VC Funding & Success of Clean Tech Startups: *Impact of Exogenous Demand Shocks*

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Abstract

Using a dataset of 51,184 global early–stage venture capital (VC) financing rounds, we examine the impact of exogenous demand shocks on VC funding and success rates in the clean technology sector. Specifically, we investigate the repercussions of the Fukushima Nuclear Disaster (2011) and the Paris Agreement (2015). Our analysis does not provide support for the hypothesis that exogenous demand shocks significantly affect VC funding, success rates or exits of clean tech startups. Instead, our findings suggest quantifiable pricing signals, notably oil and carbon prices, and early–stage fund supply exert a substantial influence on early–stage clean tech investments. Further, our research only partially confirms the popular notion of clean tech startups exhibiting risk, return, and exit characteristics which deter early–stage VC investor interest overall.

Key Words: Venture Capital, Clean Technology, Demand Shocks

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1 Introduction

Climate change, recognized as a defining challenge of our time, has propelled clean technology startups to the forefront of innovation.[1] These startups, often reliant on venture capital (VC) funding, hold the key to shape the future of the clean tech landscape through the exploration and commercialization of groundbreaking technologies (Nanda et al., 2014). However, the accessibility and success rates of VC funding for clean tech startups are profoundly influenced by various external factors.

Exogenous demand shocks, characterized as sudden, unforeseen events or policy shifts with far–reaching implications, have been acknowledged for their profound impact on industries and investor decisions alike. The Fukushima Nuclear Disaster in 2011 serves as a stark illustration. It resulted in a substantial reduction in investments in nuclear energy projects and ignited renewed interest and investment in renewable energy sources (Antoniuk and Leirvik, 2021). In parallel, the Paris Agreement of 2015, a landmark international accord, set forth stringent targets for limiting global warming and significantly elevated the urgency and commitment to clean technologies worldwide (Casey, 2023). In this paper, we assess the influence of exogenous demand shocks on VC funding and success rates within the clean tech startup sector focussing on these two pivotal exogenous shocks: the Fukushima Nuclear Disaster (2011) and the Paris Agreement (2015). Our research endeavors to address the following research questions:

i) Do positive exogenous shocks in demand for clean technologies exert a significant influence on investor willingness to invest in early–stage clean tech startups?

ii) Do positive exogenous shocks in demand for clean technologies significantly impact the success rates of early–stage VC–backed clean tech startups?

iii) Do positive exogenous shocks in demand for clean technologies significantly impact the occurrence and magnitude of VC–backed clean tech exits?

In our analysis, we employ regression models and a difference–in–differences (DiD) methodology on a dataset of 51,184 global early–stage VC financing rounds. We do not find evidence supporting the hypothesis that positive exogenous demand shocks for clean tech significantly impact early–stage funding, success rates or exits of clean tech companies.

To scrutinize this finding, we propose and test several alternative hypotheses serving as potential explanations for the null result of exogenous demand shock impacts on the willingness of VC investors to fund early–stage clean tech companies. We explore the possibility that early–stage clean tech companies may possess return, risk, and exit characteristics that deter VC investor interest irrespective of demand for clean tech goods. However, our findings only partially support this hypothesis. We consider that early–stage clean tech investments may be more closely linked to enduring regional policies rather than sudden demand shocks. Nevertheless, our analysis does not clearly substantiate this hypothesis. We examine the hypothesis that quantifiable pricing signals, rather than isolated shocks, may underpin early–stage clean tech investments. Notably, our data consistently indicates the influence of oil and carbon price fluctuations on early–stage clean tech funding rounds. We explore the possibility that the broader

[1] Authors use the terms "startup" and "early–stage company" interchangeably and refer to "clean technology" as "clean tech" in the thesis.

economic environment, including factors like interest rates and the availability of early–stage capital, could overshadow exogenous demand shocks in investor decisions and find some support for this notion. Based on signalling theory, we predict signals could significantly influence investor sentiment and confidence in the sector, even in the presence of demand shocks. However, our findings only provide limited evidence for the impact of positive signals. We consider that investors might derive nonpecuniary utility from investing in early–stage clean tech companies. Nevertheless, our analysis does not clearly substantiate this hypothesis. We qualitatively consider levels of risk aversion and information asymmetry for early–stage clean tech investments. We use similar hypotheses to explore why demand shocks for clean technologies may not affect VC–backed clean tech exits. We find a lower probability of clean tech companies achieving exit outcomes compared to non-clean tech companies, with clean tech exits strongly correlating to the overall distribution of VC–backed exits over time, potentially overshadowing demand shocks.

This research makes a substantial contribution to our understanding of the multifaceted challenges and drivers encountered in supporting clean tech innovation. It provides valuable insights for private capital investors and policymakers seeking effective models for funding clean tech innovation. Early–stage investors, often regarded as society's essential technology gatekeepers, have played a pivotal role in fostering waves of technological innovation that transform industries and society at large (Florida and Kenney, 1988). As global efforts to net zero intensify, comprehending the intricacies of early–stage funding for clean tech companies becomes imperative for multiple stakeholders, including policymakers, investors, and entrepreneurs.

The remaining paper is structured as follows. It commences with an exploration of the venture capital model, a historical overview of clean tech VC and background on the Fukushima Nuclear Disaster (2011) and the signing of the Paris Agreement (2015) as exogenous demand shocks in Section 2. Section 3 touches upon previous research and illustrates our contributions. Section 4 establishes our hypotheses and Section 5 encompasses a review of data collection and research design. Section 6 presents our empirical findings. Section 7 includes a discussion of the findings, delves into alternative hypotheses, and highlights limitations and implications of the research. Lastly, Section 8 gives our concluding remarks.

2 Background

Due to the complexity of the research, we include a brief explanation and background of a few central concepts. Understanding these background information and concepts is vital in the context of this thesis and therefore is provided in a separate section.

2.1 The venture capital model

Venture capital (VC) is a form of private equity attuned to startup and early–stage companies. VC investors encompass various types of private capital investors. However, this study primarily focuses on private equity VC, specifically involving equity investments in the early stages of a company's life, such as seed capital and startup stages (Marcus et al., 2013). Generally, these stages are in the company's development interval after basic and applied research was conducted and before large–scale deployment commences (Ghosh and Nanda, 2010). For these development stages, VC serves as a critical financing mechanism, distinguished by its ability to provide substantial capital to high–risk ventures, despite the inherent uncertainties associated with unproven technologies (Gompers and Lerner, 1998).

Within the VC ecosystem, partnerships are central, comprising Limited Partners (LPs) and General Partners (GPs). LPs, representing entities like pension funds, affluent individuals, and sovereign wealth funds, commit financial resources to VC funds, typically for a predetermined investment horizon of eight to ten years, often extendable by one to two years (Lerner and Nanda, 2020). Each VC fund is established as a separate partnership only after securing the necessary commitments from investors. GPs, entrusted with the fiduciary duty of fund management, allocate these resources toward equity investments in early–stage enterprises, with the overarching goal of delivering favourable returns to LPs. As part of their role, GPs receive management fees, usually ranging from 1% to 3% of the committed capital, and, contingent on the success of investments, a share of profits referred to as carried interest (Marcus et al., 2013).

Based on the fund structure, VC investors adhere to a predefined investment horizon, typically spanning a decade. Within this well–defined temporal framework, the primary objective is to allocate capital to startups, subsequently orchestrating profitable exits, often through initial public offerings (IPOs) or strategic acquisitions. Venture capitalists typically have five years to invest the capital and the remaining period to maximize returns (Lerner and Nanda, 2020). This structured temporal parameter serves manifold purposes, including establishing a track record, facilitating subsequent fundraising endeavours, and ensuring timely returns for LPs (Ghosh and Nanda, 2010). Consequently, VCs exhibit a preference for investments where commercial viability is typically established within three to five years, facilitating exits within the fund's lifespan (Gompers and Lerner, 1998).

The *ex post* distribution of VC returns tends to be highly skewed with a substantial portion of VC investments facing the risk of bankruptcy, while the majority of returns originate from a select few investments that perform exceptionally well (Sahlman, 1990). To manage this inherent risk, VCs adopt a staged investment approach, participating in different funding rounds, effectively acquiring a series of real options. These options enable VCs to make informed decisions regarding further financing or the exercise of the abandonment option to discontinue an investment (Gompers, 1995). Typically, VCs reserve multiple times their initial investment for follow–up financing. Evaluations occur in stages, enabling VCs to effectively mitigate the risks associated with early–stage investments (Marcus et al., 2013). This approach ensures efficient allocation of capital, allowing VCs to invest as little as possible in startups that may not succeed and allocate a larger share to those with greater potential. Consequently, startups that maximize the option value of their investments, exhibit capital efficiency, achieve large step ups in value relative to the initial investment when positive information is revealed, and reveal project viability in a short period, become more appealing prospects for VCs (Nanda et al., 2014). Hence, only a very narrow band of technological innovations fit the requirements of institutional VC investors. Even among high–potential firms engaged in innovation, Farre-Mensa et al. (2020) found that only 7 percent of firms that filed for a patent went on to raise institutional venture capital.

2.2 The history of VC in clean tech

A fundamental step in understanding the role of VC in clean tech is to establish a clear definition of this domain. While clean energy is sometimes used interchangeably with clean tech, our research distinguishes between the two, with clean energy representing a subset of clean tech. Specifically, clean energy encompasses areas such as batteries and uninterruptable power supplies, electric utilities, renewable energy (including photovoltaic solar systems and wind systems), biodiesel, biomass and biogas fuels, ethanol fuels, hydrogen fuel, hydropower equipment, renewable energy equipment and services, renewable fuels, stationary fuel cells, thermal solar systems and equipment, and waste to energy systems and equipment (appendix A.1). Clean tech, as we define it, extends beyond clean energy and incorporates environmental services, equipment, and organizations such as waste management, disposal, and recycling services, environmental research and development services, environmental services and equipment (NEC), purification and treatment equipment, environmental consultancy services, and carbon capture and storage (appendix A.1). Despite the distinction between clean tech and clean energy, extant scholarly investigations acknowledge striking similarities in funding patterns and defining factors between these domains (Knight, 2011). This observation suggests the discernments and insights gleaned from investments in clean tech are transferrable and informative for clean energy, and conversely.

The evolution of early–stage VC funding in the clean tech sector can be segmented into distinct phases as observed in the funding patterns apparent in Figure 1.

