The Misalignment of Venture Capital and Cleantechs: an empirical analysis of how the sector's dynamics shape emerging funding paradigms

Guillermo Aiex Oliveira

Dissertation written under the supervision of Professor Fatima Shuwaikh

Dissertation submitted in partial fulfilment of requirements for the MSc in International Finance, at the Universidade Católica Portuguesa, 09/10/2025.

Abstract

This dissertation examines the alignment of Venture Capital investment methods with the operational realities of cleantech startups, characterized by prolonged development cycles, high capital necessity, and complex exit scenarios. The study analyzes the impact Venture Capital, specifically looking at VC funds and Corporate Venture Capital funds, and ESG score on valuation, realized financial returns, and exit probability during the Seed, Series A and Series B funding rounds. A stratified worldwide sample of 150 cleantech companies from the Cleantech Group Database was used to create a new Dataset that quantifies ESG performance, valuation, and returns. Results indicate that CVC involvement substantially elevates valuation premiums, acting as a reliable quality indicator; however is associated with diminished realized returns. Extended funding durations diminish returns and the likelihood of successful exits. The findings emphasize a structural misalignment between established practices in Venture Capital models and the reality of cleantech startups, highlighting the significance of investor type, capital structure, and strategic orientation for this prominent segment. The dissertation offers practical insights for investors and governments on harmonizing financial and sustainability goals to effectively promote cleantech growth.

Title: “The Misalignment of Venture Capital and Cleantechs: an empirical analysis of how the sector’s dynamics shape emerging funding paradigms”

Author: Guillermo Aiex Oliveira

Keywords: Cleantech, Venture Capital, Corporate Venture Capital, Sustainable finance, ESG, Startup Financing

Resumo

Esta dissertação examina o alinhamento dos métodos de investimento de Venture Capital com as realidades operacionais das startups cleantech, caracterizadas por ciclos de desenvolvimento prolongados, elevada necessidade de capital e cenários de saída complexos. O estudo analisa o impacto do Venture Capital, com enfoque em fundos de VC e Corporate Venture Capital, e da avaliação ESG sobre o valuation, retornos financeiros e probabilidade de saída bem-sucedida durante as rondas de investimento Seed, Series A e Series B. Uma amostra estratificada de 150 empresas cleantech, retirada da base de dados do Cleantech Group, foi utilizada para criar um novo conjunto de dados que quantifica a avaliação ESG, o valuation e o retorno por rodada. Os resultados indicam que o envolvimento de CVC eleva substancialmente o valuation, funcionando como um indicador fiável de qualidade; no entanto, está associada a retornos inferiores. Períodos de financiamento prolongados reduzem os retornos e a probabilidade de saídas bem-sucedidas. As conclusões enfatizam um desalinhamento estrutural entre as práticas tradicionais de Venture Capital e a realidade das startups cleantechs, destacando a importância do tipo de investidor, da estrutura de capital e da orientação estratégica para este segmento que vêm crescendo em relevância. A dissertação oferece insights práticos para investidores e autoridades sobre como harmonizar objetivos financeiros e de sustentabilidade, promovendo de forma eficaz o crescimento das cleantechs.

Título: “O Desalinhamento do Venture Capital e das Cleantechs: uma análise empírica de como a dinâmica do setor molda os paradigmas emergentes de financiamento”

Autor: Guillermo Aiex Oliveira

Palavras-chave: Cleantech, Venture Capital, Corporate Venture Capital, Finanças Sustentáveis, ESG, Financiamento de Startups

Table of Contents

Artificial Intelligence usage declaration

In alignment with the principles of academic honesty, authorship, and intellectual responsibility outlined in the Católica Lisbon School of Business and Economics Academic Integrity Code, I hereby declare that the use of artificial intelligence tools in the development

The scope of this thesis was strictly limited to auxiliary functions and conventional academic writing aids.

Such as:

• Assistance in refinement of grammar, syntax, and clarity in English-language academic writing, and;

• Facilitate the contextual interpretation of academic sources for the literature review.

At no point were generative AI tools used to produce original content, conduct analysis, or formulate arguments. All theoretical reasoning, methodological choices, empirical findings, and written outputs reflect my own independent academic work and intellectual contribution. This limited and transparent use of AI tools is fully consistent with the ethical expectations of Católica Lisbon and does not constitute a breach of the School's Academic Integrity Code.

1.Introduction

In recent years, the necessity to confront climate change and environmental degradation has elevated sustainable innovation to a central position in global economic and governmental priorities (Bergset & Fichter, 2015). Cleantech companies, which are enterprises dedicated to developing clean and efficient technology, have become essential contributors to the shift toward a low-carbon economy (Cumming, Henriques & Sadorsky, 2016). These firms represent the intersection of entrepreneurship, innovation, and sustainability, providing solutions that aim to minimize environmental impact while promoting economic growth. The financing landscape for cleantech startups is intricate and markedly different from that of conventional startups, raising fundamental questions regarding the appropriateness of standard investment models and the function of newer funding paradigms (Gaddy et al., 2017; Hegeman & Sørheim, 2021).

Startups, broadly defined, are temporary organizations involved in the search for scalable and repeatable business models (Blank & Dorf, 2020). Their core principles include innovation, iteration, and market adaptation, focused on attaining product-market fit and sustainable growth (Ries, 2011; Osterwalder & Pigneur, 2010; Thiel, 2014). This adaptable and versatile characteristic allows entrepreneurs to innovate new technology and business models across several sectors. The category of startups referred to as “green startups” or cleantech has conceptual uncertainties that affect both academic comprehension and financial decision-making (Bergset & Fichter, 2015).

The term “green startup“ is marked by definitional ambiguity and inconsistencies in the literature. It is frequently confounded with cleantech or broadly linked to any entrepreneurial endeavor with an environmental aspect. The extensive and imprecise use jeopardizes the integrity of the concept and obstructs thorough investigation (Hegeman & Sørheim, 2021; Bendig et al., 2022; Gaddy et al., 2017; Mukherjee et al., 2024). This thesis focuses specifically on cleantech, which possesses a better-defined and well-recognized definition in academic literature. Cleantechs are defined as enterprises or projects primarily dedicated to improving energy efficiency and sustainability, frequently encompassing areas beyond conventional energy (Mukherjee et al., 2024; Cumming et al., 2016).

Financing cleantech startups follows familiar paths: venture capital (VC), government funding, debt, and crowdfunding, but with significant distinctions. Three main profiles exist within VC: (i) regular venture capital, (ii) impact venture capital (IVC), and (iii) corporate venture capital (CVC) (Gaddy, Sivaram, Jones & Wayman, 2017). Investor types significantly vary in investment horizons, strategic objectives, risk tolerance, and support systems, impacting their compatibility with cleantech ventures (Hegeman & Sørheim, 2021). Conventional venture capital funds seek exponential financial returns within a five to ten-year period, prioritizing rapid growth and profitable exits. Impact venture capitalists prioritize both social and environmental outcomes in conjunction with financial returns, frequently adopting adaptable exit methods and altruistic intentions (Gaddy, Sivaram, Jones & Wayman, 2017). CVC entails existing established firms investing directly in startups, typically with strategic goals such as operational support, technological integration, and potential acquisition (Bendig, Kleine-Stegemann, Schulz, & Eckardt, 2022; Hegeman & Sørheim, 2021).

The Cleantech investing sector displays unique traits that contest conventional venture capital assumptions. Cleantech enterprises encounter longer development cycles and a deeper "Valley of Death", the pivotal stage in which businesses must evolve from concept to market viability, requiring significant financial investment and endurance (Hegeman & Sørheim, 2021). The technological complexity and market barriers associated with Cleantechs exacerbate the challenges of scaling and exit options. Furthermore, cleantech produces multiple returns that transcend just financial profit, encompassing environmental and social effects that benefit multiple stakeholders, hence challenging traditional risk-return assessments (Cumming et al., 2016). These factors highlight the necessity of rigorously evaluating which investor profiles are most compatible with cleantech financing.

The benefits and drawbacks of different VC models are particularly evident in this context. Conventional VC provides significant strategic assistance, board participation, and networking opportunities, although it frequently encounters difficulties associated with extended exit timelines and diminished financial returns in the cleantech sector (Gaddy et al., 2017). The environmental impact produces intangible benefits that may not yield immediate returns for investors, making cleantech companies a less appealing option for funds concentrated exclusively on financial optimization. In contrast, CVCs offer specialized knowledge, extensive business networks, and more adaptable exit plans, such as strategic acquisitions, making them more aligned with cleantech requirements (Cumming et al., 2016). Nonetheless, CVC participation entails dangers, including the possibility of greenwashing or a lack of alignment with startup autonomy (Hegeman & Sørheim, 2021; Döl et al., 2022).

One important theoretical perspective for examining cleantech investment is Sustainable Business Model Innovation (SBMI). Cleantechs often embody innovative business models centered on sustainability, which can be categorized into various types, including new sustainable startups or transformations of existing models (Geissdoefer et al., 2018). Notably, studies reveal that high Environmental, Social, and Governance (ESG) scores, an increasingly prominent metric in investment evaluation, may lead to inflated early-stage valuations, reducing the risk–adjusted returned returns for investors (Mansouri & Momtaz, 2022). Despite investors' professed interest in sustainable missions, investment decisions tend to prioritize expected financial returns over ESG considerations, highlighting a tension between sustainability and profitability (De Lange, 2017).

These complexities form the foundation of this thesis, which broadly examines how venture capital dynamics intersect with the specific realities of cleantech startups. Accordingly, the central research question is: "How do venture capital investment practices and ESG-driven valuation dynamics shape the financial and strategic trajectories of cleantech startups?" To address this question, this study will examine how the length of funding periods influences both the financial returns and the likelihood of successful exits of cleantech startups, highlighting the potential role of different types of venture capital investors. It will also explore whether high ESG scores contribute to valuation premiums beyond fundamental performance and whether such valuation dynamics affect long-term financial outcomes by creating challenges in sustaining performance expectations.

Methodologically, this study employs a quantitative and descriptive approach using secondary data from a global sample of 150 cleantech companies across seven sector segments, sourced from reputable databases such as Crunchbase and the Cleantech Group. ESG performance is quantified via natural language processing techniques to produce standardized ESG scores, enabling segmentation into quintiles (Mansouri & Momtaz ,2022). The study applies regression analyses on valuation, investor returns, and exit probabilities across Seed, Series A, and Series B funding rounds, with variables transformed logarithmically to ensure robustness. The analysis specifically examines the role of CVC participation in the cap table alongside ESG score in a cleantech startup's performance.

Although the extant literature provides valuable insights into cleantech financing, significant gaps persist, which this study aims to address. Specifically, there is limited empirical evidence on how CVC participation influences both valuations and realized financial returns across early funding stages in cleantech (Gaddy, Sivaram, Jones, & Wayman, 2017). Moreover, although ESG scores are increasingly used as a proxy for sustainability performance, little is known about their impact on valuation overinflation and long-term financial returns, specifically within the cleantech sector (Mansouri & Momtaz ,2022). Finally, existing research often relies on descriptive or anecdotal accounts, leaving a need for systematic analysis that simultaneously considers funding duration, investor type, and ESG-driven valuation effects (Bergset, & Fichter, 2015). This study aims to fill these gaps by combining a comprehensive dataset of cleantech startups with regression-based analyses to evaluate how investor structure and sustainability metrics shape financial and strategic outcomes.

This study advances academic understanding by empirically demonstrating that the traditional venture capital model, which is designed to generate rapid and exponential financial returns, is misaligned with the operational and developmental realities of cleantech startups. By highlighting the impact of longer funding cycles, higher capital intensity, and delayed commercialization, the findings reinforce theoretical perspectives that question the suitability of the conventional VC thesis in sustainability-driven industries (Gaddy, Sivaram, Jones & Wayman, 2017). This contributes to the literature by clarifying the structural mismatch between investor expectations and sector-specific dynamics in cleantech financing.

