience a user has with all of a company's touch points.	Graphic Design, Interior Design, Market Research, Web Design	Low
Energy	Companies who concern themselves with researching and creating new forms of energy.	Battery, Geothermal Energy, Hydroelectric, Oil and Gas, Power Grid	High
Financial Services	Companies that provide a broad range of businesses that manage money.	Accounting, Credit, Fraud Detection, InsurTech, Wealth Management	Low
Government and Military	Companies that are involved with, make things for, and deal with the government and/or military.	GovTech, Law Enforcement, National Security, Public Safety	Mediu
Hardware	Companies concerned with a physical component of any computer or telecommunications system.	Data Storage, Drone Management, Flash Storage, Semiconductor	High
Healthcare	Companies within the economic system that provide goods and services to treat patients with curative, preventive, rehabilitative, and palliative care.	Assistive Technology, Biopharma, Cosmetic Surgery, Electronic Health Record, Medical Device	Medium

Information Technology	Companies that deal with computing, including hardware, software, telecommunications and generally anything involved in the transmittal of information or the systems that facilitate communication.	Cyber Security, IT Management, Management Information Systems, Technical Support, Video Chat	Low
Internet Services	Companies that provide a wide variety of products and services primarily online through their web sites.	Cloud Data Services, Search Engine, Unified Communications, Web Browsers	High
Lending and Investments	Companies that concern themselves with providing debt-based funding to individuals and corporations as well as those that assist individuals and corporations with where/how to invest their money.	Banking, Credit Cards, Funding Platform, Stock Exchanges, Trading Platform	Low
Manufacturing	Companies that concern themselves with the process of transforming materials or components into finished products that can be sold in the marketplace.	Advanced Materials, Industrial Manufacturing, Machinery, Textiles, Wood Processing	Medium/High
Media and Entertainment	A varied collection of companies that share the production, publication, and distribution of media texts.	Audiobooks, Digital Media, In-Flight Entertainment, Theatre, Virtual World	Medium
Messaging and Telecommunications	Companies that are involved in the transmission of signs, signals, words, messages, etc.	Email, Meeting Software, Wired Telecommunications	Low
Mobile	Companies that are involved in the manufacturing of mobile phones, including mobile phone handsets and apps.	Android, Mobile Devices, Mobile Payments, Windows Phone, Wireless	Medium
Natural Resources	Companies that are concerned with what people can use which comes from the natural environment.	Biofuel, Biomass Energy, Mineral, Mining, Solar, Water, Wind Energy	High

Payments	Companies in the massive card-processing industry.	Billing, Cryptocurrency, Debit Cards, Mobile Payments, Transaction Processing	Low
Privacy and Security	Companies that concern themselves with the ability to protect information about personally identifiable information.	E-Signature, Homeland Security, Network Security, Physical Security	Low
Professional Services	Companies in the tertiary sector of the economy requiring special training in the arts or sciences.	Business Development, Compliance, Consulting, Customer Service, Risk Management	Low
Real Estate	Companies that encompass the many facets of property including development, appraisal, marketing, selling, leasing, and management of commercial, industrial, residential, and agricultural properties.	Construction, Rental Property, Smart Building, Timeshare	Medium
Science and Engineering	Companies whose main area of focus revolves around the science and/or engineering fields.	Advanced Materials, Industrial Engineering, Nuclear, Robotics	High
Software	Companies that work on the development, maintenance, and publication of software that are using different business models, mainly either license/maintenance based, or cloud based.	Browser Extensions, Chatbot, Cloud Computing, Web Development	Low
Privacy and Security	Companies that concern themselves with the ability to protect information about personally identifiable information.	E-Signature, Homeland Security, Network Security, Physical Security	Low
Sustainability	Companies concerned with the creation of manufactured products through processes that minimize negative environmental impacts while conserving energy and natural resources.	Biofuel, Biomass Energy, Carbon Capture, Energy Efficiency, Wind Energy	High

Video	Companies that primarily concern themselves with producing video content.	Animation, Broadcasting, Film Distribution, Video Streaming	Medium