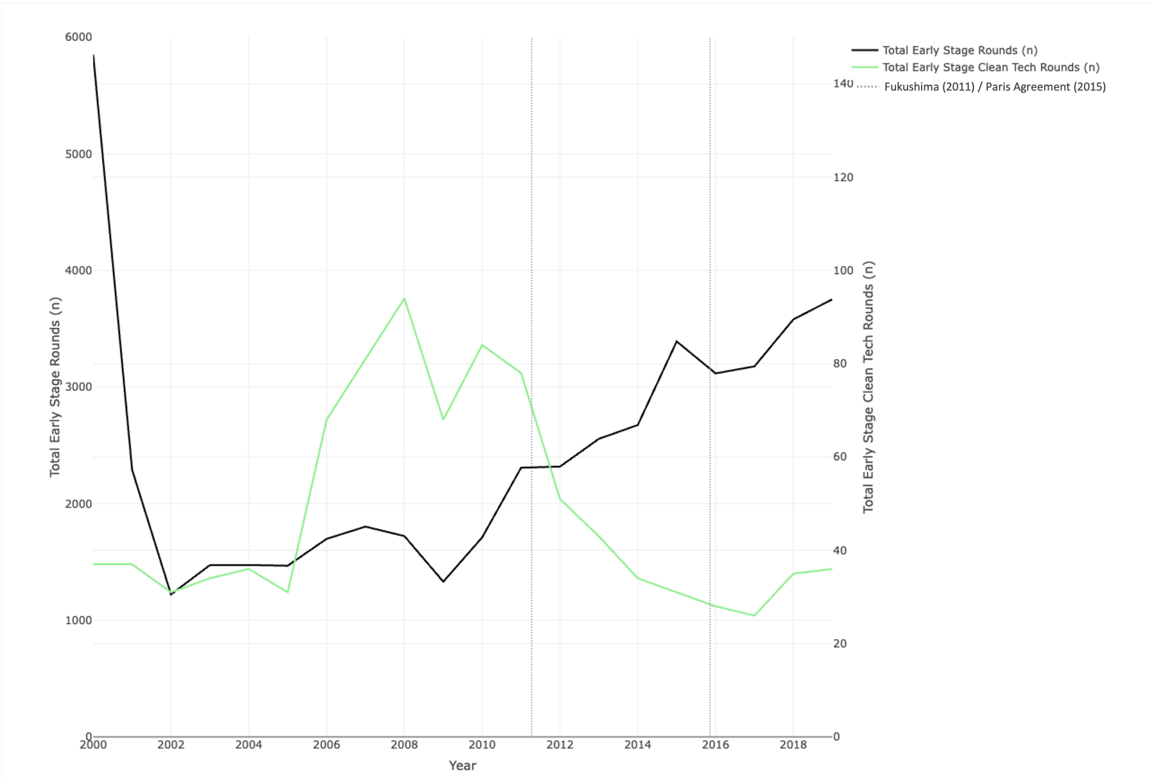

Figure 1: Early–stage funding rounds over time.
The figure shows the sample distribution of early–stage funding rounds over time for clean tech companies compared to other companies. The period shown is 2000–2019.

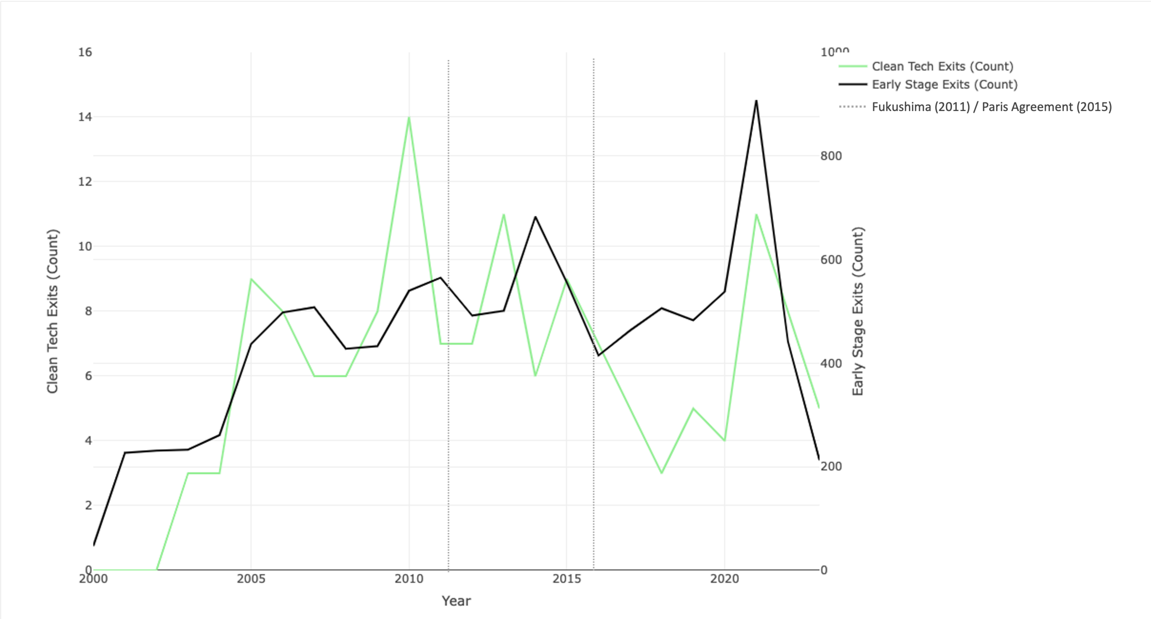

Figure 2: VC–backed exits over time.
The figure shows the sample distribution of VC–backed exits over time for clean tech companies compared to other companies. The sample period is 2000–2023.

Early–stage clean tech investments began to emerge during the pre–dotcom bubble period (1995–2000), albeit as a relatively small component of the VC landscape. The bursting of the dotcom bubble in 2001 prompted VC firms to explore alternative sectors, including clean tech. This era saw the emergence of specialized VC firms like Nth Power and EnerTech Capital dedicated to clean tech investments. By 2005, clean tech investments started generating returns, over–performing the tech sector (Marcus et al., 2013). Consequently, the larger pension funds started investing massively in VC funds with a clean tech focus, which explains the increase in the number of clean tech funds raised (Marcus et al., 2013). Following this influx of interest, between 2005 and 2011, early–stage VC investments in clean tech experienced a steep increase. However, this period presented challenges, including high upfront costs, a predominant focus on technology over viable business models, and external factors such as declining oil prices (Cumming et al., 2016; Gaddy et al., 2017). This period is often described as the Clean Tech Bubble 1.0 (Gaddy et al., 2017). Following the "bust" of the bubble after 2011, early–stage clean tech funding experienced a significant decline. In recent years, early–stage clean tech funding is rising again.

The boom–and–bust pattern is also reflected in the evolution of VC–backed exits as shown in Figure 2. However, the pattern of clean tech companies is less contrarian to the broader market than observed for early–stage companies. Based on lagged effects between early–stage investment and exit, the spike in VC–backed clean tech exits is most pronounced around 2010 and continues until 2013 before we can see a sharp decline in the number of successful VC–backed clean tech exits. Along with the overall exit market, we observe a sharp increase of VC–backed clean tech exits in 2021 followed by rapid declines in 2022 and 2023 year–to–date.

2.3 Exogenous demand shocks

Exogenous shocks, in the context of economic and industrial analysis, refer to sudden, unexpected events or changes in the external environment that have a profound and often disruptive impact on an industry, market, or economy (Chakrabarti, 2015). Exogenous demand shocks can manifest in various ways, such as a sudden increase in public awareness or regulatory mandates. Conversely, they can also result from adverse events, like environmental disasters or geopolitical conflicts, which highlight the vulnerability of existing systems. As the purpose of this paper is to investigate the influence of exogenous demand shocks on global early–stage funding and success rates within the clean tech sector, we focus on the periods preceding and following the Fukushima Nuclear Disaster (2011) and the signing of the Paris Agreement (2015).

The Fukushima Nuclear Disaster on March 11, 2011 was triggered by a massive earthquake and tsunami in Japan causing serious damage to the Fukushima I and II nuclear power plants. Although the reactors automatically and immediately shut down, its water–cooling pumps failed, resulting in several core meltdowns, an overheating of nuclear reactors, explosions of reactor buildings, and severe radiation leaks (Lopatta and Kaspereit, 2014). This accident led to heightened global concerns about the safety and sustainability of nuclear energy. Highlighting the global impact of the Disaster, Hassan et al. (2023) find significant crisis transmission patterns even to countries that usually have little perceived exposure to Japanese country risk. The Fukushima Nuclear Disaster (2011) not only accelerated the phase–out of nuclear power in some countries but also generally increased the emphasis on renewable and clean energy sources as alternatives (Basse Mama and Bassen, 2013). As a result, the Fukushima Nuclear Disaster (2011) serves as a compelling example of an exogenous shock that reshaped the demand for clean technologies.

The Paris Agreement, adopted in 2015, represents a global commitment to combat climate change by reducing greenhouse gas emissions. Globally, 195 signatory countries committed to limit global warming to well below 2 °C above pre–industrial levels (Casey, 2023). Given that previous negotiation at the Copenhagen Climate Change Conference in 2009 did not result in an agreement and opinions of developed and developing countries were highly polarized, the signing of the Paris Agreement is often regarded as highly unanticipated in that parties agreed on and signed a bill to reduce CO_2 emissions (Antoniuk and Leirvik, 2021). The signed international accord has set ambitious targets for transitioning to cleaner energy sources and decarbonizing economies worldwide. McGlade and Ekins (2015) estimate that, globally, a third of oil reserves, half of gas reserves and over 80% of coal reserves must remain unused until 2050 to meet the Paris target. Along with this, to achieve the goals set by the Paris Agreement, a rapid reduction in CO_2 emissions is needed (Rogelj et al., 2016). Following, the agreement has had a direct impact on government policies, regulations, and incentives that promote clean tech solutions.

3 Literature review

To study the impact of exogenous demand shocks for clean tech on early–stage funding, success rates and exits within the clean tech startup sector, we have found some helpful prior areas of research to relate to. One area of interest covers the well–studied public capital markets impact of the Fukushima Nuclear Disaster (2011) and the signing of the Paris Agreement (2015). Other relevant research includes how VC funding behaves after exogenous demand shocks. However, according to our knowledge, only one published paper has researched exogenous demand shock for clean tech in the private capital context. Lastly, we find it helpful to provide some context to the particularities of clean tech financing and their researched impact on VC financing of the space.

3.1 Capital market impact of Fukushima and Paris

The reaction of public market investors to external demand shocks has been covered in various ways in the literature. There is a substantial body of research assessing the effects of exogenous demand shocks caused by adverse events and regulatory mandates on public markets. As most relevant to our study, we focus on the Fukushima Nuclear Disaster (2011) and the signing of the Paris Agreement (2015).

Basse Mama and Bassen (2013) investigate the dynamics of information transmission within the electric utility industry across Europe and Japan following the Fukushima Nuclear Disaster. They employ an event study model and analyze a dataset comprising 111 firms. Their research reveals that the Fukushima Nuclear Disaster had lasting positive effects on the stocks of alternative electric utilities. In contrast, conventional utilities in both Japan and Europe experienced significant financial setbacks in the aftermath of the disaster. Furthermore, the authors identify an increase in the systematic risk of conventional electric utilities and a decrease in the systematic risk of alternative electric utilities across the entire sample. Their study underscores the idea that public investors actively respond to the Fukushima Nuclear Disaster (2011) and the resulting shifts in demand for clean technologies.

Lopatta and Kaspereit (2014) study the impact of the Fukushima Nuclear Disaster on various aspects of energy firms' performance. Specifically, they investigate how the disaster affects stock market returns, factor loadings, and idiosyncratic volatility in energy company shares. Employing an event study methodology, the authors examine abnormal returns to the Carhart four–factor model and shifts in market beta for a sample of 52 nuclear energy firms from 14 different countries in the aftermath of the Fukushima Nuclear Disaster. Furthermore, they conduct regression analyses to assess the relationships between abnormal returns, changes in benchmark model parameters, and alterations in idiosyncratic volatility concerning the firms' commitments to nuclear and renewable energy. The study's key findings suggest that, on average, nuclear energy producers worldwide experienced stock market losses in the wake of the disaster, and the market reactions were significantly influenced by a firm's specific dedication to nuclear power. Firms heavily reliant on nuclear energy witnessed more substantial declines in their share prices following the accident. While a firm's commitment to renewable energy did not directly counteract the impact on share returns, it did help mitigate increases in market beta associated with the event. Lopatta and Kaspereit (2014) underscore the ability of capital market participants to distinguish between firms based on the vulnerability of their product portfolios. They suggest energy companies can proactively manage the rise in market beta caused by the Fukushima Nuclear Disaster (2011) by transitioning some of their energy production from nuclear to renewable or alternative sources. Again, the study provides compelling evidence of investors actively responding to external shocks and induced changes in demand conditions for clean technologies.