The research also sheds light on the dual role of CVC in cleantech investments. While CVC involvement significantly drives valuation premiums and acts as a credible quality signal during later funding stages, it does not translate into superior realized financial returns. The paradox underscored the importance of distinguishing between financial and strategic motives in investor behavior (Bendig, Kleine-Stegemann, Schulz & Eckardt, 2022). The study thus contributes to the broader literature on sustainable finance and entrepreneurship by illustrating how investor type and ownership structure shape firms' trajectories in technology-intensive and impact-driven sectors.

Finally, the findings provide practical implications for both investors and policymakers. For investors, the results emphasize the need to adapt investment theses to accommodate longer time horizons, complex exit scenarios, and non-financial value dimensions inherent in cleantech ventures. For policymakers, the evidence highlights the necessity of designing de-risking mechanisms and targeted incentives that account for the unique capital requirements of the sector. In this way, the study contributes to ongoing debates on how to align private investment, corporate engagement, and public policy to more effectively foster sustainable innovation (Cumming, Henriques & Sadorsky, 2016).

In conclusion, this study contributes to the academic debate by empirically showing that the traditional VC model, designed for rapid returns and short exit horizons, is structurally misaligned with the longer funding cycles, technological complexity, and capital intensity that characterize cleantech ventures (Gaddy, Sivaram, Jones & Wayman, 2017). It further advances the understanding of CVC´s role by revealing its dual impact: while CVC participation enhances valuations and signals firm quality, it does not translate into superior financial returns, reflecting the prevalence of strategic and impact-driven motives over purely financial objectives (Hegeman, & Sørheim, 2021). Finally, the study offers practical and policy-oriented insights by stressing the need for adapted investment theses and targeted support mechanisms that accommodate cleantech's unique risk-return profiles. Taken together, these contributions underscore the importance of differentiated financing approaches and integrate both financial and sustainability objectives, ultimately enabling more effective capital deployment to foster sustainable innovation and address global environmental challenges.

For the remainder of this study, Section 2 presents a comprehensive review of the literature on the cleantech sector and its funding strategies. Section 3 outlines the methodology, detailing the newly constructed dataset and the underlying assumptions. Section 4 discusses empirical results in depth, while Section 5 concludes with the main findings and their broader implications. All Tables and Descriptive Statistics were added at the end of this thesis to improve readability

2. Literature Review

2.1 Theoretical Framework

2.1.1 Conceptual Ambiguity of Green Startups

While the concept of startup is consistently defined across business and academic literature, the same does not apply to "green startups" (Bergset & Fichter, 2015). Definitions in literature vary significantly. A broad view suggests that any firm incorporating sustainability ideals and/or generating a positive ESG impact can be defined as a green startup. However, such inclusiveness risks trivializing the term (Tiba, van Rijnsoever & Hekkert, 2021).

Scholars illustrate this tension in different ways; Hegeman & Sørheim (2021) employ "green startup" and "cleantech" interchangeably, sidestepping definitional disputes but weakening conceptual clarity. Bendig, Kleine-Stegemann, Schulz & Eckardt (2022) adopt a stricter lens, linking green entrepreneurship exclusively to environmentally beneficial endeavors. Gaddy, Sivaram, Jones & Wayman (2017) emphasize technological and business innovations that directly create environmental gains. Mukherjee, Owen, Scott & Lyon (2024) return to the interchangeable use of "green" and "cleantech," while recognizing its limitations, as cleantech excludes other sustainability-oriented innovations.

This ambiguity explains why research on green startups remains fragmented. To avoid conceptual dilution, this research focuses on cleantech, a category with clearer boundaries and greater academic consolidation, offering a more reliable foundation for theoretical and empirical analysis (Mukherjee, Owen, Scott & Lyon, 2024).

2.1.2 Defining Cleantechs

A precise working definition of cleantech must be established in order to cover the main facets of this study and serve as a roadmap for future examinations. Compared to the term "green startup," there is a more consistent and well-recognized pattern of understanding, despite the fact that the term also varies somewhat throughout the literature (Mukherjee, Owen, Scott & Lyon, 2024).

Cleantech is any program, technology, or corporate strategy whose main goal is to increase energy efficiency (Mukherjee, Owen, Scott & Lyon, 2024). Important to highlight that this term is not limited to businesses that only operate in the energy industry. Cumming, Henriques & Sadorsky (2016) support this viewpoint by offering a more succinct definition of cleantechs, characterizing them as "a company whose primary focus is on clean technology".

It is clear that, based on their particular focus or technological application, cleantechs can be divided into a number of groupings and categories. This segmentation used in this investigation will adhere to the Cleantech Group´s classification scheme, which was also used in the Cumming, Henriques & Sadorsky (2016) study. The thesis´s Methodology section will offer a brief explanation of this classification scheme.

2.1.3 Types of Investment in Cleantechs

As one might anticipate, venture capital firms serve as the main source of financing for cleantech entrepreneurs, who frequently follow the conventional venture finance route. However, a greater variety of funding sources has surfaced as pertinent stakeholders in the cleantech ecosystem, considering recent political directives and growing global awareness of environmental fragility (Neumeyer & Santos, 2018). The participation of venture investors in the cleantech sector has increased dramatically in recent years, although access to capital is difficult, frequently because of underdeveloped business models or missions that don´t meet due diligence standards (Cumming, Henriques & Sadorsky, 2016).

It should be noted that this research will focus on the funding stages from Seed to Series, even though early-stage startups (the study´s focus) usually start their funding journey with FFF (Friends, Family, and Fools), angel investors, or even debt instruments (Gaddy et al., 2017).

2.1.4 Diving into Venture Capital for Cleantechs

The three venture capital models central to cleantech investments illustrate different logics regarding returns, impact, advantages, and limitations:

1. **Venture Capital Funds** manage concentrated portfolios, often including 10 to 12 startups, with defined time horizons ranging from five to ten years. Success relies on a limited number of companies producing exponential returns, whilst the majority yield small or negative results (Gaddy et al., 2017). These funds typically exert moderate influence over firm operations, participate on boards, and offer governance, networks, and visibility to founders. Investments frequently garner media attention and enhance the fund's reputation following a successful exit (De Lange, 2017). Nonetheless, cleantech companies tend to present lower returns, longer exit horizons, and higher market-entry barriers relative to other sectors (Gaddy, Sivaram, Jones & Wayman, 2017). The primary added value resides in their socio-environmental impact, which may not directly convert into financial returns for venture capital funds (Cumming, Henriques & Sadorsky, 2016).
2. **Impact Venture Capital** mirrors VC structure while integrating sustainability principles. Boards often comprise field experts, exit deadlines exhibit greater flexibility, and success is evaluated in both financial and socio-environmental dimensions (Hegeman & Sørheim, 2021). These investors may tolerate diminished or postponed financial returns, regarding a portion of the investments as "lost" in pursuit of favorable sustainability results (Gaddy, Sivaram, Jones & Wayman, 2017). This dual focus makes IVC well-suited for cleantech, since the intangible socio-economic and environmental advantages correspond with their goals, despite potentially limited immediate financial returns. Since IVC is not the emphasis of this study, this group will not be examined any further.
3. **Corporate Venture Capital** entails direct investments by established companies in startups and is frequently regarded as particularly suitable for cleantech. In addition to

capital, corporations can offer operational, logistical, and specialized knowledge, almost serving as incubators (Hegeman & Sørheim, 2021). Exits often occur through acquisitions, synchronizing startup growth with corporate strategy, despite valuations potentially being lower than anticipated by venture capitalists (Cumming, Henriques & Sadorsky, 2016). Further benefits encompass enhanced reputation, a rise in patent applications, and the opportunity for corporations to regard cleantech initiatives as externalized R&D, thereby minimizing accounting repercussions and mitigating internal risk (Bendig, Kleine-Stegemann, Schulz & Eckardt, 2022; Dol, Ulloa, Zammar, Prado & Piekarski, 2022). Risks arise when firms engage in such investments mainly for greenwashing, but overall, the strategic alignment between CVC and cleantechs remains strong.

2.2 Funding Startups vs. Cleantech

The disparities in investment stages and risk perception are among the first indications that cleantechs might not fully fit the traditional startup model and thus might not totally match venture capital´s expectations (Gaddy, Sivaram, Jones & Wayman, 2017).

1. **Timeline and Exit Challenges**

The typical lifecycle of a venture capital fund is five to ten years, which is also the timeframe for early-stage investments in firms (Gaddy, Sivaram, Jones & Wayman, 2017). It is anticipated that during this time, businesses would transition from the ideation stage, in which they develop a product and determine its fit with the market, to the scale-up stage, which concentrates on commercialization. Startups have to demonstrate their worth in the market during this transitional phase, which sometimes is called the "Valley of Death" (Hegeman & Sorheim, 2021). Cleantechs, however, paints a more nuanced Picture. Cleantechs typically endure a longer and more profound Valley of Death because of the high level of technological expertise and substantial hurdles to market entrance. Higher capital investment becomes necessary as a result, raising risk and decreasing return predictability. These worries are made worse by cleantech's generally low commercialization prospects. At the time of investment, these businesses might inspire excitement and be seen as "cool", but the scalability of disruption is limited by their niche markets, which are frequently controlled by a small number of players. Cleantechs are therefore more likely to end up in strategic acquisitions (M&A´s) rather than achieving exponential exits (Cumming, Henriques, & Sadorsky, 2016).

2. **Perception of Returns**

How returns are realized is another significant distinction between cleantechs and conventional companies. Beyond the aforementioned problems, cleantechs have a special advantage: a portion of their return is non-monetary and frequently helps the larger Community, including possible rivals. Put another way, because cleantechs´ rewards are intangible, they not only come with higher expenses but also higher risk (Hegeman & Sorheim, 2021). To be clear, the goal of a typical startup investment is a successful exit that yields returns for the fund in terms of Money and reputation. The venture model is sustained by this (Gaddy, Sivaram, Jones & Wayman, 2017).

On the other hand, cleantech reinterprets what a "successful outcome" is. In addition to monetary returns, their influence is gauged by improvements in the environment, Society, and reputation. Cleantech's primary goal is to increase sustainability or energy efficiency; therefore, the advantages they produce frequently benefit a variety of stakeholders (Mukherjee, Owen, Scott & Lyon, 2024). When combined with the previously indicated decreased chance of high multiple exits, this may improve the fund's reputation or ESG credentials, but it does not always result in immediate financial gain (Cumming, Henriques, & Sadorsky, 2016).

Given these structural differences, such as longer development timelines, higher capital necessities, and potential lower scalability, it follows that extended funding periods may directly undermine both financial outcomes and exit probabilities.

Hypothesis 1 (H1): Longer funding periods in cleantech startups reduce (h1a) expected financial returns and (h1b) the likelihood of a successful exit.

2.3 The Impact of Business Model, Mission, and ESG on an early-stage firm's valuation and funding process

It is crucial to address a couple of more issues that haven´t been covered yet. The business model, mission, and ESG score of the investee company can be used to further assess the funding process and the possible repercussions of underperformance in Cleantech investments (Mansouri & Momtaz, 2022).

In summary, the business model establishes how a company extracts value from its operations in accordance with its mission; the mission is basically the company´s declared purpose (De Lange, 2017), and the ESG score indicates the degree of dedication to Environmental, Social, and Governance principles that are incorporated into the business model (Mansouri & Momtaz, 2022).

The literature on business models is vast and provides a variety of definitions. However, the idea of Sustainable Business Model Innovation (SBMI) is the main focus of this conversation. When identifying the characteristics of a startup, SBMI is essential. It can also provide theoretical support for the idea that Cleantech's can be classified as startups.

Geissdoerfer, Vladimirova & Evans (2018) distinguished four categories of SBMI:

1. **Sustainable Startups:** a new company is founded from the ground up with a sustainable business plan;
2. **Sustainable Business Model Transformation:** To make the current business model sustainable, it needs to be drastically changed;
3. **Sustainable Business Model Diversification:** Without making significant adjustments to the current model, a new sustainable business model is added alongside it;
4. **Sustainable Business Model Acquisition**: A sustainable business model is found, purchased, and incorporated into the current company.

With this framework in place, it is possible to make a crucial deduction: research shows that early-stage companies with high ESG scores are frequently overvalued, which lowers the expected return-to-risk ratio for investors (Mansouri & Momtaz, 2022). This leads back to the current debate about whether or not traditional venture capitalists should enter the Cleantech market, particularly in light of the particular difficulties that these startups already encounter (Gaddy, Sivaram, Jones & Wayman, 2017).

Furthermore, studies indicate that while investors actively seek out companies with sustainable missions and business models, these aspects are usually examined during the due diligence stage, the actual investment decision–making process tends to ignore these factors in favor of the anticipated financial return (De Lange, 2017). As a result, ESG-related valuation effects may create a discrepancy between perceived and actual firm quality. In this context, it follows that cleantech startups with higher ESG scores might experience inflated valuations relative to their underlying fundamentals, which could in turn hinder long-term financial performance by setting expectations that are difficult to sustain.

Hypothesis 2 (H2): Cleantech startups with higher ESG scores present higher valuation during early-stage rounds.

Hypothesis 3 (H3): The overinflation translates into weaker long-term financial returns.

3. Research Methodology

3.1 Research Design

This study uses a quantitative and descriptive research approach to address the research objectives and offer insightful information about the cleantech investment landscape. Secondary data from both structured and semi-structured data sources forms the foundation of the study. Evaluating the connection between investor profiles, ESG performance, and financial returns in the cleantech industry is the main goal. The analysis focuses specifically on cleantech businesses' exit results and early-stage funding (Seed, Series A, and Series B).

This analysis uses well-known and reliable datasets, especially the Cleantech Group's yearly "Global Cleantech 100" lists. In order to produce a more thorough and chronologically dispersed pool of businesses, information from the "50 Cleantechs to Watch" reports, which were released between 2015 and 2020, was also added. In addition to ensuring diversity in technological focus, region, and investment history, the use of numerous list editions enables the sample to represent enterprises at various stages of maturation.

A case-level analysis was used because the study focused on investor performance and company trajectories. Since each business is viewed as a unit of observation, cross-sectional comparisons between factors like investor type, ESG performance, and exit success are made possible. Furthermore, the study offers scholarly insights into sustainability-linked investment performance thanks to the use of a strong and up-to-date ESG grading mechanism.

3.2 Data Collection and Sample Construction

An initial list of 595 cleantech businesses was created using the Global Cleantech 100 and the 50 Cleantechs to Watch reports. In accordance with the Cleantech Group's classification, these businesses were divided into seven segments:

1. Agriculture & Food
2. Enabling Technologies
3. Energy & Power

4. Materials & Chemicals
5. Resources & Chemicals
6. Transportation & logistics
7. Industrial & Manufacturing

By dividing up operational activities within the cleantech industry into these categories, it is possible to analyze whether particular subsectors draw more venture capital interest or produce better investor results

A stratified random sample of 150 companies was chosen from the 595-company master list. This method reduces sampling bias and guarantees a representative distribution throughout the seven segments. Crunchbase was used to gather data for each selected company, such as (i) country of incorporation, (ii) year of foundation, (iii) company overview (summary), (iv) funding duration, (v) quantity of VC and CVC funds participating in Seed, Series A and Series B, (vi) the exit status, (vii) type of exit, and (viii) capital invested per round (if provided).

Company summaries were examined using the ESG scoring methodology put forward by Mansouri & Momtaz (2022) in order to evaluate ESG performance. This coding framework creates an approximate ESG score from qualitative descriptions using natural language processing and predetermined criteria. Using this approach guarantees academic rigor and methodological consistency when assigning ESG ratings.

After generating ESG scores, the 150 companies were ranked and divided into quintiles, forming five ESG-based groups. This segmentation enables the exploration of whether cleantech startups with higher ESG alignment tend to be overvalued during early-stage funding rounds, potentially implying higher investment risk.

Additionally, the dataset monitors whether early-stage investors made an exit and, if so, the financial details of that exit. This makes it possible to examine investor return trends directly.

3.3 Sample Statistics

Strong geographic diversity is ensured by the final sample's 150 cleantech enterprises, which are spread across five continents and 21 nations. The sample's average company stayed venture-backed for 8.12 years. Each company is funded by an average of 1.5 CVC investors and 5.46 VC investors. The companies were founded between 1980 and 2023.

It is significant to note that 176 CVCs and 464 distinct VCs were discovered to be investing in businesses within this dataset. By the time the data was gathered, 68 companies had either closed or not reached an investor exit. Of the 82 businesses that went through an exit event, 15 used initial public offerings (IPOs) to exit, while 28 were acquired through an M&A, and 38 left through later-stage funding rounds conducted by corporations or private equity. These figures show that the sample is suitable for comparison analysis and is also diversified.

3.4 Exit Analysis and Investor Return Estimation

This study evaluates the possible financial return for investors who took part in Seed, Series A, and Series B rounds as a fundamental part of the process. Estimating returns depends on the date and type of investor exits, with three exit possibilities receiving special consideration:

1. Mergers & Acquisitions (M&A)
2. Later stage Private Equity or Corporate-led rounds (Series E or later)
3. Initial Public Offerings (IPO's)

Because of their importance in cleantech funding and their effects on investor liquidity, these exit methods were selected. M&A is still the most popular exit strategy in the industry according to the research (Cumming et al., 2016), although IPOs provide greater visibility but have lengthier lock-up periods. Early investors can leave through secondary market transactions in Series E or subsequent rounds, which are frequently headed by corporations or private equity funds. Each funding round's capital investment is matched with a standardized estimate of the equity percentages obtained by new investors (Carta, 2024):

- Seed: ~ 18-20%
- Series A: ~ 20-25%
- Series B: ~ 15-18%
- Series E: ~ 7-10%

Only the highest percentages within each range were selected in order to provide a conservative valuation estimate. The following formula was used to estimate the post-money valuation for each invested round:

$$Post\ Money\ Valuation = \frac{\text{Invested Capital}}{\text{Percentage Acquired}}$$

For instance, a company's anticipated post-money valuation would be $50 million if it obtained $10 million in a seed round and sold 20% of its equity. All Seed, Series A, Series B, and, when applicable, Series E rounds were treated using the same methodology.

Exit multiples for early-stage investors were estimated using this value trajectory. Early investors are presumed to sell their whole ownership at the exit valuation in M&A exits. Partial liquidation after lockup is considered in IPO situations. To predict the expected secondary sale pricing in Series E exits, valuation growth is evaluated.

3.4.1 Estimating Dilution and Return Calculation

Accurately accounting for the stock dilution experienced by early-stage investors throughout multiple funding rounds is a crucial component of return estimation. Recent market data and industry standards indicate that a dilution rate of roughly 20% every fundraising round is typical for firms in the seed to growth stages (Carta, 2024; Lighter Capital, 2024). This means that in order to make room for new capital inflows, current shareholders, including founders and previous investors, usually see their ownership stakes lowered by about 20% with each new funding round.

A simplification is required because the dataset only includes data up to Series B rounds, even though exits can happen at Series E, IPO, or M&A stages:

- Two more investment rounds (Series C and Series D) are presumed to follow Series B if the departure is through a Series E round, each of which results in a 20% dilution per round.

- It is conservatively assumed that one more funding round (such as Series C) occurred after Series B if the exit happened through an IPO or M&A before a Series E round, resulting in one instance of roughly 20% dilution.

The following formula can be used to model the dilution impact on an early investor's ownership stake:

$$Final\ Ownership = Initial\ Ownership\ x\ (1 - Dilution\ Rate)^{n}$$

- Dilution Rate: 20% (or 0.20);
- Initial Ownership: The investor's equity percentage right after their funding round (20% for seed investors, for example); and
- n: The number of subsequent funding rounds that dilute the stake.

Despite the lack of comprehensive intermediate funding data, the effective equity interest owned by early investors at exit can be approximated by using this dilution paradigm. This makes it possible to calculate exit returns by multiplying the exit valuation, adjusted for capital invested, by the investor's final ownership percentage.

3.5 ESG Scoring Methodology

This study uses the natural language processing (NLP), based methodology recommended by Mansouri and Momtaz (2022) to integrate environmental, social, and governance (ESG) factors into the investment analysis of startups, especially in the cleantech industry. Due to their early stage, lack of standard disclosures, and informational opacity, startups are frequently left out of traditional ESG rating systems. The methodology used here is one of the most thorough and repeatable attempts to date to quantify ESG performance for startups.

Converting qualitative textual information released by startups, including press releases, whitepapers, website content, and Crunchbase profiles, into structured ESG scores is the core of the Mansouri & Momtaz method. This procedure is two-step: first, a domain-specific ESG vocabulary is created using machine learning techniques; second, the dictionary is used on the textual data of the startups to get normalized ESG scores.

The Stanford CoreNLP pipeline is used by the authors to parse sentence structure and find important term collocations (like "initial coin offering") that are essential for correctly interpreting domain-specific phrases in order to construct the ESG dictionary. The authors then create vector embeddings of words related to ESG topics using Word2Vec model that was trained on Financial Times articles tagged with " ESG Investing " and " Moral Money". The model expands these "seed" terms, 70 pertaining to environmental issues, 38 to social issues, and 46 to governance issues, to find semantically related terms, producing a final ESG dictionary with 1,495 terms spread across the three dimensions.

The frequency of ESG-related terms in each startup's textual data is measured using this dictionary to determine its ESG score. The E, S, and G components each have their own sub-score when this frequency is normalized to take dictionary size into consideration. These normalized sub-scores are added together to get the final ESG score, which provides a scalable and impartial measurement tool. By classifying businesses into ESG quintiles (first 20%, second 20%, etc), this methodology makes it easier to compare investment dynamics across various ESG performance levels, including firm value, investor engagement, and exit success.

This exact methodology was used in this analysis to calculate ESG scores for the 150 companies presented in the dataset using the author's freely available code. In particular, each company’s Crunchbase profile’s summary field was used as the standardized text source, extracting and analyzing it. This guaranteed uniformity across all observations and lessened subjectivity in the grading procedure. This way, it was possible to reproduce and expand on previous research on the overvaluation of the high-ESG businesses by classifying the startups into ESG quintiles (first 20%, second 20%, etc.) based on the derived ESG scores. This segmentation allows to investigate the hypothesis that companies with better ESG scores would encounter more investor enthusiasm, which could result in higher risk and lower predicted returns, as covered in the results section.

This method’s replicability and less subjectivity are among its significant advantages over earlier techniques that mainly depend on self-reporting or the inclusion of specific keywords in project descriptions. For instance, prior research, frequently lacking a thorough foundation in linguistic modeling or relevance testing, employed subjective classification or binary indicators to gauge sustainability orientation (Vismara, 2019; Horisch, 2015).

Mansouri and Momtaz perform a number of “sanity checks” to verify their methodology. Based on manual content assessment, they confirm if startups with high environmental scores actually exhibit strong environmental commitments. Additionally, they examine ESG score trends by industry and discover that they are consistent with intuitive assumptions (for example, manufacturing and energy sectors have lower governance scores, health scores have greater social signals, and energy and manufacturing sectors have higher environmental scores).

Nevertheless its resilience, the method has drawbacks. First, using NLP models like Word2Vec introduces sensitivity to model hyperparameters; using other architectures, such LSTM or transformers, could produce different results. Second, semantic ambiguity is still an issue: too narrow seed terms may leave out pertinent content, while the inclusion of terms that are only loosely associated with ESG (such as “pension fund”) may reduce score precision. Lastly, although there are encouraging external validity indications from the substantial correlations between the ESG scores and Refinitiv’s ratings for S&P 500 companies, care should be used when extrapolating findings outside of the startup setting, particularly in cases where textual disclosures are scant or inconsistent.