Antoniuk and Leirvik (2021) employ an event study approach, examining daily price data from 118 global sector–specific equity exchange–traded funds (ETFs) to explore the influence of unforeseen climate change–related events on stock market returns within climate–sensitive sectors. Utilizing the Fama–French three–factor model, their analysis reveals climate change policy–related events have a substantial impact on returns. Notably, clean energy sector ETFs saw positive gains in response to events like the Fukushima Nuclear Disaster (2011) and the Paris Agreement (2015). Conversely, events that weakened climate change policy were associated with positive abnormal returns for the fossil energy sector. Hence, investors are likely to factor in considerations related to climate risk in their expectations regarding sector growth. This underscores investors' active response to shifts in demand conditions for clean technologies.

Bolton and Kacperczyk (2021) conduct a cross–sectional analysis to investigate the impact of scope 1–3 carbon emissions on US stock returns. Their findings indicate a consistent and statistically significant positive relationship between emissions across all three categories and firms' stock returns. Companies with higher emissions tend to yield higher returns, even after adjusting for factors like size, book–to–market ratio, momentum, and various other predictors of returns, as well as firm–specific characteristics such as the value of property, plant & equipment (PPE) and investment over assets. The authors characterize the increased returns associated with higher emissions as a "carbon premium". Moreover, they propose this carbon premium is influenced by changes in investor awareness of carbon risk. To test this hypothesis, with the Paris Agreement (2015) as a pivotal event, they divide their analysis into two sub–periods: 2005–2015 and 2016–2017. Notably, the carbon premium associated with all three categories of emissions is more pronounced during the 2016–2017 subperiod. This could be interpreted as evidence of investors becoming more attuned to carbon risk following the Paris Agreement. However, the sample size increases after 2015, raising the possibility that the difference in returns before and after the Paris Agreement may be attributed to the inclusion of new firms in the sample. To, among others, address this concern, they conduct a difference–in–differences (DiD) analysis, comparing the returns of firms in a treatment group to those in a control group during the one–year period surrounding the Paris Agreement. The DiD estimation allows them to measure the differential impact on firms with high emissions and those with low emissions. The results show a significant and positive impact on returns for firms with high scope 1 emissions but no significant effects for the other two scopes of emissions. The magnitude of this effect is substantial, implying the Paris Agreement led to an average increase in returns of more than 10.6% over a six–month period. Overall, the study suggests firms are affected differently by policies aimed at reducing carbon emissions. The findings support the notion that investors can distinguish these differences across companies and price in carbon risk, reflecting public market investors' active response to policy shifts.

We contribute to the literature on the impact of the Fukushima Nuclear Disaster (2011) and the signing of the Paris Agreement (2015) on capital markets by specifically focusing our study on the implications for private capital. While the impact on public markets is well-studied, to our knowledge, no published paper investigates the effects of these shocks on clean tech companies in the private capital context.

3.2 Exogenous shocks and VC funding

To the best of our knowledge, only one published study has delved into the behavior of VC funding following exogenous demand shocks. Based on data for US startups founded between 2000 and 2020, van den Heuvel and Popp (2022) test several hypotheses to understand why VC initially did not prove successful in funding new clean energy technologies. The hypothesis of interest posits changes in expected demand – caused by changes in policy support – explain early–stage investment patterns observed for clean energy companies. To examine this hypothesis, the authors conduct a difference–in–differences (DiD) study concerning the unexpected victory of Republican Scott Brown in a special election in January 2010. This event stripped Democrats of a filibuster–proof majority and, according to the authors' assessment, rendered the passage of comprehensive climate legislation highly improbable. As a consequence, the authors anticipate, following this negative exogenous demand shock, Series A investors would become more discerning, elevating their quality standards and reducing their investments in clean energy startups. The study is conducted within six– and nine–month windows around the election date. Assessing the portion of VC portfolios allocated to clean energy startups, the researchers discover 4.9% of startups securing their initial Series A funding before the Brown election were in the clean energy sector, in contrast to only 3.7% after the event. Analyzing the quality standards of investors, they proxy for the quality threshold by *ex post* success with measures of the probability of securing follow–on Series B or C funding, an exit and IPO dummy variable, Cash–on–Cash performance metrics, and a 5x return on invested capital. They compare these metrics for the treatment group of clean energy startups to a control group of information and communication technology (ICT) startups. In the analysis, startups that secured their initial Series A funding just before the Brown election had a notably lower likelihood of securing follow–on Series B and C funding, achieving favorable Cash–on–Cash performance, and attaining 5x returns on invested capital compared to those funded immediately afterward. Although the coefficients for IPO and exit dummy variables affirm the direction of this trend, they do not reach statistical significance. In conclusion, van den Heuvel and Popp (2022) suggest early–stage VC investors tend to adjust their investment behavior in response to shifts in demand for products or services offered by startups. Specifically when VCs anticipate a decline in demand for these offerings, they tend to lower their return expectations. Consequently, they become more cautious in funding early–stage clean energy startups and elevate the quality standards such startups must meet to secure investment. However, these conclusions are based on a limited sample comprising 34 explicitly clean energy startups that secured their initial Series A funding within the nine months before and after the Brown election. Among these, only eleven clean energy startups managed to exit, and only three disclosed exit values.

We add to private capital research by examining two global positive exogenous shocks in demand for clean technologies that have not been previously investigated. Additionally, to our knowledge, this study is the first to specifically address global shocks in demand for clean technologies within the context of private capital markets. Furthermore, our contribution expands the scope of previous research by not only exploring the effects on early–stage funding and success rates but also assessing the impact on exits among clean tech companies.

3.3 Clean tech and VC compatibility

The suitability of the VC model for financing clean tech innovation has generated a substantial body of research, with both general and more nuanced perspectives emerging from studies conducted in the aftermath of the Clean Tech Bubble 1.0 (2005–2011). In a general review, Lerner and Nanda (2020) present computations from Sand Hill

Econometrics capturing the gross returns of all active venture transactions between December 1991 and September 2019. The indexes indicate clean tech investments yield notably lower annualized gross returns (2 percent) compared to software (24 percent), hardware (17 percent), and healthcare (13 percent). While most studies confirm this view on returns (Gaddy et al., 2017; van den Heuvel and Popp, 2022), a more nuanced perspective emerges from studies acknowledging exceptions and specifications within the clean tech sector. Ghosh and Nanda (2010) highlight structural challenges associated with clean tech VC investments, particularly for those involved in the production of clean energy. Gaddy et al. (2017) employ publicly available data to examine the risk–return profile of clean tech companies in the US, contrasting it with medical and software technology firms. Their analysis reveals a discouraging risk–return profile for clean tech investments, primarily attributed to companies engaged in developing new materials, chemistry, or processes that failed to attain manufacturing scale. This nuanced view recognizes the varying suitability of clean tech for VC funding depending on the specific subsectors and venture characteristics. During the debate, several challenges have been linked to the suitability of the VC model for financing clean tech innovation.

First, clean tech startups frequently encounter extended development timelines. This results in illiquidity, making them less appealing to VCs seeking short timeframes for returns (Hargadon and Kenney, 2012; van den Heuvel and Popp, 2022).

Second, the availability of exit opportunities significantly impacts VC investment decisions. Lerner and Nanda (2020) find clean tech startups may face challenges in finding suitable exit paths, such as acquisitions or initial public offerings (IPOs).

Third, clean tech innovation often demands substantial upfront capital, leading to financing constraints for startups. Capital intensity can deter VC investors looking for opportunities with lower capital requirements (Gaddy et al., 2017; Saha and Muro, 2017).

Fourth, clean tech innovations may involve unproven technologies and commercialization uncertainties. VC investors may be cautious about supporting ventures with uncertain paths to market (Gaddy et al., 2017; van den Heuvel and Popp, 2022).

Fifth, clean tech goods may lack differentiation and face substitution challenges, reducing their attractiveness to VCs seeking unique and defensible market positions (Cumming et al., 2016; Gaddy et al., 2017).

Sixth, the success of clean tech startups hinges on market demand for sustainable products and services. Low demand or dependence on external pricing mechanisms can hinder the growth of clean tech startups (Hargadon and Kenney, 2012; Nanda et al., 2014).

Seventh, clean tech startups may be regionally dispersed due to their ties to specific physical locations, making it challenging for VCs to engage with a concentrated portfolio of startups and estimate market size accurately (Knight, 2011; Saha and Muro, 2017).

Eight, clean tech innovations often rely on a complex interplay of technologies, which can increase the complexity of investment decisions (Lerner and Nanda, 2020).

We contribute to the literature on clean tech and VC compatibility by presenting both challenging and confirmatory evidence for hypothesized and observed drivers of global early–stage clean tech investment. Moreover, our study expands the discourse by analyzing not only the determinants of early–stage investment but also the factors influencing clean tech exits.

4 Theoretical framework

Our hypotheses are grounded in the idea that investors, including early–stage venture capitalists, are not passive players in the market but actively respond to external factors, such as changes in demand conditions for clean technologies. Therefore, within the framework of our research, we anticipate the dynamics of demand will play a substantial role and investors will actively respond to exogenous demand shocks. A positive demand shock on clean technologies may signal increased market opportunities, prompting VCs to invest more readily in clean tech startups.

Hypothesis 1 Following a positive exogenous shock in demand for clean technologies, early–stage investors will exhibit an increased willingness to fund clean tech startups.

In the context of a positive exogenous demand shock, clean tech startups often find themselves in a more favorable environment marked by supportive policies and heightened demand. This, in turn, might prompt investors to hold higher expectations for the potential success of these startups. Following, we hypothesize early–stage investors, in response to a positive exogenous demand shock, might relax their investment criteria. This implies startups funded after such demand shock may inherently exhibit lower quality compared to those funded just before, during a period when expectations for clean tech demand were less pronounced. Consequently, we anticipate startups funded post–shock may encounter greater challenges in achieving success.

Hypothesis 2 Clean tech startups funded after a positive exogenous demand shock for clean technologies will experience lower success rates compared to those funded prior to the shock.

Our third hypothesis centers on the impact of external demand shocks on clean tech exit activity. We posit that, following a positive exogenous demand shock, not only early–stage financing but also clean tech exit activity will be stimulated as acquirers and public market investors will actively respond to exogenous demand shocks. This should result in an increase in the number and scale of exits for clean tech companies.

Hypothesis 3 Following a positive exogenous shock in demand for clean technologies, the occurrence and magnitude of clean tech exits will increase.

5 Data & Methodology

We construct deal–by–deal return data for global early–stage companies funded between 1st of January 2000 and 1st of July 2020, allowing us to measure their respective financial successes. We design six regression models to test our hypotheses.

5.1 Data

We match raw data from Refinitiv Eikon early–stage deals with the respective exit database, CapitalIQ and independent research to construct a dataset of deal–by–deal return metrics of global startups funded from 2000 to 2020 with imputation assumptions.

5.1.1 Raw data

We download global VC and PE financing rounds from Refinitiv Eikon database in the period from 1st of January 2000 until 1st of July 2020 consisting of investee company name, investee company nation, investee company TRBC industry classification, round number, investment stage, round equity total, investee company city, total company funding received to date, first and last investment received date, number of investments, investor funds and firms received to date, short and long business description, investee company founded date, investee company current public status, portfolio status, company status, IPO date and PermID. We filter Eikon deal–by–deal investment rounds data by "Investment Stage", focusing only on "Seed" and "Early Stage" deals for the purposes of our research. Out of the 184,586 total investment rounds in the database, our data includes 82,827 relevant investment rounds involving 51,831 unique companies.