All things considered, the ESG scoring approach significantly increases the rigor and originality of ESG evaluation in early-stage and startup businesses. It is a useful tool in the developing field of impact-oriented investment analysis since it enables both researchers and investors to more accurately capture the complex sustainability profile of startup companies.

3.6 Calculations

To address the research question, multiple regression analysis were conducted. The dependent variables regarding Valuation and Returns as well were logarithmically transformed using their natural logarithm. This transformation fulfills three primary objectives: (i) to linearize potential non-linear relationships, as financial and economic variables frequently exhibit proportional rather than absolute changes; (ii) to diminish the skewness commonly found in variables such as valuation and returns, which are often right-skewed with an extended tail of large values; and (iii) to enhance the interpretation of coefficients in terms of elasticities, allowing estimates parameters to be understood as the as the percentage change in the dependent variable corresponding to a one percent change in the independent variable (Cohn, Liu & Wardlaw, 2022).

Additionally, factors including the proportion of CVC in the cap table (%CVC), the ESG Quintile and the firm's foundation year were mean-centered prior to their incorporation into the models. This modification is especially pertinent for variables that are improbable to assume a value of zero, as it enhances interpretability: the regression intercept can subsequently be understood as the anticipated value of the dependent variable when the predictors are at this sample means, rather than at zero, which in this case could be unrealistic. Moreover, mean-centering mitigates potential multicollinearity, particularly when interaction terms are included, and improves numerical stability during the estimate process (Iacobucci, Schneider, Popovich & Bakamitsos, 2016).

The regressions were then performed using the variables to assess the influence of the mean-centered ESG Quintile on valuation and returns throughout each fundraising round, from Seed to Series B. Considering the elevated ESG performance anticipated within the chosen segment of study, cleantechs, it was assumed that the "hype" effect identified by Mansouri and Montaz (2022) for ESG scores in general companies might be reflected by the proportion of CVC involvement in the capitalization table. If all firms in the sample demonstrate high ESG performance, it is plausible to anticipate that increased CVC participation could be regarded as an indicator of exceptional quality, potentially leading to elevated valuations and consequent lower returns, similar to the positive correlation between ESG scores and valuation in wider markets, followed by lower expected returns (Mansouri & Momtaz, 2022).

To further analyze the determinants of financial outcomes in early-stage cleantechs, the following regressions were conducted utilizing two primary dependent variables: the likelihood of exit, quantified with a binary exit dummy, and the logarithm of average return across investment rounds. The primary independent variables in these models were the proportion of Corporate Venture Capital (%CVC) in the capitalization table and the length of the funding period (in years). This analysis aimed to evaluate how CVC involvement and the extended funding horizons, typical in cleantechs, affect realized returns and the probability of a successful exit.

Two distinct sets of control variables were incorporated in all regressions to enhance the robustness and interpretability of the models. For each funding round valuation and return, as well as for exit probability and average return (dependent variables), two parallel regressions were conducted: the first included controls for the firm's founding year and a dummy variable representing the continent of the company's location. Given that the majority of the companies were either from North America and Europe, the reference group chosen was what was called as Rest of the World. The second incorporated controls were, once again, the founding year and the company's Cleantech Group's segment. The reasoning for using control variables is to enhance the reliability of the estimated connections and to isolate the effects of the independent variables. The founding year is crucial as it reflects prospective cohort effects and variations in market conditions at the time of establishment. The continent dummy facilitates the examination of regional variations in investment environments and exit prospects. Simultaneously, the cleantech sector variable handles the diversity among subsectors that may encounter unique technology risks, capital demands, or market dynamics (Gaddy, Sivaram, Jones & Wayman, 2017). The analysis seeks to obtain more accurate and dependable insights into the influence of CVC involvement and funding duration on valuation, returns, and exit probability including these controls.

4.Results

4.1 Descriptive Statistics

Tables 1-5, which can be found at the end of this thesis, present descriptive statistics for the five subsamples: the average return sample, the exit probability sample, and the stage-based samples for valuation and return (Seed, Series A, and Series B)

Valuations and returns are highly skewed and display heavy tails, with few extreme cases driving the means far above the medians. For instance, in the average return sample, most returns cluster near zero, while a handful of observations exceed 700%, highlighting the need for logarithmic transformations in the regressions to reduce distortion from outliers. Similarly, valuations increase across financing stages, from lower Seed rounds to larger Series B rounds, but remain unevenly distributed, reinforcing the decision to log-transform.

The subsamples also differ meaningfully. Seed rounds have lower valuations and more concentrated returns, Series A and Series B rounds show higher capital inflows and greater dispersion, and the exit probability sample allows testing for survivorship bias while showing intermediate characteristics in funding and returns.

Control variables such as founding year, industry composition, and geography remain stable across subsamples, ensuring that observed differences in valuations and returns are not driven by structural factors.

Overall, the descriptive statistics highlight the heterogeneity of firms across financing stages and support the use of the log-transformed dependent variables.

4.2 Valuation by Funding Round

The regression results reveal distinct patterns in valuation across Seed, Series A, and Series B funding rounds.

For the seed stage, the models show very low explanatory power (R^2 between 14.6% and 18.6%), indicating that the included variables explain only a small portion of the variation in log variation. ESG Quintile is not statistically significant (coefficient between 0.077 and 0.121), suggesting no meaningful relationship with valuation at this stage. In contrast, CVC% trends positively (coefficients 0.390-0.563) but fails to reach significance, implying a potential but weak association. The foundation year has a small but significant positive effect, indicating that more recently founded firms tend to have slightly higher valuations. Geographical dummies indicate that firms in Europe and North America may have slightly lower valuations relative to the reference group (rest of the world), though these effects are only marginally significant. Overall, Seed valuations appear largely driven by qualitative and firm-specific factors rather than ESG performance or CVC involvement.

Moving to Series A, the explanatory power of the models increases (R^2 ~25%), with CVC% emerging as a strong and statistically significant predictor of valuation (coefficient ~1.15-1.25, $p < 0.01$). This suggests that CVC participation serves as a credible signal for investors at this stage. ESG remains non-significant and close to zero, indicating no measurable impact on valuation. The foundation year continues to have a positive effect, while group dummies show some industry-specific patterns. These results imply that for Series A firms, corporate attributes such as CVC involvement and age are more influential in determining valuation than ESG performance.

In Series B, the pattern persists, though with slightly lower explanatory power in some specifications (R^2 between 13.62 and 23.9%). CVC% retains a significant positive effect (coefficient ~ 0.92 -1.06, $p < 0.01$), indicating that firms with higher CVC participation enjoy substantial valuation premiums. ESG remains non-significant and slightly negative, suggesting no evidence that ESG performance contributes to valuation at this stage for cleantechs. Certain industry dummies show positive and significant effects, highlighting that sectoral characteristics become increasingly relevant as firms mature. Foundation year remains positively associated with valuation, though the magnitude decreases slightly to relatively earlier stages.

The intercept values for each funding stage indicate that firms in the sample start with moderately high baseline valuations even at Seed (~US$11.3 million), increasing through Series A (~US$25.7 million) and Series B (~US$104.6 million). These rising intercepts reflect the typical growth trajectory of cleantech firms as they progress through funding rounds and suggest that the sample overall consists of companies with substantial investor interest and capital backing (Gaddy, Sivaram, Jones & Wayman, 2017).

Considering that ESG scores are inherently high within this sector compared to typical firms (De Lange, 2017), the lack of ESG impact on valuation is likely to reflect limited variability and a ceiling effect. Thus, %CVC ownership becomes a primary company attribute that signals quality and contributes to valuation premiums, potentially leading to overvaluation at early stages.

4.3 Return by Funding Round

The return regressions reveal patterns broadly consistent with the valuation results, while highlighting important nuances in performance outcomes across funding stages and regions.

At the Seed stage, neither ESG nor % CVC has a statistically significant effect on returns, considering $\alpha = 1\%$, and model fit is modest (R^2 between 20.6% and 24.2%), indicating that most variation arises from factors outside the model. ESG coefficients are small and negative

(-0.226 to -0.284), reaching marginal significance in some specifications, while %CVC is positive but non-significant. The foundation year shows a negative effect, implying slightly lower returns for younger firms. Geography also plays a minor role: firms in Europe tend to have slightly lower returns relative to other regions, though effects are not statistically robust at this stage. Intercepts indicate high baseline returns (~66-96%), consistent with typical early-stage venture returns and reflecting an overperforming sample of cleantech firms.

In Series A, ESG remains non-significant. %CVC exhibits a marginally significant negative effect (coefficients 1.05 to -1.29, $p < 0.10$), suggesting that higher CVC participation correlates with reduced returns (roughly 65–75% lower per standard deviation increase), even though it positively affects valuation. The foundation year continues to negatively influence returns. Geography now becomes more relevant: European firms show significantly lower returns (coefficients ~ -1.91, $p < 0.01$), and North American firms also exhibit a negative effect (-1.21, $p < 0.05$), suggesting that regional factors, such as market conditions or exit dynamics, also shape performance outcomes.

For Series B, ESG remains irrelevant, while %CVC maintains a marginally significant negative association with returns (coefficients -0.81 to -0.86, $p < 0.05$), corresponding to roughly a 50% decrease per unit increase. The foundation year continues to negatively affect returns. Geography effects are weaker than in Series A, though European firms still display lower returns (-1.01, $p < 0.02$). Intercepts indicate high baseline returns (~115-138%), confirming that the sample consists of cleantech firms achieving outstanding performance outcomes. Overall, these results highlight that while CVC participation boosts valuation, it may not translate into higher realized returns, and regional factors significantly influence performance, particularly at intermediate funding stages.

4.4 Average Return and Exit Probability

Further models examining average returns reinforce the previously observed negative association between %CVC and financial performance, although statistical significance is marginal. Across specifications, the coefficient for %CVC ranges from approximately -0.68 to -0.83 ($p = 0.14$-0.08), suggesting a moderate tendency for increased CVC involvement to be linked with lower realized returns. Funding period consistently shows a significant negative effect (-0.145 per unit increase, $p < 0.01$), indicating that longer funding cycles may reduce average returns, potentially reflecting delayed exit timing or prolonged investment horizons, common within cleantechs. Foundation year also exhibits a robust negative relationship with returns (-0.53 to -0.158, $p < 0.01$), implying that younger firms tend to achieve lower financial performance, independent of funding stage or corporate structure. This is expected since this could simply mean that the company still hasn't reached exit yet.

Geographic factors further nuance the results. European firms display significantly lower returns relative to the rest of the world group (-1.29, $p < 0.01$), while North American firms show a negative but not statistically significant effect (-0.64, $p > 0.1$). Cleantech segments indicate that certain sectors (Transportation & Logistics) consistently experience higher returns, highlighting the relevance of sector-specific dynamics in explaining performance outcomes. Overall, the model explains a substantial portion of variation in average returns (R^2 = 28–33%), underscoring that while %CVC may signal company quality for valuation, it does not necessarily translate into higher realized gains.

Exit probability models reveal complementary insights. %CVC shows no statistically significant impact on exit likelihood (coefficients -0.21 to -0.19, $p > 0.1$), suggesting that CVC involvement neither accelerates nor delays exit directly. In contrast, the funding period exhibits a consistent and significant negative effect (-0.047, $p < 0.01$), indicating that extended financing durations reduce the probability of exit. Foundation year also negatively affects exit likelihood (-0.045, $p < 0.01$), further suggesting that more recently founded firms are less likely to exit or have not yet reached an exit. Geographic controls highlight that European firms are significantly less likely to exit (-0.29, $p < 0.05$), while North American firms show no statistically meaningful difference. Base exit probabilities are relatively high (~55%), reflecting a mature or successful subset of cleantech companies.

Overall, these results underscore a subtle but persistent trade-off: while CVC participation enhances valuation, it may depress realized returns without materially affecting exit likelihood, and longer funding cycles consistently reduce both performance outcomes and exit probability. Geographic and sectoral factors further shape these dynamics, emphasizing that performance is influenced by a combination of firm characteristics, funding strategies, and contextual conditions.

4.5 Synthesis and Implications

The collective evidence from the descriptive statistics and regression analyses underscores many unique dynamics in cleantech financing and firm success. CVC participation in the cap table consistently serves as a crucial factor in pricing across financing stages, indicating business quality to investors and producing significant valuation premiums, especially in Series

A and B rounds. Conversely, ESG performance exhibits negligible explanatory power, possibly due to consistently elevated ratings within the cleantech sector and limited cross-firm variability, which constrains its capacity to differentiate firm value (De Lange, 2017).

Despite its positive effect on valuation, a higher %CVC does not result in enhanced financial results. Conversely, regressions of both stage-specific and average returns indicate a consistent negative correlation between %CVC and realized gains. Prolonged funding durations reduce average returns and the probability of an exit. Geographic and sectoral further modulate these effects: European firms systematically achieve lower returns and exit likelihoods, while industry-specific segments indicate sectoral variation in performance outcomes.

This combination of results suggests a possible overvaluation of early-stage cleantech companies influenced by CVC participation in the cap table, signaling effects rather than actual financial robustness. The disparity between value and returns suggests that CVCs, although improving perceived quality, may prioritize strategic, impact-oriented or long-term goals that do not optimize immediate financial results. Investors who depend exclusively on valuation indicators, neglecting structural and strategic complexities, risk overestimating anticipated profits in cleantech ventures.

Due to the exploratory nature of the analysis, marginal significance levels ($\alpha = 10\%$) are employed to identify emergent trends and patterns that warrant consideration. These results highlight the significance of accounting for investor type, capital structure, and funding dynamics in the assessment of cleantech investments. Portfolio strategies that account for these factors, such as those from CVC and IVC, may better align with investment objectives and sector-specific realities.

5. Conclusions

This study examines whether VC funds are suited to invest in cleantech startups, a sector characterized by unique operational, temporal, and performance dynamics that often diverge from standard VC investment frameworks. The research also investigates whether valuation premiums associated with elevated ESG scores or CVC involvement correspond with actual financial results. Quantitative analyses of valuation, returns, and exit likelihood during Seed, Series A, and Series B funding rounds provide empirical evidence regarding these dynamics.

The findings indicate that cleantech ventures significantly diverge from traditional startup models, affirming that early-stage VC investments thesis may inadequately encompass the sector's characteristics. During the Seed stage, neither ESG Score nor %CVC consistently influences value or returns, indicating that investors predominantly depend on qualitative evaluations, including founding teams, product potential, or technological viability (Gaddy, Sivaram, Jones & Wayman, 2017). As companies progress to Series A and B funding rounds, CVC participation increasingly impacts valuation, acting as a reliable indicator of company quality. ESG performance, conversely, remains predominantly non-influential, probably because of the consistently elevated ESG scores inherent in cleantech companies, which limits variability and explanatory power (De Lange, 2017)..

Significantly, although CVC involvement enhances valuation premiums, it correlates with lower actual financial returns, especially from Series A and B rounds investors. Average return regressions indicate a moderate yet consistent negative with %CVC, suggesting once again that increased CVC ownership is associated with diminished financial performance. Prolonged investments durations typically diminish returns and exit probabilities, reflecting the prolonged development and commercialization timelines characteristic of cleantech ventures (Hegeman & Sørheim, 2021). Likewise, younger companies yields diminished returns and exhibit a reduced likelihood of exiting, indicating that certain organizations within the sample may have not yet attained liquidity events. Geographic factors further refine these results: Europeans companies demonstrate lower returns and higher exit probabilities compared to the reference group, while Nort American companies display minimal or negligible effects. Industry-specific dynamics represented by Cleantech Group's sectors, indicate that sectoral features influence performance outcomes, hence emphasizing the heterogeneity across cleantech subsectors.

Taken Together, these findings indicate a consistent disconnect between valuation and performance: although CVC participation improves perceived form quality and valuation, it fails to yield increased investor returns, implying that corporate investors may prioritize strategic, impact-oriented, or long-term goals over immediate financial benefits. ESG factors, although theoretically significant, do not substantially influence value or returns in this high-ESG sample, suggesting that investor focus may be better directed towards capital structure and corporate engagement.

From a practical standpoint, these results highlight the importance of investor type, funding structure, and contextual variables in cleantech financing. Conventional venture capital funds may encounter misaligned expectations stemming from prolonged development timelines, complex exit scenarios, and non-financial goals intrinsic to cleantech companies. Conversely, corporate venture capitalists and impact-oriented funds seem more adept at fostering cleantech growth, leveraging strategic synergies and allowing for prolonged investment timelines. Policymakers seeking to promote sustainable innovation might consider targeted de-risking mechanisms or incentives to facilitate investments in this sector, acknowledging that VC models may be inadequate for achieving significant environmental results.

In conclusion, this study enhances the comprehension of cleantech financing by empirically illustrating that conventional VC frameworks insufficiently reflect the sector's operational and performance reality. CVC involvement enhances valuation premiums but may reduce realized returns, whereas ESG performance exhibits no notable financial impact. These findings underscore the need for distinct strategies that align cleantech sustainability goals with financial objectives, ultimately enabling more effective capital allocation to promote a sustainable economy without disregarding financial benefits to investors.

6. Validity and Limitations

Although useful and repeatable, this methodology's reliance on secondary data and standardized estimating methodologies has drawbacks. Since not all businesses reveal all their financial information, some funding amounts and exit values must be estimated. Additionally, industry medians, rather than firm-specific disclosures, are the basis for equity acquisition percentages.

Internal validity is nevertheless supported by the sample's size, uniform coding techniques, and foundation in peer-reviewed scoring frameworks. The global nature of the dataset and the alignment of methodological decisions with those employed in current scholarly literature suggest external validity.

Despite being methodical, the ESG ranking is based on publicly available descriptions and might not account for all their risks or sustainability efforts. Nonetheless, the framework offers a reliable stand-in for comparison analysis and has been validated in earlier research.

7. Ethical Considerations

Only publicly accessible data and secondary sources, such as Cleantech Group, Crunchbase, and Carta, were used in this study. No private, sensitive, or sensitive data was gathered. All processes adhere to accepted ethical research standards, guaranteeing the confidentiality of any potentially identifiable company information. The research process closely followed the guidelines for responsible data use, academic integrity, and transparency. The methodology offers a strong basis for investigating the connection between investor profiles, financial outcomes, and ESG performance in the cleantech industry. It is based on strict data collection procedures, established analytical frameworks, and a systematic sampling strategy. The outcomes of this strategy will be presented in the upcoming chapters together with their implications for sustainability-driven innovation and venture capital decision-making.

References

Bendig, D., Kleine-Stegemann, L., Schulz, C., & Eckardt, D. (2022). The effect of green startup investments on incumbents' green innovation output. *Journal of Cleaner Production, 376*, 134316.

Hegeman, P. D., & Sørheim, R. (2021). Why do they do it? Corporate venture capital investments in cleantech startups. *Journal of Cleaner Production, 294*, 126315.

Gaddy, B. E., Sivaram, V., Jones, T. B., & Wayman, L. (2017). Venture capital and cleantech: The wrong model for energy innovation. *Energy Policy, 102*, 385–395.

Mukherjee, A., Owen, R., Scott, J. M., & Lyon, F. (2024). Financing green innovation startups: A systematic literature review on early-stage SME funding. *Venture Capital*, 1–27. https://doi.org/10.1080/13691066.2024.2410730

Cumming, D., Henriques, I., & Sadorsky, P. (2016). 'Cleantech' venture capital around the world. *International Review of Financial Analysis, 44*, 86–97.

Tiba, S., van Rijnsoever, F. J., & Hekkert, M. P. (2021). Sustainability startups and where to find them: Investigating the share of sustainability startups across entrepreneurial ecosystems and the causal drivers of differences. *Journal of Cleaner Production, 306*, 127054.

De Lange, D. E. (2017). Start-up sustainability: An insurmountable cost or a life-giving investment? *Journal of Cleaner Production, 156*, 838–854.

Mansouri, S., & Momtaz, P. P. (2022). Financing sustainable entrepreneurship: ESG measurement, valuation, and performance. *Journal of Business Venturing, 37*(6), 106258.

Geissdoerfer, M., Vladimirova, D., & Evans, S. (2018). Sustainable business model innovation: A review. *Journal of Cleaner Production, 198*, 401–416.

Bocken, N., Boons, F., & Baldassarre, B. (2019). Sustainable business model experimentation by understanding ecologies of business models. *Journal of Cleaner Production, 208*, 1498–1512.

Shakeel, J., Mardani, A., Chofreh, A. G., Goni, F. A., & Klemeš, J. J. (2020). Anatomy of sustainable business model innovation. *Journal of Cleaner Production, 261*, 121201.

Neumeyer, X., & Santos, S. C. (2018). Sustainable business models, venture typologies, and entrepreneurial ecosystems: A social network perspective. *Journal of Cleaner Production, 172*, 4565–4579.

Pizzi, S., Corbo, L., & Caputo, A. (2021). Fintech and SMEs sustainable business models: Reflections and considerations for a circular economy. *Journal of Cleaner Production, 281*, 125217.

Bergset, L., & Fichter, K. (2015). Green start-ups–a new typology for sustainable entrepreneurship and innovation research. *Journal of Innovation Management, 3*(3), 118–144.

Bocken, N. M. (2015). Sustainable venture capital–catalyst for sustainable start-up success? *Journal of Cleaner Production, 108*, 647–658.

Döll, L. M., Ulloa, M. I. C., Zammar, A., do Prado, G. F., & Piekarski, C. M. (2022). Corporate venture capital and sustainability. *Journal of Open Innovation: Technology, Market, and Complexity, 8*(3), 132.

Vismara, S. (2019). Sustainability in equity crowdfunding. *Technological Forecasting and Social Change*, *141*, 98-106.

Hörisch, J. (2015). Crowdfunding for environmental ventures: an empirical analysis of the influence of environmental orientation on the success of crowdfunding initiatives. *Journal of cleaner production*, *107*, 636-645.

Blank, S., & Dorf, B. (2020). *The startup owner's manual: The step-by-step guide for building a great company*. John Wiley & Sons.

Ries, E. (2011). *The lean startup: How today's entrepreneurs use continuous innovation to create radically successful businesses*. Crown Business.

Osterwalder, A., & Pigneur, Y. (2010). *Business model generation: A handbook for visionaries, game changers, and challengers*. Wiley.

Thiel, P. (2014). *Zero to one: Notes on startups, or how to build the future*. Crown Business.

Pflaum, S. (2024). *The Founder's Guide to Startup Equity Dilution*. Lighter Capital. https://www.lightercapital.com/blog/the-founders-guide-to-equity-dilution

Gray, D. (2024). *Equity Percentages to Offer Investors at Different Stages*. Equidam. https://www.equidam.com/ranges-of-negotiation-at-different-stages-of-a-startup/

Dowd, K. (2024). *How a decline in dilution is reshaping the fundraising landscape*. Carta Data. https://carta.com/data/dilution-q1-2024/

Cohn, J. B., Liu, Z., & Wardlaw, M. I. (2022). Count (and count-like) data in finance. Journal of Financial Economics, 146(2), 529-551.

Iacobucci, D., Schneider, M. J., Popovich, D. L., & Bakamitsos, G. A. (2016). Mean centering helps alleviate “micro” but not “macro” multicollinearity. Behavior research methods, 48(4), 1308-1317.