Further, we download all 40,243 global exits from the same Refinitiv Eikon database consisting of IPO, Merger, Buyback, Reverse Takover (RTO), Secondary Sales and Write Off exit types between 1st of January 2000 and the date of download, the 20th of September 2023. The data includes the portfolio company name, exit type, exit date announced and completed, ticker symbol, equity proceeds, acquiror name, rank value, deal value, earnout value, purchase price, exit duration, number of deals, number of IPOs, TRBC industry classification, exit date completed/issued, exit ID, deal value, disclosed post round company valuation, disclosed debt contribution, primary security type, disclosed non confidential equity total, investment date, round number, number of investors, investment stage, company PermID, portfolio company status, total funding received to date, short and long business description, current operating stage, current public status, first investment received date, company founded date, most recent financial year end date, company founded year, company nation and city, acquiror nation and public status, M&A date announced, completed, percent acquired, deal status, consideration structure, form of the deal deal value, earnout value and purchase price, primary exchange, offering deal status, proceeds amount all markets, offer price, post offer value, date filed and issued, number of shares offered and overallotment sold, trade date, number of shares offered all markets, number of overallotment shares sold all markets, shares outstanding after offer, first day closing price and selling shareholder shares.

5.1.2 Data manipulation

We pair the investment rounds with exits from the Eikon database according to PermID numbers. For our study, the most important exit types are mergers, acquisitions, and IPOs as we seek for successful exits and their magnitudes. We manually check companies marked as "Went Public" or having an IPO date recorded by Eikon in the investment data but missing the corresponding deal in the Eikon exit database. Since IPO exits are the most important exit type for VC–backed companies (Bygrave et al., 2014), we seek to know the value of these exits. We check against the Capital IQ IPO database and add the missing IPO exit data points. For companies recorded in neither database, we check press releases, news articles and regulatory filings. In cases where we cannot find specific data, we mark these cases as "successful IPO exits" (1x), but not as achieving a significant return (at least 5x) unless there is evidence that no IPO happened (0x). As such, we complete the database with 246 manual entries for cases where we are aware of an IPO and can find the corresponding data by internet search. In cases of missing proceeds but available information about the post offer value, we defensively approximate the ownership stake sold in the IPO as 25% in line with Ritter (2023).

We create a dummy variable for exited companies, labelling IPOs, Mergers, Buybacks, Secondaries and Reverse Takeovers (RTOs) as successful exits. We classify Reverse Takeovers as IPOs. Companies labelled as Write Off are not assigned the successful exit dummy and their proceeds are marked as $0. For companies having several exit events, we take the first event that took place as we assume early–stage investors take the earliest full exit they can. This excludes secondaries if a large exit event was subsequently achieved. For the exit proceeds of non–IPO exits we use the higher of "Exits: Deal Value (USD)" and "Purchase Price Sum (USD)". For 429 companies with missing "Exit Date Completed / Issued" we replace the exit date with "Exit Date Announced / Filed". Since we exclude announced unrealised IPOs, we minimize the possibility of marking incomplete exits as exited. We record 6,069 companies that exited (excluding IPOs and Write Offs) with an undisclosed purchase price. In line with Gaddy et al. (2017), we assume undisclosed exits are often an indication an investment did not return significant capital to investors. For these cases, we proxy the company has successfully exited (1x) but did not yield a 5x, 10x or 100x return. We do not manually check incomplete M&A exits as such instances are highly likely to not have to be publicly disclosed due to the private nature of VC and PE markets.

For 12,769 companies we estimate missing round equity totals by the average round size in the given year. To account for varying ticket sizes, we insert proxy ranges for assumed ownership in the early–stage companies. For companies with ticket sizes below $100,000 we assume 5% ownership on investment date, below $1 million we assume 10%, below $5 million we assume 20% and above we assume 30%. With each additional round of funding we assume 20% dilution to the initial stake. For uncertainty bounds see Appendix A.2.

In total, 38 investment rounds and 244 exits are excluded due to inconsistencies found in the data such as investment happening after the IPO, contradicting information, less than 30 days between investment and exit, no reliable proceeds data, incomplete or in–progress IPOs, secondary sales before an IPO or cases of mergers after an IPO. In total, 609 investment rounds were excluded due to indicated age at funding above 20, round number above 4 and round equity total below $10,000. These data points indicate investment rounds are either not early–stage funding or were creating outlier issues with fractional metrics due to extremely low round equity totals. With such assumptions in place, we calculate Cash–on–Cash (CoC) multiples and categorize them into four distinct categories: exited, 5x, 10x, 100x.

5.1.3 Data limitations

Our classification of clean tech according to TRBC industry codes can be found in Appendix A.1. Other studies might define clean tech either more broadly or more narrowly. Therefore, they might obtain different sample sizes of companies classified as clean tech. In making the sample too wide, we risk including companies not in the clean tech category. In case of too small of a sample, we risk missing clean tech companies with our categorization. Some early–stage companies might have incentives to self–promote themselves in misleading industries to attract more funding, resulting in being categorized incorrectly in the Eikon database. We inherit categorization issues from the database providers within our research.

It is likely we miss instances of IPOs unavailable in our sources Eikon, CapitalIQ IPO or the open internet. IPOs need to be disclosed to regulators; however, companies change names, and early–stage investors might sell their stakes in secondaries before the IPO. Therefore, even disclosed IPO data is challenging to analyze. Merger proceeds are even more difficult to collect reliably due to the private nature of the data. Overall, the data for VC funding rounds and exits is notoriously difficult to find in high quality (Kaplan and Lerner, 2016). If available, more innovative and successful companies are more likely to appear in the data collected by database providers—causing survivorship bias during the data collection. Unsuccessful companies might never share their early–stage rounds as neither the founders nor the investors have an incentive to associate with a failure. Additionally, different definitions of VC and early–stage investing make the collection process even more challenging. Overall, rounds are expected to be missing and errors are present.

5.2 Variables

Dependent variables used in this research can be classified into two categories. Independent variables in our study can be clustered into three distinct types.

5.2.1 Dependent variables

First, company type binary variables simply note whether an event is associated with a specific company type. Clean tech is a binary variable representing whether an early–stage funding round i at time t is for a clean tech startup (1) or not (0). Clean tech exit is a binary variable representing whether the exit I at a time T is for a clean tech startup (1) or not (0). Clean energy is a binary variable representing whether an early–stage funding round i at time t is for a clean energy startup (1) or not (0).

Second, success variables measure whether the funded startup has subsequently achieved success. Success variables proxy for quality of the funded company *ex post* as in van den Heuvel and Popp (2022). Round size clean tech represents the amount of funding the respective clean tech startup received in early–stage funding round i at time t. Follow on is a binary variable representing whether the startup that received early–stage funding round i at time t had a follow–on round (1) or not (0) after the initial funding. Exit is a binary variable indicating whether the startup that received early–stage funding round i at time t had an exit event (1) or not (0). IPO is a binary variable indicating whether the startup that received early–stage funding round i at time t went public with an IPO (1) or not (0). 5X return is a binary variable indicating whether the startup that received early–stage funding round i at time t achieved at least a 5x return on investment (1) or not (0). CoC multiple represents the Cash–on–Cash (CoC) multiple (the ratio of the returned over invested capital) for the startup that received early–stage funding round i at time t. CoC clean tech exit represents the CoC multiple above 1x for a clean tech startup that achieved exit I at a time T.

5.2.2 Independent variables

First, event dummies represent time relevance of the specific company to the exogenous demand shocks. They categorize companies before and after the demand shocks to proxy for the effects of these events. Fukushima funding is an event dummy, indicating post–event (1) or pre–event (0) for early–stage funding round i at time t for the Fukushima

Nuclear Disaster (2011). Paris funding is an event dummy, indicating post–event (1) or pre–event (0) for early–stage funding round i at time t for the Paris Agreement (2015). Fukushima exit indicates post–event (1) or pre–event (0) for the exit I at time T for the Fukushima Nuclear Disaster (2011). Paris exit indicates post–event (1) or pre–event (0) for the exit I at a time T for the Paris Agreement (2015). Shock × Clean tech (Fukushima funding × Clean tech; Paris funding × Clean tech) is an interaction term capturing the combined effect of an event and the type of the startup that received early–stage funding round i at time t.

Table 1: Descriptive statistics

Table 1 reports summary statistics for the variables used for the regression models. The sample period is 2000–2023. All variables are defined in subsection 5.2.

	data type	vars	n	mean	sd	median	min	max
Panel A: Dependent Variables								
Clean tech	integer	1	51,184	0.019	0.137	0	0	1
Round size clean tech	numeric	2	976	5.491	9.937	3.578	0.015	130
Follow on	integer	3	51,184	0.592	0.491	1	0	1
IPO	integer	4	51,184	0.037	0.189	0	0	1
Exit	integer	5	51,184	0.201	0.401	0	0	1
5X return	integer	6	51,184	0.025	0.156	0	0	1
CoC multiple	numeric	7	51,184	1.208	30.461	0	0	5,549
Clean tech exit	integer	8	10,305	0.014	0.117	0	0	1
CoC clean tech exit	numeric	9	50	19.451	29.474	9.705	1.129	174
Clean energy	integer	10	51,184	0.013	0.113	0	0	1
PANEL B: Independent Variables								
Fukushima funding	integer	11	51,184	0.559	0.496	1	0	1
Fukushima funding × Clean tech	integer	12	51,184	0.007	0.085	0	0	1
Paris funding	integer	13	51,184	0.308	0.462	0	0	1
Paris funding × Clean tech	integer	14	51,184	0.003	0.054	0	0	1
Fukushima exit	integer	15	10,604	0.628	0.483	1	0	1
Paris exit	integer	16	10,604	0.378	0.485	0	0	1
Clean tech	integer	1	51,184	0.019	0.137	0	0	1
Clean tech exits	numeric	17	51,184	4.967	3.064	6	0	11
Oil price	numeric	18	51,184	63.269	29.334	59.826	18.681	133.585
MSCI price	numeric	19	51,184	1,532	392	1,472	738	2,358
Interest rate	numeric	20	51,184	1.938	2.131	1.160	0.040	7.030
US	integer	21	51,184	0.463	0.499	0	0	1
Europe	integer	22	51,184	0.233	0.423	0	0	1
APAC	integer	23	51,184	0.228	0.420	0	0	1
Age at funding	numeric	24	51,184	2.053	1.582	2.043	0	14.499
Round size	numeric	25	51,184	6.732	30.557	3.600	0.010	3,300
Fund supply	numeric	26	51,184	21,158	15,295	13,096	4,656	55,709
Average round size	numeric	27	51,184	6.732	3.266	5.180	3.067	14.785
Total funding raised	numeric	28	51,184	38.424	208.930	7.000	0.010	19,038
Investment rounds	integer	29	51,184	2.927	2.723	2	1	36
PRI AUM	numeric	30	51,184	36.831	33.008	32.000	0	103.400
Oil price exit	numeric	31	10,604	72.614	26.620	70.510	18.681	133.585
Interest rate exit	numeric	32	10,604	1.347	1.702	0.250	0.040	6.860
MSCI price exit	numeric	33	10,604	1,733	634	1,610	738	3,231
PRI AUM exit	numeric	34	10,604	50.033	41.546	34.000	0	121
SPAC count exit	numeric	35	10,119	91.358	172.564	20	1	613
CoC average exit	numeric	36	10,604	5.802	4.798	5.305	1.013	19,518
Carbon price	numeric	37	51,184	0.113	8.043	6.190	0	27.900

Second, macro variables proxy for the general macroeconomic conditions for all companies at the time of funding or exit. Return patterns of startups funded during different macroeconomic conditions behave differently as seen in the more profitable vintages of VC funds in times of crises. (Brown et al., 2020) We control for these conditions with the inclusion of the following variables: Clean tech exits is the average number of clean tech exits in the respective year of early–stage funding round i. Fund supply measures the total available early–stage funding in each respective year. Average round size measures the average early–stage funding round size in each respective year. Interest rate is the interest rate prevailing at the month the respective startup received early–stage funding round i or for Interest rate exit when it achieved exit I. MSCI price is the MSCI World Index price at the month the respective startup received early–stage funding round i or for MSCI price exit when it achieved exit I. Oil price is the oil price in USD per barrel prevailing at the month the respective startup received early–stage funding round i or for Oil price exit when it achieved exit I. Carbon Price is the average closing spot price of European Union Allowances (EUA) in EUR per metric ton of CO_2 prevailing at the month the respective startup received early–stage funding round i. PRI AUM represents the assets under management (AUM) of UN Principles for Responsible Investment (PRI) signatories in each respective year from 2006. SPAC count exit is the number of Special Purpose Acquisition Companys (SPACs) in the respective year when a company achieved exit I. CoC average exit represents the respective years average CoC multiple above 1x. Interest rate, MSCI price, and Oil price data are all collected from the FRED database. PRI AUM data is obtained based on PRI reporting, SPAC count exit data is collected from specialist data provider SPAC Analytics, and Carbon price data is obtained from the Refinitiv Eikon database.