Tables

	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count
Independent Variable Base													
Valuation Seed	19,139	2,057	15	15	17,812	317,276	7,651	2,447	99,6	0	100,000	1435	75
Return Seed	17,948	7,392	0	0	64,015	4097,948	38,017	5,724	480,6	0	480,597	1346	75
Independent Variable													
Log Valuation Seed	2,577	0,109	3	3	0,947	0,897	1,796	-0,784	5,5	-1	4,605	193	75
Log Return Seed	0,867	0,189	0	0	1,636	2,675	1,680	1,705	6,2	0	6,177	65	75
Dependent Variables													
CVC%	0,190	0,029	0,125	0,000	0,248	0,061	2,120	1,600	1,0	0	1	14	75
ESG Quintile	2,773	0,159	3,0	1,0	1,381	1,907	-1,177	0,200	4,0	1	5	208	75
Control Variables													
Foundation Year	2012,533	0,501	2012	2014	4,335	18,793	0,815	-0,129	24,0	1999	2023	150940	75
Dummy Group 1	0,187	0,045	0	0	0,392	0,154	0,712	1,641	1,0	0	1	14	75
Dummy Group 2	0,053	0,026	0	0	0,226	0,051	14,857	4,057	1,0	0	1	4	75
Dummy Group 4	0,067	0,029	0	0	0,251	0,063	10,861	3,546	1,0	0	1	5	75
Dummy Group 5	0,093	0,034	0	0	0,293	0,086	6,309	2,853	1,0	0	1	7	75
Dummy Group 6	0,240	0,050	0	0	0,430	0,185	-0,469	1,243	1,0	0	1	18	75
Dummy Group 7	0,027	0,019	0	0	0,162	0,026	34,889	5,997	1,0	0	1	2	75
Europe Dummy	0,333	0,055	0	0	0,475	0,225	-1,521	0,722	1,0	0	1	25	75
North America Dummy	0,640	0,056	1	1	0,483	0,234	-1,691	-0,595	1,0	0	1	48	75

Table 1: Descriptive Analysis for sub sample of valuation and return for Seed Round.

	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count
Independent Variable Base													
Valuation Series A	54,429	7,074	36	20	79,411	6306,069	62,879	7,020	794,8	5	800,000	6858	126
Return Series A	29,149	13,197	0	0	148,140	21945,339	70,619	8,168	1422,2	0	1422,222	3673	126
Independent Variable													
Log Valuation Series A	3,599	0,074	4	3	0,829	0,687	0,775	0,405	5,0	2	6,685	453	126
Log Return Series A	1,182	0,153	0	0	1,720	2,959	0,705	1,235	7,3	0	7,261	149	126
Dependent Variables													
CVC%	0,198	0,022	0,143	0,000	0,249	0,062	2,065	1,561	1,0	0	1	25	126
ESG Quintile	2,960	0,126	3,0	1,0	1,411	1,990	-1,279	0,002	4,0	1	5	373	126
Control Variables													
Foundation	2011,270	0,460	2012	2010	5,167	26,695	10,221	-1,971	43,0	1980	2023	253420	126
Dummy Group 1	0,143	0,031	0	0	0,351	0,123	2,304	2,066	1,0	0	1	18	126
Dummy Group 2	0,056	0,020	0	0	0,230	0,053	13,641	3,927	1,0	0	1	7	126
Dummy Group 4	0,079	0,024	0	0	0,271	0,074	8,049	3,150	1,0	0	1	10	126
Dummy Group 5	0,079	0,024	0	0	0,271	0,074	8,049	3,150	1,0	0	1	10	126
Dummy Group 6	0,230	0,038	0	0	0,423	0,179	-0,322	1,298	1,0	0	1	29	126
Dummy Group 7	0,056	0,020	0	0	0,230	0,053	13,641	3,927	1,0	0	1	7	126
Europe Dummy	0,278	0,040	0	0	0,450	0,202	-1,008	1,004	1,0	0	1	35	126
North America Dummy	0,643	0,043	1	1	0,481	0,231	-1,662	-0,603	1,0	0	1	81	126

Table 2: Descriptive Analysis for sub sample of valuation and return for Series A Round.

Table 3: Descriptive Analysis for sub sample of valuation and return for Series B Round.

	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count
Independent Variable Base													
Valuation Series B	213,582	27,606	139	167	297,324	88401,854	48,344	6,009	2765,6	12	2777,778	24776	116
Return Series B	5,046	1,565	0	0	16,857	284,162	54,638	6,790	153,6	0	153,600	585	116
Independent Variable													
Log Valuation Series B	4,940	0,081	5	5	0,872	0,760	0,608	0,313	5,4	3	7,929	573	116
Log Return Series B	0,780	0,107	0	0	1,153	1,329	1,448	1,427	5,0	0	5,041	90	116
Dependent Variables													
CVC%	0,206	0,024	0,134	0,000	0,259	0,067	1,480	1,425	1,0	0	1	24	116
ESG Quintile	3,052	0,129	3,0	3,0	1,388	1,928	-1,231	-0,054	4,0	1	5	354	116
Control Variables													
Foundation	2011,190	0,456	2011	2011	4,906	24,068	13,733	-2,323	43,0	1980	2023	233298	116
Dummy Group 1	0,129	0,031	0	0	0,337	0,114	3,064	2,239	1,0	0	1	15	116
Dummy Group 2	0,060	0,022	0	0	0,239	0,057	12,207	3,741	1,0	0	1	7	116
Dummy Group 4	0,069	0,024	0	0	0,254	0,065	10,053	3,447	1,0	0	1	8	116
Dummy Group 5	0,086	0,026	0	0	0,282	0,079	7,046	2,987	1,0	0	1	10	116
Dummy Group 6	0,224	0,039	0	0	0,419	0,175	-0,207	1,340	1,0	0	1	26	116
Dummy Group 7	0,060	0,022	0	0	0,239	0,057	12,207	3,741	1,0	0	1	7	116
Europe Dummy	0,267	0,041	0	0	0,444	0,198	-0,880	1,066	1,0	0	1	31	116
North America Dummy	0,638	0,045	1	1	0,483	0,233	-1,691	-0,582	1,0	0	1	74	116

	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count
Independent Variable Base													
Average Return	17,709	6,594	0	0	78,020	6087,146	61,678	7,556	732,4	0	732,444	2479	140
Independent Variable													
Log Average Return	1,030	0,134	0	0	1,582	2,503	0,890	1,330	6,6	0	6,598	144	140
Dependent Variables													
CVC%	0,194	0,021	0,134	0,000	0,246	0,061	1,893	1,500	1,0	0	1	27	140
Funding Period	8,150	0,300	8,0	8,0	3,550	12,603	0,855	0,460	20,0	0	20	1141	140
Control Variables													
Foundation	2011,393	0,433	2011	2010	5,123	26,240	9,653	-1,781	43,0	1980	2023	281595	140
Dummy Group 1	0,143	0,030	0	0	0,351	0,123	2,290	2,063	1,0	0	1	20	140
Dummy Group 2	0,050	0,018	0	0	0,219	0,048	15,648	4,174	1,0	0	1	7	140
Dummy Group 4	0,071	0,022	0	0	0,258	0,067	9,454	3,364	1,0	0	1	10	140
Dummy Group 5	0,079	0,023	0	0	0,270	0,073	8,143	3,167	1,0	0	1	11	140
Dummy Group 6	0,221	0,035	0	0	0,417	0,174	-0,163	1,356	1,0	0	1	31	140
Dummy Group 7	0,057	0,020	0	0	0,233	0,054	13,065	3,857	1,0	0	1	8	140
Europe Dummy	0,307	0,039	0	0	0,463	0,214	-1,304	0,845	1,0	0	1	43	140
North America Dummy	0,607	0,041	1	1	0,490	0,240	-1,830	-0,444	1,0	0	1	85	140

	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count
Independent Variable													
Exit Dummy	0,528	0,042	1	1	0,501	0,251	-2,016	-0,114	1,0	0	1	75	142
Dependent Variables													
CVC%	0,198	0,021	0,134	0,000	0,254	0,065	1,879	1,518	1,0	0	1	28	142
Funding Period	8,099	0,298	8,0	8,0	3,552	12,614	0,837	0,480	20,0	0	20	1150	142
Control Variables													
Foundation	2011,373	0,427	2011	2010	5,089	25,895	9,774	-1,779	43,0	1980	2023	285615	142
Dummy Group 1	0,141	0,029	0	0	0,349	0,122	2,389	2,087	1,0	0	1	20	142
Dummy Group 2	0,049	0,018	0	0	0,217	0,047	15,935	4,208	1,0	0	1	7	142
Dummy Group 4	0,070	0,022	0	0	0,257	0,066	9,654	3,394	1,0	0	1	10	142
Dummy Group 5	0,077	0,023	0	0	0,268	0,072	8,325	3,195	1,0	0	1	11	142
Dummy Group 6	0,232	0,036	0	0	0,424	0,180	-0,365	1,281	1,0	0	1	33	142
Dummy Group 7	0,056	0,019	0	0	0,231	0,054	13,316	3,890	1,0	0	1	8	142
Europe Dummy	0,303	0,039	0	0	0,461	0,213	-1,265	0,867	1,0	0	1	43	142
North America Dummy	0,613	0,041	1	1	0,489	0,239	-1,807	-0,468	1,0	0	1	87	142

Tables 4 & 5: Descriptive Analysis for sub sample of Average Return and Exit Probability.

Valuation by Funding Round	Seed	Series A	Series B
Constant	2,4241***	3,4302***	4,6353***
	(12,862)	(30,675)	(38,09)
ESG Quintile Mean Centered	0,1214	-0,0296	-0,0714
	(209)	(-0,608)	(-1,308)
CVC% Mean Centered	0,5634	1,2527***	1,0552***
	(1,206)	(4,379)	(3,442)
Foundation Year Mean Centered	0,0762***	0,0483***	0,0379**
	(2,852)	(3,566)	(2,422)
Dummy Group 1	0,1906	0,275	0,6662***
	(0,583)	(1,29)	(2,729)
Dummy Group 2	-0,0622	0,2387	0,5147
	(-0,122)	(0,784)	(1,583)
Dummy Group 4	0,4215	0,316	0,4568
	(0,911)	(1,189)	(1,473)
Dummy Group 5	0,0544	0,0238	-0,1265
	(0,135)	(0,091)	(-0,454)
Dummy Group 6	0,2977	0,3247*	0,5634***
	(1,028)	(1,818)	(2,831)
Dummy Group 7	0,6196	0,2622	0,6796**
	(0,888)	(0,837)	(2,027)
Observations	75	126	116
R-squared	0,1458	0,2488	0,2391

Table 6: Regressions Results for Valuation per funding round using Cleantech Group's Sector as control variables

Columns report coefficient estimates and t-statistics (in parentheses) for each variable in each funding round, along with the corresponding constant term. R-squared (R^2) values indicate model fit. Asterisks denote statistical significance at the 10%, 5%, and 1% levels.

Valuation by Funding Round	Seed	Series A	Series B
Constant	3,9449***	3,6591***	4,8583***
	(6,07)	(15,637)	(19,319)
ESG Quintile Mean Centered	0,0769	-0,0226	-0,0712
	(0,977)	(-0,473)	(-1,246)
CVC% Mean Centered	0,3902	1,1544***	0,921***
	(0,915)	(4,266)	(3,032)
Foundation Year Mean Centered	0,0634**	0,0486***	0,0351**
	(2,556)	(3,799)	(2,216)
Europe Dummy	-1,563**	-0,3151	-0,1084
	(-2,332)	(-1,188)	(-0,371)
North America Dummy	-1,3225*	0,0426	0,8282
	(-1,984)	(0,172)	(0,645)
Observations	75	126	116
R-squared	0,1862	0,2536	0,1362

Table 7: Regressions Results for Valuation per funding round using Continents as control variables
Columns report coefficient estimates and t-statistics (in parentheses) for each variable in each funding round, along with the corresponding constant term. R-squared (R^2) values indicate model fit. Asterisks denote statistical significance at the 10%, 5%, and 1% levels.