Third, micro variables represent firm specific information proxying for heterogenous types of funded companies. Age at funding represents the calculated age of the startup at time t when the respective startup received early–stage funding round i including imputation assumptions. It is included as a control variable to compare companies at similar levels of development. Investment rounds represents the total number of investment rounds for the startup that received early–stage funding round i or achieved exit I. US, Europe, and APAC represent the regions where the startup that received early–stage funding round i or achieved exit I is located, with each coded as (1) if the startup is headquartered in that region and (0) otherwise. US represents United States, Europe Europe and APAC Asia Pacific according to the Eikon database regions. Round size represents the amount of early–stage funding the respective startup received in early–stage funding round i including imputation assumptions. Total funding raised represents the total funding received by the startup that received early–stage funding round i or achieved exit I including imputation assumptions. All monetary variables are in millions of US Dollars (MUSD), unless otherwise specified.

5.3 Research design

In pursuit of a comprehensive understanding of the relationships posited in our research hypotheses, we conduct a series of regression analyses. Building upon the methodological framework set forth by, among others, Stone and Rasp (1991), we deploy a logistic regression model for binary dependent variables, and a standard linear regression model for continuous outcome variables.

For our first hypothesis, to evaluate the impact of exogenous demand shocks on the willingness of investors to invest in early–stage clean tech companies, we analyze both the occurrence of securing early–stage funding and the extent of equity investment. We utilize a binary logit regression model for each exogenous shock to investigate how external demand shocks affect the likelihood of an early–stage funding round being for a clean tech company.

$$\text{Logit}(P(\text{Clean tech}_{i,t})) = \alpha_0 + \alpha_1(\text{Shock}_{i,t}) + \alpha_2\text{Controls}_{i,t} \quad (1)$$

In Regression 1, Clean tech$_{i,t}$ is the dependent variable, representing whether a funding round i at time t is for a clean tech startup (1) or not (0). Shock$_{i,t}$ is an event dummy indicating post–exogenous demand shock (1) or pre–exogenous demand shock (0) for early–stage funding round i at time t. The vector of controls includes variables potentially predicting the likelihood of an early–stage funding round being for a clean tech company. Our coefficient of interest is α_1. A positive and statistically significant α_1 would imply exogenous demand shocks increase the likelihood of an early–stage funding round being for a clean tech company, indicating a positive impact of the exogenous demand shock event on investor interest.

To probe the influence of exogenous demand shocks on the extent of early–stage investment received by clean tech companies, we employ a cross–sectional OLS regression model for each exogenous shock.

$$\text{Round size clean tech}_{i,t} = b_0 + b_1(\text{Shock}_{i,t}) + b_2\text{Controls}_{i,t} \quad (2)$$

In Regression 2, Round size clean tech$_{i,t}$ is the dependent variable, representing the round equity total the respective clean tech startup received in early–stage funding round i at time t. Shock$_{i,t}$ is an event dummy indicating post–exogenous demand shock (1) or pre–exogenous demand shock (0) for early–stage funding round i at time t. The vector of controls includes variables potentially predicting the early–stage equity funding round size for clean tech companies. Our coefficient of interest is b_1. A positive and statistically significant b_1 would suggest exogenous demand shocks lead to higher early–stage equity funding round totals for clean tech companies, indicating increased investor confidence and larger investments in the post–event period.

For our second hypothesis, to gauge the success of funding clean tech startups, we adopt the perspective of early–stage VC investors. In line with the studies by Gaddy et al. (2017) and van den Heuvel and Popp (2022), success, in this context, encompasses the probability of securing follow on funding, an exit event, an IPO, or achieving an outsized return.

Following the approach of van den Heuvel and Popp (2022), we employ a difference–in–differences (DiD) methodology to isolate the causal effect of an exogenous demand shock for clean tech on VC funding decisions. We compare changes in funding behavior before and after the shock, thus allowing us to control for time–invariant and unobserved factors that may influence investment choices.

Further, we study the differential effect of this treatment on a treatment group compared to a control group (Angrist and Pischke, 2009). We compare the success patterns of early–stage clean tech companies with the success pattern of other early–stage companies, excluding clean tech startups, over the same period. Thus, the treatment is the positive demand shock, as embodied by the Fukushima Nuclear Disaster (2011) and the Paris Agreement (2015), the treatment group is early–stage clean tech companies, and our control group is other early–stage companies excluding early–stage clean tech companies. The latter is a good control group due to its many observations and should not be affected by the exogenous demand shocks. Hence, the control group should not incorporate any spillover effects, while still controlling for changes in the broader economic outlook. Because we only consider companies that receive early–stage funding at similar points in time, we are comparing companies at similar levels of development.

The DiD method includes a parallel trends assumption. We assume other early–stage funding rounds provide an appropriate counterfactual trend the early–stage clean tech companies would have followed, if it were not for the exogenous demand shocks. Without the demand shocks, we expect the success behavior to be parallel before and after the respective event. With these shocks, however, we expect the patterns to differ.

We employ five DiD estimations for each exogenous shock with a host of control variables.

$$\text{Logit}(P(\text{Success}_{i,t})) = c_0 + c_1\text{Clean tech}_{i,t} + c_2\text{Shock}_{i,t} + c_3\text{Shock}_{i,t} \times \text{Clean tech}_{i,t} \quad (3)$$

In Regression 3, $\text{Success}_{i,t}$ is a binary dependent variable representing whether the company that received early–stage funding round i at time t had a follow on round (1) or not (0), had an exit event (1) or not (0), went public with an IPO (1) or not (0), or achieved at least a 5x return on investment (1) or not (0).

$$\text{CoC multiple}_{i,t} = d_0 + d_1\text{Clean tech}_{i,t} + d_2\text{Shock}_{i,t} + d_3\text{Shock}_{i,t} \times \text{Clean tech}_{i,t} \quad (4)$$

In Regression 4, $\text{CoC multiple}_{i,t}$ is the dependent variable, representing the Cash–on–Cash (CoC) multiple for the company that received early–stage funding round i at time t. In both regressions, $\text{Shock}_{i,t}$ is an event dummy indicating post–exogenous demand shock (1) or pre–exogenous demand shock (0) for funding round i conducted at time t. $\text{Clean tech}_{i,t}$ is a dummy that represents whether the company that received early–stage funding round i at time t is a clean tech company (1) or not (0). $\text{Shock}_{i,t} \times \text{Clean tech}_{i,t}$ represents the interaction term (difference–in–differences variable) which is the product of the two aforementioned binary variables. The vector of controls includes variables potentially predicting the likelihood of success for early–stage companies. Our coefficients of interest are c_3 and d_3. A negative and statistically significant c_3 would indicate the interaction between being a clean tech company and receiving early–stage funding in the post–exogenous demand shock period has a significant, negative impact on the likelihood of success. A negative and statistically significant d_3 would imply the interaction between being a clean tech company and receiving early–stage funding in the post–exogenous demand shock period significantly and negatively influences the realized CoC multiple. Both would indicate clean tech startups receiving early–stage funding post–shock may encounter greater challenges in achieving success.

For our third hypothesis, to evaluate the impact of exogenous demand shocks on VC–backed clean tech exits, we analyze both the comparative number and scale of clean tech exits. We utilize a cross–sectional binary logistic regression model for each demand shock to investigate how these shocks affect the occurrence of clean tech exits.

$$\text{Logit}(P(\text{Clean tech exit}_{I,T})) = e_0 + e_1\text{Shock}_{I,T} + e_2\text{Controls}_{I,T} \quad (5)$$

In Regression 5, $\text{Clean tech exit}_{I,T}$ is the dependent variable, representing whether the exit I at a specific time T is for a clean tech company (1) or not (0). $\text{Shock}_{I,T}$ is an event dummy indicating post–exogenous demand shock (1) or pre–exogenous demand shock (0) for the exit I at specific time T. The vector of controls includes variables potentially predicting the likelihood of an exit outcome being for a clean tech company. Our coefficient of interest is e_1. A positive and statistically significant e_1 would suggest exogenous clean tech demand shocks increase the likelihood of exits being associated with clean tech companies, indicating a positive impact on the occurrence of clean tech exits following such events.

To probe the influence of exogenous demand shocks on the CoC outcomes for clean tech companies when they achieve exits, we employ a cross–sectional OLS regression model for each exogenous shock.

$$\text{CoC clean tech exit}_{I,T} = f_0 + f_1\text{Shock}_{I,T} + f_2\text{Controls}_{I,T} \quad (6)$$

In Regression 6, CoC clean tech $\text{exit}_{I,T}$ is the dependent variable, representing the CoC multiple greater than 1x for a clean tech startup that achieved exit I at a specific time T. $\text{Shock}_{I,T}$ is an event dummy indicating post–exogenous demand shock (1) or pre–exogenous demand shock (0) for the exit I at a specific time T. The vector of controls includes variables potentially predicting the CoC outcomes for clean tech companies when they achieve exits. Our coefficient of interest is f_1. A positive and statistically significant f_1 would indicate the post–shock period has a significant, positive influence on the CoC multiple of clean tech exits, implying exogenous demand shocks for clean tech are associated with improved CoC outcomes for clean tech companies when they achieve exits.

6 Empirical results

Our analysis does not provide coherent support for the notion that positive exogenous shocks in demand for clean technologies significantly and systematically impact early–stage funding, success rates or exits of clean tech companies.

6.1 Funding of clean tech startups

Regarding Hypothesis 1, we find at best contradictory evidence for the impact of positive exogenous demand shocks for clean technologies on the willingness of investors to fund early–stage clean tech companies. We cannot find a clearly directed, significant impact of demand shocks on neither the likelihood of early–stage funding being for a clean tech company, nor the early–stage equity investment size received by clean tech companies.

Hypothesis 1 Following a positive exogenous shock in demand for clean technologies, early–stage investors will exhibit an increased willingness to fund clean tech startups.

Table 2 shows the results for Regression 1, which examines the impact of exogenous demand shocks on the likelihood of an early–stage funding round being for a clean tech company. The regression and all following regression models are performed for the full dataset, the three–year window, and the one–year window prior and after each exogenous shock. A positive coefficient of the variable of interest (Fukushima funding; Paris funding) would be in line with Hypothesis 1 where we anticipate a favorable impact of the positive demand shock on the likelihood of an early–stage funding round being for a clean tech company.

Table 2: Regression 1: Likelihood of early–stage clean tech funding

Table 2 displays the results of a binary logistic regression model, showing the probability of an early–stage funding round being for a clean tech company. The dependant variable Clean tech$_{i,t}$ represents whether a funding round i at time t is for a clean tech startup (1) or not (0). All independent variables are defined in subsection 5.2. The sample period is 2000–2020. The standard errors are reported in parentheses below. Panel A comprises of the whole dataset, Panel B comprises of a 3 year time window around the events, Panel C comprises of a 1 year time window around the events. *** 0.1% significance; ** 1% significance; * 5% significance; · 10% significance.

	Panel A		Panel B		Panel C	
	Fukushima (2011)	Paris (2015)	Fukushima (2011)	Paris (2015)	Fukushima (2011)	Paris (2015)
Intercept	−3.401 ***	−3.428 ***	−2.011 ***	−4.459 ***	−2.825 *	−1.383
	(0.151)	(0.153)	(0.517)	(0.735)	(1.352)	(2.540)
Fukushima funding	−1.272 ***	—	−0.229	—	0.041	—
	(0.127)		(0.270)		(0.439)	
Paris funding	—	0.751 ***	—	0.040	—	0.211
		(0.198)		(0.280)		(0.805)
Clean tech exits	0.006	0.045 **	0.011	0.020	—	−0.024
	(0.015)	(0.015)	(0.030)	(0.049)		(0.288)
Fund supply	0.000 ***	0.000 ***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Interest rate	−0.017	0.037	−0.169	—	0.878	—
	(0.025)	(0.025)	(0.140)		(3.484)	
Oil price	0.012 ***	0.008 ***	0.006	0.007 *	−0.014	0.005
	(0.001)	(0.001)	(0.004)	(0.004)	(0.012)	(0.021)
PRI AUM	0.010 ***	−0.014 ***	−0.061 ***	—	—	—
	(0.003)	(0.003)	(0.018)			
APAC	−0.848 ***	−0.811 ***	−0.169	−1.282 ***	−0.095	−1.148 **
	(0.123)	(0.123)	(0.243)	(0.257)	(0.423)	(0.426)
Europe	−0.288 **	−0.242 *	0.472 *	−0.143	0.576	−0.487
	(0.106)	(0.105)	(0.219)	(0.226)	(0.380)	(0.427)
US	−0.902 ***	−0.853 ***	−0.330	−1.020 ***	−0.252	−1.040 *
	(0.105)	(0.105)	(0.221)	(0.228)	(0.387)	(0.409)
R^2_N	0.052	0.044	0.037	0.028	0.020	0.019
AIC	9,177	9,259	3,443	2,155	1,300	665.7
df	51,174	51,174	12,313	18,569	4,233	6,471

For the Fukushima Nuclear Disaster (2011), in the full dataset and the three–year window, the coefficient is negative, but it takes a positive direction in the one–year window. However, neither the three–year nor the one–year window coefficients achieve statistical significance. In contrast, the coefficient for the full dataset is statistically significant at 0.1% level. This significant negative coefficient contradicts our Hypothesis 1. Conversely, for the signing of the Paris Agreement in 2015, we observe a positive direction of the coefficient of interest across all three time windows. This aligns with our hypothesis, indicating a positive impact of demand shocks. The coefficient for the full dataset is statistically significant at 0.1% level, whereas the coefficients for the three–year and one–year windows do not attain statistical significance.

Overall, only the coefficients for the full dataset are statistically significant, and these results exhibit a contradiction. The Fukushima Nuclear Disaster (2011) shows an unexpected negative coefficient, and the Paris Agreement (2015) shows a positive coefficient as predicted in Hypotheses 1. Following, we cannot find a clearly directed, significant impact of exogenous demand shocks for the full dataset and find no significant impact for the three–year and one–year windows. Additionally, our model demonstrates notably low pseudo–R^2 values, indicating the model can only explain a small fraction of the variation in the binary response variable. We anticipate this outcome, as the phenomenon of early–stage venture capital investment decisions is inherently complex and challenging to predict accurately. We test our regression model and its independent variables for multicollinearity by calculating the Variance Inflation Factors (VIF). Control variables with a VIF value above the standard threshold value of 10 are excluded for the respective regression (appendix A.3). Thus, we conclude multicollinearity is not a concern for our results (Pallant, 2020).

Table 3 shows the results for Regression 2, which assesses the impact of external demand shocks on the early–stage equity round size received by clean tech companies. We predict a positive coefficient of the variable of interest (Fukushima funding; Paris funding) which implies larger equity funding round sizes for clean tech companies after the positive exogenous demand shock.

Table 3: Regression 2: Equity round size of clean tech companies

Table 3 displays the results of a OLS regression model, showing the equity round size received by clean tech companies. The dependant variable Round size clean tech$_{i,t}$ represents the round equity total the respective clean tech startup received in early–stage funding round i at time t. All independent variables are defined in subsection 5.2. The sample period is 2000–2020. The standard errors are reported in parentheses below. Panel A comprises of the whole dataset, Panel B comprises of a 3 year time window around the events, Panel C comprises of a 1 year time window around the events. *** 0.1% significance; ** 1% significance; * 5% significance; · 10% significance.

	Panel A		Panel B		Panel C	
	Fukushima (2011)	Paris (2015)	Fukushima (2011)	Paris (2015)	Fukushima (2011)	Paris (2015)
Intercept	−2.889 ·	−3.428 ·	8.629	−10.955	71.288 **	−12.754
	(1.533)	(1.773)	(9.357)	(13.880)	(26.043)	(20.821)
Fukushima funding	−1.969 *	—	−1.285	—	0.890	—
	(0.922)		(2.348)		(5.786)	
Paris funding	—	−1.866	—	−2.004	—	1.755
		(2.010)		(3.377)		(3.913)
Average round size	1.025 ***	1.066 ***	−0.458	1.660 ·	−8.961 *	0.210
	(0.150)	(0.274)	(1.426)	(0.855)	(3.807)	(1.528)
Interest rate	−0.254	−0.093	0.861	—	−30.887	—
	(0.199)	(0.182)	(1.435)		(40.895)	
Oil price	0.038 **	0.023 ·	−0.002	0.036	−0.226	−0.047
	(0.015)	(0.013)	(0.043)	(0.039)	(0.149)	(0.112)
APAC	4.294 ***	4.444 ***	5.540 *	2.604	−1.680	2.417
	(1.173)	(1.173)	(2.526)	(2.763)	(5.102)	(2.024)
Europe	1.095	1.239	0.442	1.580	−0.998	0.791
	(1.023)	(1.023)	(2.268)	(2.442)	(4.564)	(2.085)
US	2.127 *	2.293 *	1.475	3.067	0.738	1.116
	(1.013)	(1.012)	(2.298)	(2.458)	(4.641)	(2.003)
$\sqrt{\text{Clean tech exits}}$	−0.279	−0.051	−0.843	0.324	—	6.164
	(0.476)	(0.470)	(1.554)	(3.224)		(6.186)
R^2	0.076	0.072	0.037	0.097	0.048	0.074
$\bar{R}^2$	0.068	0.064	0.017	0.063	0.002	−0.056
df	967	967	395	191	144	50

For the Fukushima Nuclear Disaster (2011), we see a negative direction of the coefficient for the full dataset and the three–year window, which then turns to a positive coefficient in the one–year window. However, only the full dataset coefficient is significant at 5% level. Again, as for Regression 1, a negative coefficient contradicts our Hypothesis 1. Similar to the findings for the Fukushima Nuclear Disaster (2011), we observe a negative direction of the coefficient for the Paris Agreement (2015) in both the full dataset and the three–year window, with a transition to a positive coefficient in the one–year window. However, none of these coefficients attains statistical significance at 10% level.

Overall, only the coefficient for the Fukushima (2011) shock in the full dataset achieves statistical significance, presenting contradictory evidence for Hypothesis 1. However, it is crucial to interpret this coefficient cautiously due to the potential overshadowing effects of the Clean Tech Bubble 1.0 (Figure 1). Again, we observe the R^2 values are very low, especially for the three–year and one–year window. We anticipate this outcome, recognizing the inherent challenges in acquiring accurate data, modeling, and making precise predictions for early–stage equity investments, which we already encounter in the context of the binary investment decision in Regression 1. These challenges are further amplified in the context of Regression 2. We test for multicollinearity and exclude control variables with a VIF value above the value of 10 (appendix A.3). We test for heteroscedasticity by plotting standardized residuals against predicted values, finding no evidence of heteroscedasticity (appendix A.4).

6.2 Success rates of clean tech startups

With respect to Hypothesis 2, our analysis reveals no discernible evidence of a significant impact of positive exogenous demand shocks on the success rates of clean tech startups. This observation holds true for all success proxies considered in our analysis.

Hypothesis 2 Clean tech startups funded after a positive exogenous demand shock for clean technologies will experience lower success rates compared to those funded prior to the shock.

Table 4 shows the results for difference–in–differences (DiD) estimations in Regression 3 which assess the impact of exogenous demand shocks for clean technologies on the success of companies that received early–stage funding prior to and after the respective exogenous shock. In Regression 3, we define success by four binary variables representing whether the startup received a follow on round (1) or not (0), had an exit event (1) or not (0), went public with an IPO (1) or not (0), and achieved at least a 5x return on investment (1) or not (0). The independent variable of interest is the interaction term (Fukushima funding × Clean tech; Paris funding × Clean tech) indicating whether early–stage clean tech companies funded after the positive exogenous demand shock experience a distinct change in success outcomes compared to early–stage clean tech companies funded prior to the respective shock. We predict a negative coefficient indicating lower success outcomes for early–stage clean tech companies funded after the positive exogenous demand shock. This would be supportive of the notion that companies receiving early–stage funding after such a shock may inherently exhibit lower quality and encounter greater challenges in achieving success.

For the Fukushima Nuclear Disaster (2011) and full dataset, the interaction term coefficients for all success metrics are positive which contradicts our prediction of negative coefficients. However, none of the coefficients is significant at 10% level. This also applies

Table 4: Regression 3: Success of clean tech companies

Table 4 displays the results of 4 DiD estimations, showing the respective post–funding success of early–stage companies. $\text{Success}_{i,t}$ is an binary dependent variable representing whether the company that received early–stage funding round i at time t had a follow on round, exit event, IPO, at least a 5x return (1) or not (0). All independent variables are defined in subsection 5.2. The sample period is 2000–2023. The standard errors are reported in parentheses below. Panel A comprises of the whole dataset, Panel B comprises of a 3 year time window around the events, Panel C comprises of a 1 year time window around the events. *** 0.1% significance; ** 1% significance; * 5% significance; · 10% significance.