Return by Funding Round	Seed	Series A	Series B
Constant	0,5137*	0,6906***	0,4961***
	(1,676)	(2,979)	(3,103)
ESG Quintile Mean Centered	-0,2841**	0,0173	-0,0059
	(-2,125)	(0,171)	(-0,083)
CVC% Mean Centered	0,0739	-1,0514*	-0,858**
	(0,097)	(-1,773)	(-2,13)
Foundation Year Mean Centered	-0,1556***	-0,109***	-0,0775***
	(-3,577)	(-3,882)	(-3,77)
Dummy Group 1	1,2119**	0,7601*	0,3986
	(2,277)	(1,719)	(1,243)
Dummy Group 2	-0,2032	0,0217	-0,0482
	(-0,245)	(0,034)	(-0,113)
Dummy Group 4	0,7548	0,3162	0,2306
	(1,003)	(0,574)	(0,566)
Dummy Group 5	0,3478	-0,0493	-0,0855
	(0,53)	(-0,091)	(-0,233)
Dummy Group 6	0,3446	1,3244***	0,9089***
	(0,732)	(3,576)	(3,476)
Dummy Group 7	-1,0384	1,0097	0,3745
	(-0,915)	(1,555)	(0,85)
Observations	75	126	116
R-squared	0,2418	0,2501	0,2494

Table 8: Regressions Results for Return per funding round using Cleantech Group's Sector as control variables

Columns report coefficient estimates and t-statistics (in parentheses) for each variable in each funding round, along with the corresponding constant term. R-squared (R^2) values indicate model fit. Asterisks denote statistical significance at the 10%, 5%, and 1% levels.

Return by Funding Round	**Seed**	**Series A**	**Series B**
Constant	0,8321	2,4915***	1,3832***
	(0,75)	(5,039)	(4,34)
ESG Quintile Mean Centered	-0,2258*	0,0145	0,0001
	(-1,68)	(0,144)	(0,001)
CVC% Mean Centered	-0,5642	-1,2898**	-0,805**
	(-0,775)	(-2,256)	(-2,091)
Foundation Year Mean Centered	-0,1313***	-0,1171***	-0,0812***
	(-3,1)	(-4,329)	(-4,05)
Europe Dummy	-0,5097	-1,9094***	-1,0052***
	(-0,446)	(-3,408)	(-2,712)
North America Dummy	0,3199	-1,2112**	-0,5252
	(0,281)	(-2,307)	(-1,534)
Observations	75	126	116
R-squared	0,2057	0,2262	0,207

Table 9: Regressions Results for Return per funding round using Continents as control variables
Columns report coefficient estimates and t-statistics (in parentheses) for each variable in each funding round, along with the corresponding constant term. R-squared (R^2) values indicate model fit. Asterisks denote statistical significance at the 10%, 5%, and 1% levels.

	Avg. Return	Exit Probability
Constant	1,7017***	0,8345***
	(4,967)	(7,312)
CVC% mean Centered	-0,6762	-0,2112
	(-1,391)	(-1,346)
Funding Period	-0,1453***	-0,0472***
	(-3,987)	(-3,908)
Foundation Year Mean Centered	-0,1582***	-0,0459***
	(-6,088)	(-5,293)
Dummy Group 1	0,9528***	0,0214
	(2,626)	(0,176)
Dummy Group 2	0,3092	0,0928
	(0,569)	(0,51)
Dummy Group 4	0,3568	0,0568
	(0,764)	(0,362)
Dummy Group 5	0,2439	-0,0058
	(0,546)	(-0,039)
Dummy Group 6	1,2683***	0,2508**
	(4,186)	(2,51)
Dummy Group 7	0,6293	0,114
	(1,204)	(0,65)
Observations	140	142
R-squared	0,3323	0,2495

Table 10: Regressions Results for Average Return and Exit Probability using Cleantech Group's Sectors as control variables
Columns report coefficient estimates and t-statistics (in parentheses) for dependent each variable by independent variable (column labels), along with the corresponding constant term. R-squared (R^2) values indicate model fit. Asterisks denote statistical significance at the 10%, 5%, and 1% levels.

	Avg. Return	Exit Probability
Constant	2,9878***	1,0212***
	(6,072)	(6,496)
CVC% mean Centered	-0,834*	-0,1858
	(-1,759)	(-1,274)
Funding Period	-0,1435***	-0,047***
	(-3,907)	(-4,044)
Foundation Year Mean Centered	-0,1533***	-0,0454***
	(-6,008)	(-5,566)
Europe Dummy	-1,2915***	-0,2928**
	(-2,882)	(-2,039)
North America Dummy	-0,644	-0,0388
	(-1,517)	(-0,286)
Observations	140	142
R-squared	0,2838	0,2656

Table 11: Regressions Results for Average Return and Exit Probability using Continent as control variables

Columns report coefficient estimates and t-statistics (in parentheses) for dependent each variable by independent variable (column labels), along with the corresponding constant term. R-squared (R^2) values indicate model fit. Asterisks denote statistical significance at the 10%, 5%, and 1% levels.

Appendix

1. Companies Within the Dataset:

Cleantechs								
1-37			38-74			75-111		
Company Name	Country	Foundation	Company Name	Country	Foundation	Company Name	Country	Foundation
Agreena	Denmark	2018	Descartes Labs	US	2014	Einride	Sweden	2016
Arkeon	Austria	2021	Jupiter	US	2017	Evgo	US	2010
eAgronom	Estonia	2016	Tipa	Israel	2010	Gogoro	Taiwan	2011
PowBio	US	2019	Winnow	UK	2013	Joby Aviation	US	2009
Rumin8	Australia	2021	Electriphi	US	2018	Lilium	Germany	2015
Accure battery intelligence	Germany	2020	Enevate	US	2005	Nuvve	US	2010
Amogy	US	2020	Norsepower	Finland	2012	Peloton	US	2011
Antora	US	2017	Shippeo	France	2014	Proterra	US	2004
AtmosZero	US	2021	Streetlight Data	US	2012	Vulog	France	2006
CorPowerOcean	Sweden	2009	Swiftly	US	2014	Impossible Foods	US	2011
Crux	US	2023	Viriciti	Netherlands	2012	Indigo	US	2014
deepki	France	2014	AeroFarms	US	2004	Advanced Microgrid Solution	US	2013
Energydome	Italy	2019	Apeel Sciences	US	2012	Bidgely	US	2011
Benson Hill	US	2012	Calysta	US	2011	CoolEdge	Canada	2009
Imperfect Foods	US	2015	Farmers Business Network	US	2014	Electron	UK	2015
infarm	Germany	2013	Plenty	US	2014	ferroamp	Sweden	2010
Iron ox	US	2015	Ripple	US	2014	GlassPoint	US	2008
Karma	Sweden	2015	Semios	Canada	2010	Heimdall	Norway	2016
NewLeaf Symbiotics	US	1999	FogHorn	US	2014	LO3 Energy	US	2012
Ynsect	France	2011	Konux	Germany	2014	Open Energi	UK	1999
Citrine	US	2013	Orbital Insight	US	2013	Powerhive	Kenya	2011
Planet	US	2010	Sight Machine	US	2012	Primus Power	US	2009
Vecna Robotics	US	2018	AutoGrid	US	2011	Simple energy	US	2011
Cloud & Heat	Germany	2011	Axiom Exergy	US	2014	SkySpecs	US	2012
ecobee	Canada	2007	Carbon Lighthouse	US	2010	Sonnen	Germany	2010
Enapter	Germany	2017	Dandelion	US	2017	Thermondo	Germany	2012
Envelio	Germany	2017	GreenSync	Australia	2010	Voltus	US	2016
kWh analytics	US	2012	GridBeyond	UK	2007	Actility	France	2010
Parity	Canada	2016	Moixa	UK	2004	Carbon	US	2013
Principle Power	US	2007	Sense	US	2013	Desktop Metal	US	2015
Sierra Energy	US	2004	SolShare	Bangladesh	2015	Caribou Biosciences	US	2011
Smart Wires	US	2010	Stem	US	2009	Cnano Technology	China	2007
Solid Power	US	2011	Sunfolding	US	2012	DCM Biotechnologies	US	2014
Zola Eletric	Netherlands	2011	ubitricity	Germany	2008	EpiGan	Belgium	2010
Axine	Canada	2010	Arzeda	US	2009	FRX Polymers	US	2007
C-Capture	UK	2009	Altered	Sweden	2015	Terramera	Canada	2010
Climacell	US	2016	Bestmile	US	2014	Optoro	US	2010

Cleantechs								
112-124			125-137			138-150		
Company Name	**Country**	**Foundation**	**Company Name**	**Country**	**Foundation**	**Company Name**	**Country**	**Foundation**
BlaBlaCar	France	2006	Farmers Edge	Canada	2005	OSIsoft	US	1980
Byton	China	2016	Aledia	France	2011	Sigfox	France	2010
EasyMile	France	2014	Blue Pillar	US	2006	SpaceTime Insight	US	2007
Flexport	US	2013	Enlighted	US	2009	Bolt Threads	US	2009
Greenlots	US	2008	Geli	US	2010	Enerkem	Canada	2000
Innoviz	Israel	2016	Heliatek	Germany	2006	NuMat Technologies	US	2013
Jing-Jin Eletric	China	2008	Mosaic	US	2011	Aclima	US	2010
Lyft	US	2007	Onzo	UK	2007	OxyMem	Ireland	2013
Moovit	Israel	2012	Powerhouse Dynamics	US	2007	Voltea	Netherlands	2006
Otonomo	Israel	2015	Sunverge	US	2010	ChargePoint	US	2007
Prophesee	France	2014	TAE Technologies	US	1998	Didi Chuxing	China	2012
Ridecell	US	2009	Airware	US	2011	Navya	France	2014
Volta Charging	US	2010	Cosmo Tech	France	2010	nuTonomy	US	2013