	Fukushima (2011)				Paris (2015)			
	Follow On	Exit	IPO	5x	Follow On	Exit	IPO	5x
Panel A (full dataset window)								
Intercept	0.461 ***	−1.441 ***	−4.174 ***	−4.099 ***	0.453 ***	−1.801 ***	−4.526 ***	−4.269 ***
	(0.042)	(0.056)	(0.130)	(0.170)	(0.038)	(0.053)	(0.126)	(0.164)
Clean tech	−0.154 ·	−0.693 ***	0.330 *	0.345 ·	−0.143 *	−0.581 ***	0.387 *	0.362 ·
	(0.085)	(0.112)	(0.164)	(0.208)	(0.072)	(0.100)	(0.151)	(0.186)
Fuk. funding	−0.035	−0.690 ***	−0.729 ***	−0.268 **	—	—	—	—
	(0.033)	(0.040)	(0.083)	(0.093)				
FF × CT	0.122	0.279	0.029	0.044	—	—	—	—
	(0.137)	(0.220)	(0.360)	(0.401)				
Paris funding	—	—	—	—	0.250 ***	−0.733 ***	−0.573 ***	−0.557 ***
					(0.032)	(0.045)	(0.094)	(0.112)
PF × CT	—	—	—	—	0.256	0.078	−0.048	0.266
					(0.188)	(0.387)	(0.580)	(0.623)
Fund supply	0.000	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Round size	0.001 **	0.004 ***	0.003 ***	−0.002 *	0.001 **	0.005 ***	0.004 ***	−0.002 *
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Interest rate	−0.019 *	0.061 ***	0.030 ·	−0.003	0.009 ·	0.123 ***	0.105 ***	0.008
	(0.007)	(0.009)	(0.017)	(0.021)	(0.005)	(0.006)	(0.013)	(0.016)
Age at funding	−0.070 ***	0.010	0.067 ***	−0.036 ·	−0.072 ***	0.017 *	0.073 ***	−0.031
	(0.006)	(0.007)	(0.013)	(0.019)	(0.006)	(0.007)	(0.013)	(0.019)
Inv. rounds	—	0.111 ***	0.146 ***	0.073 ***	—	0.114 ***	0.149 ***	0.075 ***
		(0.004)	(0.006)	(0.008)		(0.004)	(0.006)	(0.008)
Tot. fund. r.	—	0.000 ***	0.001 ***	0.001 ***	—	0.000 ***	0.001 ***	0.001 ***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
APAC	−0.321 ***	−0.491 ***	1.037 ***	0.912 ***	−0.333 ***	−0.489 ***	1.030 ***	0.922 ***
	(0.038)	(0.056)	(0.121)	(0.161)	(0.038)	(0.056)	(0.121)	(0.161)
Europe	−0.361 ***	−0.183 ***	0.308 *	−0.071	−0.359 ***	−0.159 **	0.334 **	−0.063
	(0.037)	(0.052)	(0.124)	(0.173)	(0.037)	(0.051)	(0.124)	(0.173)
US	0.564 ***	0.633 ***	0.545 ***	1.007 ***	0.566 ***	0.631 ***	0.554 ***	1.008 ***
	(0.035)	(0.046)	(0.113)	(0.152)	(0.035)	(0.046)	(0.113)	(0.152)
R^2_N	0.035	0.119	0.099	0.066	0.036	0.119	0.096	0.068
AIC	66,797	45,315	14,664	11,215	66,734	45,346	14,703	11,197
df	51,173	51,171	51,171	51,171	51,173	51,171	51,171	51,171
Panel B (3 year window)								
Intercept	0.166	−1.392 ***	−4.870 ***	−4.498 ***	0.456 ***	−1.739 ***	−5.198 ***	−4.758 ***
	(0.133)	(0.168)	(0.423)	(0.447)	(0.085)	(0.130)	(0.328)	(0.397)
Clean tech	−0.290 *	−0.921 ***	−0.056	0.059	0.004	−0.323	0.591	0.907 ·
	(0.138)	(0.207)	(0.333)	(0.374)	(0.198)	(0.312)	(0.524)	(0.471)
Fuk. funding	−0.019	−0.359 ***	−0.355 **	−0.051	—	—	—	—
	(0.047)	(0.055)	(0.123)	(0.125)				
FF × CT	0.240	0.256	0.323	−0.280	—	—	—	—
	(0.215)	(0.339)	(0.573)	(0.699)				
Paris funding	—	—	—	—	0.074	−0.053	−0.066	−0.132
					(0.052)	(0.081)	(0.166)	(0.189)
PF × CT	—	—	—	—	0.197	0.046	−0.241	−0.130
					(0.297)	(0.508)	(0.840)	(0.775)
Fund supply	0.000	0.000	0.000	0.000	0.000	0.000 **	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Round size	0.007 **	0.013 ***	0.019 ***	0.002	0.001 *	0.005 ***	0.005 ***	−0.001
	(0.002)	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Interest rate	−0.052	0.008	0.102	−0.014	0.009	−0.082	−0.453 *	0.098
	(0.039)	(0.044)	(0.090)	(0.103)	(0.055)	(0.086)	(0.188)	(0.199)

table continued on next page

Table 4 – continued

	Fukushima (2011)				Paris (2015)			
	Follow On	Exit	IPO	5x	Follow On	Exit	IPO	5x
Age at fund.	−0.101***	−0.036*	0.047	−0.019	−0.123***	0.023	0.066·	−0.042
	(0.013)	(0.016)	(0.032)	(0.037)	(0.013)	(0.018)	(0.036)	(0.044)
Inv. rounds	—	0.075***	0.204***	0.105***	—	0.038***	0.159***	0.109***
		(0.008)	(0.014)	(0.014)		(0.010)	(0.014)	(0.016)
Tot. fund. r.	—	0.001***	0.001***	0.001***	—	0.000***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
APAC	−0.132	−0.388***	1.380***	1.404***	−0.194**	−1.020***	0.107	0.563
	(0.082)	(0.115)	(0.297)	(0.337)	(0.064)	(0.111)	(0.278)	(0.358)
Europe	−0.306***	−0.238*	0.529·	−0.009	−0.342***	−0.269*	−0.090	0.512
	(0.078)	(0.107)	(0.305)	(0.363)	(0.067)	(0.107)	(0.303)	(0.372)
US	0.830***	0.693***	0.719*	1.224***	0.516***	0.594***	0.990***	1.475***
	(0.075)	(0.098)	(0.284)	(0.326)	(0.063)	(0.094)	(0.260)	(0.341)
R^2_N	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053
AIC	16,026	16,026	16,026	16,026	16,026	16,026	16,026	16,026
df	12,312	12,312	12,312	12,312	12,312	12,312	12,312	12,312
Panel C (1 year window)								
Intercept	0.869*	−1.736***	−5.138***	−5.206***	1.221**	−2.973***	−4.653***	−4.941***
	(0.439)	(0.525)	(1.201)	(1.228)	(0.439)	(0.709)	(1.306)	(1.501)
Clean tech	−0.488*	−0.901*	−0.256	−0.776	−0.075	0.476	0.904	1.885**
	(0.243)	(0.366)	(0.739)	(1.023)	(0.356)	(0.472)	(0.772)	(0.651)
Fuk. funding	−0.031	−0.337*	−0.387	0.049	—	—	—	—
	(0.138)	(0.162)	(0.353)	(0.367)				
FF × CT	0.309	0.064	0.078	−13.275	—	—	—	—
	(0.348)	(0.547)	(1.050)	(447.664)				
Paris funding	—	—	—	—	0.195*	−0.248·	−0.014	−0.058
					(0.084)	(0.132)	(0.254)	(0.285)
PF × CT	—	—	—	—	0.029	−0.863	−0.366	−0.875
					(0.543)	(0.886)	(1.301)	(1.227)
Fund supply	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Round size	0.009*	0.012**	0.030***	0.014·	0.008**	0.009***	0.011***	−0.001
	(0.004)	(0.004)	(0.005)	(0.007)	(0.002)	(0.002)	(0.002)	(0.001)
Interest rate	−0.048	0.640	−0.657	0.738	—	—	—	—
	(1.382)	(1.630)	(3.586)	(3.725)				
Age at fund.	−0.101***	−0.035	0.045	0.035	−0.165	0.007	0.038	−0.112
	(0.022)	(0.026)	(0.053)	(0.056)	(0.022)	(0.031)	(0.059)	(0.082)
Inv. rounds	—	0.068***	0.193***	0.109***	—	0.036*	0.172***	0.129***
		(0.014)	(0.023)	(0.024)		(0.017)	(0.024)	(0.027)
Tot. fund. r.	—	0.001**	0.001***	0.001***	—	0.001**	0.001***	0.001***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
APAC	−0.529***	−0.497**	0.787·	0.770·	−0.321**	−1.344***	−0.667	0.188
	(0.149)	(0.188)	(0.414)	(0.459)	(0.109)	(0.181)	(0.419)	(0.626)
Europe	−0.616***	−0.574**	−0.314	−0.486	−0.315**	−0.402*	−0.154	0.574
	(0.140)	(0.176)	(0.436)	(0.492)	(0.115)	(0.176)	(0.437)	(0.646)
US	0.598***	0.428**	0.071	0.548	0.488***	0.443**	0.813*	1.601**
	(0.137)	(0.162)	(0.391)	(0.433)	(0.108)	(0.153)	(0.372)	(0.591)
R^2_N	0.062	0.069	0.143	0.099	0.031	0.081	0.117	0.085
AIC	5,469	4,378	1,244	1,225	8,528	4,418	1,451	1,183
df	4,230	4,228	4,228	4,228	6,469	6,467	6,467	6,467

for the three–year and one–year window where the interaction term coefficient for the success variable of achieving at least a 5x return on investment turns negative but all coefficients remain insignificant at 10% level.

For the Paris Agreement (2015) and full dataset, the interaction term coefficients for all success metrics except for achieving an IPO are positive which, again, contradicts our prediction. While the interaction term coefficients for the success metrics of achieving at least a 5x return and an exit turn negative in the three–year and one–year window respectively, none of the coefficients is significant at 10% level.

Overall, none of the interaction term coefficients for the two exogenous demand shocks shows statistical significance, providing no evidence for a significant (negative) impact stemming from exogenous demand shocks on the success rates of early–stage clean tech companies funded after the shock. Again, we observe very low pseudo–R^2 values and anticipate this outcome, recognizing the inherent challenges in modeling success as a

Table 5: Regression 4: CoC multiples of clean tech companies

Table 5 displays the results of DiD estimations, showing the respective Cash–on–Cash (CoC) multiples of early–stage companies. $COC_{\mathrm{i,t}}$ is the dependent variable representing the CoC multiple for the company that received early–stage funding round i at time t. All independent variables are defined in subsection 5.2. The sample period is 2000–2023. The standard errors are reported in parentheses below. Panel A comprises of the whole dataset, Panel B comprises of a 3 year time window around the events, Panel C comprises of a 1 year time window around the events. *** 0.1% significance; ** 1% significance; * 5% significance; · 10% significance.

	Panel A		Panel B		Panel C	
	Fukushima (2011)	Paris (2015)	Fukushima (2011)	Paris (2015)	Fukushima (2011)	Paris (2015)
Intercept	1.042	0.894	2.255	3.550 ·	−3.673	0.270
	(0.652)	(0.592)	(3.485)	(1.858)	(4.069)	(2.885)
Clean tech	−0.167	−0.252	0.054	−0.623	−0.736	1.237
	(1.251)	(1.069)	(3.527)	(4.160)	(2.229)	(2.429)
Fukushima funding	−0.229	—	0.968	—	0.362	—
	(0.481)		(1.201)		(1.273)	
FF × Clean tech	−0.003	—	−1.039	—	−0.315	—
	(2.023)		(5.503)		(3.201)	
Paris funding	—	−0.751	—	0.356	—	−0.152
		(0.465)		(1.088)		(0.556)
PF × Clean tech	—	0.639	—	1.112	—	−1.127
		(2.731)		(6.166)		(3.689)
Fund supply	0.000 **	0.000	0.000	0.000 **	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Round size	−0.030 ***	−0.030 ***	−0.072	−0.016 ·	−0.038	−0.006
	(0.005)	(0.005)	(0.055)	(0.009)	(0.039)	(0.004)
Interest rate	0.006	−0.020	−0.062	2.719 *	15.401	—
	(0.109)	(0.079)	(1.005)	(1.143)	(12.721)	
Age at funding	−0.031	−0.024	−0.239	−0.225	−0.067	−0.046
	(0.085)	(0.085)	(0.332)	(0.260)	(0.198)	(0.145)
Investment rounds	0.063	0.064	0.286	0.418 **	−0.182	0.198 *
	(0.053)	(0.053)	(0.190)	(0.152)	(0.120)	(0.082)
Total funding raised	0.014 ***	0.014 ***	0.019 ***	0.007 ***	0.022 ***	0.003 **
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
APAC	0.877	0.901	1.933	0.620	1.825	0.145
	(0.569)	(0.569)	(2.181)	(1.359)	(1.430)	(0.738)
Europe	0.080	0.083	0.549	0.259	0.196	0.187
	(0.562)	(0.562)	(2.075)	(1.422)	(1.343)	(0.785)
US	0.755	0.751	1.869	1.164	1.084	0.795
	(0.526)	(0.526)	(1.980)	(1.320)	(1.301)	(0.728)
R^2	0.009	0.009	0.013	0.003	0.099	0.005
$\bar{R}^2$	0.009	0.009	0.012	0.002	0.096	0.003
df	51,171	51,171	12,310	18,564	4,228	6,467

result of investor–employed quality thresholds for early–stage equity investments. We test for multicollinearity and exclude control variables with a VIF value above the value of 10 (appendix A.3).