2. Venture Capital Funds Within the Dataset

VC Funds				
1-38	**39-76**	**77-114**	**115-152**	**153-190**
7percent Ventures	Balderton Capital	Cisco Investments	Ecap Invest	Foxhelm Ventures
88 Green Ventures	Barclays Sustainable and Impact Banking	Citius VC	eCAPITAL ENTREPRENEURIAL PARTNERS	Fresh Shour Capital
8VC	Bee Partners	Citizen VC	Ecotechnologies Fund	Frog Capital
A-Grade Investments	Bessemer Venture Partners	Civitas Learning Ventures	EDBI	Fuel Capital
Acre Venture Partners	Better Ventures	Clean Energy Finance Corporation	Elemental Impact	FundersClub
Act Venture Capital	BioGenerator	Clean Energy Venture Group	Elaia	Future Energy Ventures
ACVC Partners	Birchmere Ventures	Clay Capital	Elevate Capital	Future Positive Capital
AENU	Blackhorn Ventures	ClearSky	Emerson Collective	G2 Venture Partners
AGORANOV	BlackRock	Clearvision Ventures	Energy Impact Partners	Genoa Ventures
Airspeed Equity	Bloomberg Beta	Climate Capital	Engel Ventures	Giant Ventures
Airbus Ventures	Blue Bear Capital	Climate Investment	Eniac Ventures	GingerBread Capital
Ajax Strategies	Blue Lagoon Capital	Collaborative Fund	Eni Next	Glory Ventures
Alafi Capital	Blueberry Ventures	Commonweal Ventures	Envision Ventures	GOOSE Capital
Allen & Company	Bolt	Comcast Ventures	Epic Ventures	Great Circle Ventures
Aliment Capital	BoxGroup	Conversion Ventures	Essential Capital	Green Bay Ventures
Almi Invest	Bpifrance	Correlation Ventures	Estag Capital	Green Tree Equity
Alpaca VC	Braemar Energy Ventures	Counterpart Advisors	ETF Partners	Greencoat Capital
Alumni Ventures	Breakthrough Energy Ventures	Course Correction Capital	Europe Capital Partners	Greener Capital
AME Cloud Ventures	Bronze Investments	Cowboy Ventures	European Investment Bank	GRC SinoGreen Fund
Amiti Ventures	Building Ventures	Cox Investment Holdings	European Innovation Council	Grok Ventures
Amplify Partners	Business Finland	Crédit Agricole	Evergy Ventures	Ground Up Ventures
Anorak Ventures	Cabiedes & Partners	Crosslink Capital	Evolution VC Partners	GroundForce Capital
Anthemis	Canapi Ventures	Cultivation Capital	Export and Investment Fund	GSR Ventures
AQUA Spark	Capnamic	Cultivian Sandbox Ventures	Fall Line Capital	Gullspång Re:food
ArcTern Ventures	Capricorn Investment Group	DBL Partners	Fenway Summer Ventures	HackCapital
Arctos Ventures	Capricorn Partners	DCVC	Felicis	Hartree Partners
Ardent Venture Partners	Cargill	Decarbonization Partners	First Imagine!	Harvest Road
Argonautic Ventures	Casdin Capital	Demeter	First Round Capital	Haywood Securities Inc.
Ascend Venture Capital	Cathay Innovation	Demeter Partners	Flagship Pioneering	Headline
Astanor Ventures	CEA Investissement	DHS Venture Partners	Flat6Labs	Heritage Group
Aster	CDP Venture Capital	DI Technology	Floodgate	Hi Inov
Atomico	Ceyuan Ventures	DNX Ventures	Flybridge	Highland Capital Partners
ATEL Ventures	Cherry Ventures	Drive Capital	Fontinalis Partners	Horizons Ventures
Autotech Ventures	Cherubic Ventures	DST Global	FoodLabs	HSBC Asset Management
Aviv Venture Capital	Chrysalix Venture Capital	E8 Angels	Formic Ventures	HTGF
AXA Venture Partners	Cipio Partners	E-Fund	Formica Capital	Huron River Ventures
Axeleo Capital	CIV	East Innovate	Founders Fund	IA Ventures
Band of Angels	Circularity Capital	Eberhart Ventures	Founder Collective	IBERIS Capital

VC Funds				
191-228	**229-266**	**267-304**	**305-342**	**343-380**
IDEO	Liberty Mutual Strategic Ventures	NGP Energy Technology Partners	Portugal Ventures	Samsung NEXT
ID Capital	LocalGlobe	Next47	Presidio Ventures	Sand Hill Angels
IDO Investments	Lowercarbon Capital	Norwest Venture Partners	Prelude Ventures	Sarsia
IEG Capital	Lunch Van Fund	North Sky Capital	Project 11 Ventures	Sarsia Seed Management
IFC Venture Capital Group	Lux Capital	Northgate Capital	Promus Ventures	SBK
iLab Ventures	Macquarie Capital	Northzone	Propel(X)	SBVA
Initialized Capital	Maersk Growth	Norrsken VC	Prolog Ventures	Schmidt Family Foundation
Ingka Group	Magna Ventures	Norrsken VCm	Pritzker Group Venture Capital	Searchlight Capital Partners
Incharge Capital Partners	Magma Venture Partners	NRP Zero AS	QED Investors	Seb Greentech Venture Capital
Industry Ventures	Mainport Innovation Fund	Omidyar Network	Quadriplay Venture	Seedcamp
Inven Capital	March Capital	OMERS Ventures	Quadia	Seabed VC
Invest Michigan	MassMutual Ventures	One Peak	R/GA Accelerator	Sequoia Capital
Investinor	Maverick Ventures	One Planet Capital	R/GA Ventures	Serena
Ironwood Ventures	Maveron	One Planet Group	R7 Partners	Serious Change
iRobot	Mayfield Fund	Open Prairie	Radicle Growth	SET Ventures
ISAI	McWin Partners	Opus Capital	Radicle Impact	Shasta Ventures
Iselect Fund	Mercury	Orfin Ventures	Ranch Ventures	SHAKTI
Jacobs Startup	Meson Capital	Orkos Capital	Rapoport Foundation	Sherpalo Ventures
Jane Capital Partners	Middleland Capital	OS Fund	ReGen Ventures	Shrysalix Venture Capital
Japan Energy Fund	Mig Capital	Otive	RECAPEX	Sigma Capital Group
JetBlue Ventures	Mission Bay Capital	OurCrowd	Renewal Funds	Silver Lake Kraftwerk
Jump Capital	Mission Ventures	Outlier Ventures	Reshape	SJF Ventures
Karista	Momentum VC	Overture VC	Revaia	SmartCap
Keiretsu Forum	Mons Investment	Paca Investissement	Revolution	Social Capital
Kerala Ventures	Morado Ventures	Palo Alto Investors	Revolution Growth	SoftBank Vision Fund
Khosla Ventures	MoreVC	Pangaea Ventures	Rho Ventures	Sofimac Innovation
Kinnevik	Morningside	Partech	Rigged Ventures	Sofinnova Partners
Kleiner Perkins	Mustard Seed	Pathbreaker Ventures	Riverstone Holdings	Soulmates Ventures
KLP Norfund Investments	Natexa	Pathfinder	RiverVest	Southern Cross Venture Partners
King Hill Capital	Natacor Inc.	PBJ Capital	Road Ventures	Spring Ventures
Koa Labs	National Grid Partners	Penta Group	Rocketship.vc	Square Peg Capital
Lacuna Sustainable Investments	Nephila Capital	Perot Jain	RockPort Capital	StageOne Ventures
LaunchCapital	Neva SGR	Piedmont Capital Partners	Roda Group	Starlight Ventures
Lead Edge Capital	New Enterprise Associates	Pillar VC	RRE Ventures	Start Up Farms International
Lemnos VC	New System Ventures	Plaug and Play	Ruttenberg Gordon Investments	Starshot Capital
LenX	Newlab	Plug and Play	S2G Investments	Star Farm Ventures
Lewis & Clark AgriFood	NGP Capital	Plum Alley	Saga Pure	Statkraft Ventures
Lewis & Clark Ventures	NGP Energy Capital Management	Polaris Partners	Samarthya Investment Advisors	Steinsvik Family Office

VC Funds				
381-397	**398-414**	**415-431**	**432-448**	**449-464**
Susa Ventures	The House Fund	Tuesday Capital	Vectors	WI Harper Group
Sustainable Conversion Ventures	The Ingenious Group	Trust Ventures	Via ID	Wind Capital
Swedbank	The March Group	Trog Hawley Capital	Victory Capital	Winklevoss Capital
SWaN & Legend Venture Partners	The Nature Conservancy	Trucks Venture Capital	Vietnam Oman Investment	Wirefram Ventures
Synthesis Capital	The Ontario Capital Growth	Truffle Capital	VentureSouth	Women's VC Fund
Systemiq	The Roda Group	UL Ventures	Verizon Ventures	WorlQuant Ventures LLC
Tao Capital Partners	The Syndicate.com	Union Grove Venture Partners	Vertical Partners	Wyse Meter Solutions
Techammer	Thia Ventures	Universal Materials Incubator	Vertex Ventures	Xandex Investments LLP
Tech Capital Partners	Third Derivative	Upbeat Ventures	Vertex Ventures Israel	Xfactor Ventures
Tech Coast Angels	Three Bridges Venture Partners	Upfront Ventures	VNT Management	Xseed Capital
Techstars	Three Cains Group	Upstate Carolina Angel Network	VoLo Earth Ventures	Y Combinator
Techstars Ventures	Tiger Global	Urban Innovation Fund	Volta Circle	Yaletown Partners
Tectonic Ventures	Tola Capital	Ulu Ventures	Voyager Capital	ZGI Capital
Temasek Holdings	Trident Capital	ValueStream Ventures	Vopak Ventures	ZhenFund
Tet Ventures	Trill Impact	Vaekstfonden	Walden Riverwood Ventures	Zouk Capital
The Amherst Fund	Trind Ventures	Valve Ventures	Washington Research Foundation	Zygote Ventures
The California Endowment	TriplePoint Capital	Vectors Angel	WestWave Capital	

3. Corporate Venture Capital Funds Within the Dataset

CVC Funds				
1-38	**39-76**	**77-114**	**115-152**	**153-176**
3ppm	Cox Enterprises	Harmony Auto Holding	Omnitracs	Tencent
A123 Systems	DENSO International America	Hears Ventures	OpenGov	The Hartford
AGL Energy	Dell	Hitachi Ventures	Orstead	The Hive
ATI Technologies	Dell Technologies Partners	Honeywell Ventures	Panasonic	Tin Shed Ventures
Alexandria	Dell Thechnologies Capital	IKEA GreenTech AB	Pattern Energy Group	Tokyo Eletric Power
Alibaba Group	Denso	IP Group	Penske Automotive Group	TotalEnergies Ventures
Alstom	Deutsche Bahn Digital Ventures	Iberdrola	Pentair	Toyota Tsusho
Amazon	Deutsche Telekom Strategic Investments	Infinite Potential Technologies	Propel Capital	Toyota Ventures
Amazon Alexa Fund	Drax Group	Intel Capital	QBE Ventures	Tsing Capital
Aptiv	E.ON	Intersect Power	RATP Dev	Tushholdings
AquaSpark	EDF Renewable Energy	JCI Ventures	RWE	Twynam Agricultural Group
Asahi Kasei	EDP	Just Energy	Renault Group	UPS Ventures
Autodesk	EDP Ventures	Kaluza	Repsol Energy Ventures	Ulopono Initiative
BASF Venture Capital	EIT InnoEnergy	Keolis	SK Innovation	Unilever Ventures
BKK	EIT innoEnergy	Korea Zinc	SLB	Valeo
BMW Group	ESB	LG Technology Ventures	SSE	Volta Energy Technologies
BMW i Ventures	Edison Energy	LS Power	Samsung Catalyst Fund	Volvo Group Venture Capital
BNP Paribas Private Equity	Electrolux	Landis+Gyr	Samsung Venture Investment	YONDEN
BP Ventures	Enel Green Power	Lennar Corporation	Samsung Ventures	Yanmar Ventures
Block	Engie	Lenovo	Sanoh Industrial Co.	Yokogawa Eletric Corp.
Bosch	Ericsson	Lockhead Marin Ventures	Santander Asset Management	Zeon Ventures
Bosch Capital	Ericsson Ventures	Lyse Group	Saudi Aramco Energy Ventures	eBay
Bosch Ventures	Eviny Ventures	MOL PLUS	Schneider Eletric	iSelect
Breakthrough Energy Ventures	Export Development Canada	Magna International	Shell	innogy New Ventures LLC
Breakthrough Fuel	FAW Group	Michelin Ventures	Shell Ventures	
Burge Ventures	Family Offices	Microsoft Climate Innovation Fund	Signal Ventures	
CEC Capital Management LLC	First Philippine Holdings Corporation	Mitsubishi Corporation	SolarCity	
CRADLE	Ford Motor	Mitsubishi Heavy Industries	Solvay	
Castrol innoVentures	Ford Smart Mobility	Mitsui & CO	Sony Innovation Fund	
Caterpillar Ventures	Foxconn Technology Group	Mitsui & Co	Southern Company	
Centrica	Fullshare Holdings	Mitsui Global Investment	Stratasys	
Cintemporary Amperex Technology	GE Ventures	Munich Re/ERGO Corporate Venture Fund	Sumitomo	
Clearway Energy Group	General Eletric	Naver	Suning.com	
Constellation Technology Ventures	General Motors Ventures	Nesta	Sustainable Futures	
Conti Ventures	Google Ventures	NextEra Energy Resources	Sweedish Energy Agency	
Continental	Group8	NextStage	Syensqo Ventures	
Continental Grain Company	Groupe ADP	Novartis	TechAccel	
Cox Automotive	HTC	OKAYA & CO	Temasek Holdings	