Table 5 shows the results for DiD estimations in Regression 4 which evaluates the impact of exogenous demand shocks for clean technologies on the realized Cash-on-Cash (CoC) multiples of companies that received early–stage funding prior to and after the respective exogenous shock. Again, the independent variable of interest is the interaction term (Fukushima funding × Clean tech; Paris funding × Clean tech) indicating whether early–stage clean tech companies funded after a positive exogenous demand shock experience a distinct change in success outcomes compared to early–stage clean tech companies funded prior to the respective shock. We predict a negative coefficient indicating lower realized CoC multiple outcomes for early–stage clean tech companies funded after the positive exogenous demand shock. This would support the notion that early–stage companies funded after such a shock may inherently exhibit lower quality and encounter greater challenges in achieving success.

For the Fukushima Nuclear Disaster (2011), the interaction term coefficient across all time windows is negative in line with our prediction. However, all coefficients are insignificant at 10% level. For the signing of the Paris Agreement (2015) the interaction term coefficients in the full dataset and the three–year window are positive against our expectations, but the coefficient takes a negative direction in the one–year window. Still, none of the three coefficients is significant at 10% level.

Again, overall, none of the interaction term coefficients show statistical significance, providing no evidence for a significant (negative) impact stemming from exogenous demand shocks on the realized CoC multiples of clean tech companies. We, again, observe anticipated, low R^2 values. We test for multicollinearity and exclude control variables with a VIF value above the value of 10 (appendix A.3). We test for heteroscedasticity by plotting standardized residuals against predicted values, finding no evidence of heteroscedasticity (appendix A.4).

6.3 Clean tech exits

Examining Hypothesis 3, our analysis reveals no evidence of a significant impact of exogenous demand shocks for clean technologies on clean tech exits. We cannot find a significant impact on neither the likelihood of an exit outcome being for a clean tech company nor the scale of clean–tech exits.

Hypothesis 3 Following a positive exogenous shock in demand for clean technologies, the occurrence and magnitude of clean tech exits will increase.

Table 6 shows the results for Regression 5, which examines the impact of exogenous demand shocks for clean tech on the likelihood of an exit outcome being for a clean tech company. A positive and significant coefficient of the variable of interest (Fukushima exit; Paris exit) would be in line with Hypothesis 3 and suggest exogenous demand shocks for clean tech increase the likelihood of exits being associated with clean tech companies. This would support the notion of a positive impact on the occurrence of clean tech exits following such shocks.

For the Fukushima Nuclear Disaster (2011), in the full dataset and the three–year window, the coefficient is negative against our expectations but takes a positive direction in the one–year window. However, only the three–year window coefficient is significant

Table 6: Regression 5: Likelihood of clean tech exits

Table 6 displays the results of a binary logistic regression model, showing the occurrence of clean tech exits. Clean tech $\text{exit}_{\text{I,T}}$ is the dependent variable representing whether the exit I at a specific time T is for a clean tech company (1) or not (0). All independent variables are defined in subsection 5.2. The sample period is 2000–2023. The standard errors are reported in parentheses below. Panel A comprises of the whole dataset, Panel B comprises of a 3 year time window around the events, Panel C comprises of a 1 year time window around the events. *** 0.1% significance; ** 1% significance; * 5% significance; · 10% significance.

	Panel A		Panel B		Panel C	
	Fukushima (2011)	Paris (2015)	Fukushima (2011)	Paris (2015)	Fukushima (2011)	Paris (2015)
Intercept	−3.322 ***	−3.332 ***	−4.093 ***	−6.789 ***	−18.003	−24.835
	(0.386)	(0.392)	(0.873)	(1.605)	(1,191.791)	(6,506.902)
Fukushima exit	−0.455	—	−1.127 ·	—	12.495	—
	(0.322)		(0.617)		(1,191.790)	
Paris exit	—	−0.199	—	−1.178	—	14.242
		(0.446)		(1.367)		(6,506.902)
APAC	−0.629 *	−0.633 *	—	−17.034	—	−17.390
	(0.320)	(0.320)		(1,084.452)		(1,748.658)
Europe	−0.643 *	−0.651 *	0.145	−0.732	−0.113	−1.811
	(0.278)	(0.278)	(0.456)	(0.685)	(1.014)	(1.263)
US	−1.395 ***	−1.401 ***	−0.626	−1.502 *	0.142	−1.489 ·
	(0.250)	(0.250)	(0.400)	(0.603)	(0.784)	(0.875)
Interest rate exit	−0.060	−0.018	−0.222	−0.002	−0.237	−0.139
	(0.059)	(0.057)	(0.236)	(0.174)	(0.323)	(0.245)
PRI AUM exit	0.003	0.001	0.013	0.011	0.017 ·	0.022
	(0.004)	(0.006)	(0.009)	(0.031)	(0.009)	(0.054)
MSCI price exit	—	—	—	0.002	—	0.003
				(0.001)		(0.002)
Oil price exit	0.004	0.002	0.009	−0.018	0.001	−0.019
	(0.004)	(0.004)	(0.007)	(0.018)	(0.012)	(0.029)
SPAC count exit	−0.001	0.000	−0.001	−0.002	—	−0.004
	(0.001)	(0.001)	(0.001)	(0.002)		(0.003)
R^2_N	0.026	0.025	0.022	0.088	0.029	0.145
AIC	1,395	1,396	440.8	220.1	157.2	96.12
df	9,691	9,691	2,732	2,248	996	761

at 10% level. The Paris Agreement (2015) coefficients shows the same pattern and none of the three coefficients is significant at 10% level.

Overall, only one of the variable of interest coefficients for the two exogenous demand shocks shows statistical significance. As the significant coefficient is negative against our expectations, we find no evidence for a significant positive impact stemming from exogenous demand shocks on the likelihood of an exit outcome being for a clean tech company. Again, our model demonstrates notably low pseudo–R^2 values. We anticipate this outcome as the drivers of company exits are inherently complex and challenging to predict. We test for multicollinearity and exclude control variables with a VIF value above the value of 10 (appendix A.3).

Table 7 shows the results for Regression 6, which assesses the impact of external demand shocks on the CoC–multiple outcomes larger than 1x for clean tech companies when they achieve exits. We predict a positive coefficient of the variable of interest (Fukushima exit; Paris exit) suggesting exogenous shocks in demand for clean technologies are associated with improved CoC–multiple outcomes for clean tech companies when they achieve exits.

Due to the small sample size, we conduct Regression 6 only for the time window of the full dataset. For both, the Fukushima Nuclear Disaster (2011) and the Paris Agreement (2015), the coefficient of the variable of interest is positive and, hence, in line with our expectations. However, both coefficients are not significant at 10% level. Following,

Table 7: Regression 6: CoC multiples of clean tech exits

Table 7 displays the results of a OLS regression model, showing the Cash-on-Cash multiples of clean tech exits larger than 1x. CoC clean tech $\text{exit}_{\text{I,T}}$ is the dependent variable representing the CoC multiple above 1x for a clean tech startup that achieved exit I at a specific time T. All independent variables are defined in subsection 5.2. The sample period is 2000–2023. The standard errors are reported in parentheses below. *** 0.1% significance; ** 1% significance; * 5% significance; · 10% significance.

	Fukushima (2011)	Paris (2015)
Intercept	7.383	11.110
	(26.935)	(26.134)
Fukushima exit	9.022	—
	(14.810)	
Paris exit	—	0.464
		(13.155)
CoC average exit	1.582	1.215
	(1.123)	(1.072)
Interest rate exit	0.790	0.189
	(2.596)	(2.419)
PRI AUM exit	−0.125	—
	(0.202)	
Oil price exit	0.304	0.340 ·
	(0.196)	(0.190)
US	−1.811	−4.413
	(16.856)	(16.300)
Europe	−12.204	−14.858
	(17.902)	(17.302)
APAC	11.756	9.950
	(18.325)	(17.944)
Total funding raised	0.033	0.033
	(0.046)	(0.046)
Round size	−0.948 ·	−0.993 ·
	(0.524)	(0.513)
Investment rounds	−3.959 ·	−4.171 *
	(1.992)	(2.027)
Fund supply	0.000	0.000
	(0.001)	(0.001)
Age at funding	−1.370	−1.495
	(2.815)	(2.789)
R^2	0.337	0.329
$\bar{R}^2$	0.098	0.112
df	36	37

we are not able to provide evidence for a significant (positive) impact stemming from exogenous demand shocks on CoC–multiple outcomes for clean tech companies. Again, we observe the R^2 values are very low. We attribute this to the inherent challenges in acquiring accurate data, modeling, and making precise predictions for company exits, which we already encounter in the context of the binary exit outcome in Regression 5. However, these challenges are further amplified in the context of Regression 6. We test for multicollinearity and exclude control variables with a VIF value above the value of 10 (appendix A.3). We test for heteroscedasticity by plotting standardized residuals against predicted values but could not rule out heteroscedasticity based the pattern observed (appendix A.4). Therefore, we perform Breusch–Pagan tests for heteroscedasticity. We fail to reject the null hypothesis based on p–values of 0.2049 and 0.2704 respectively. This suggests no strong evidence to support the presence of heteroscedasticity in our regression model and we conclude the assumption of homoscedasticity is not violated.

6.4 Robustness

For all regressions, to improve the model's accuracy, we control for factors that might impact early–stage funding, success rates or exits of clean tech companies irrespective of exogenous demand shocks. We utilize a set of observable control variables to capture broader market, sector–level, and company–level dynamics. Further, we proxy for differential regional impacts of the demand shocks by including binary control variables indicating the regions of US (US), Europe (Europe), and Asia Pacific (APAC) in our regression models.

To account for uncertainty in imputed variables, we calculate the impact of changing the assumed ownership for early–stage investors on Cash–on–Cash (CoC) multiple ranges. Comparing the observations for uncertainty bounds of 10%, 20%, and 30% dilution for each additional round of funding, we find no clearly directed changes in the share of early–stage clean tech companies that achieved the respective CoC multiple ranges (Appendix A.2). Still, based on the few observations for outsized returns, the share of early–stage clean tech companies achieving outsized returns is sensitive by nature.

We address the difficulty in defining clean tech startups by running a control regression for the subsample of clean energy startups. We explicitly focus on the Fukushima Nuclear Disaster (2011) to address concerns that the Nuclear Disaster and the respective demand shock would have had the most impact on early–stage companies directly involved in producing and storing clean energy. We include all early–stage companies defined as clean energy in our data sample (appendix A.1) and focus on Regression 1 due to the

Table 8: Event window

Table 8 shows the number of observations in the dataset in each studied window before and after respective events. The sample period is 2000–2023.

	Full dataset		3 year window		1 year window	
	Before	After	Before	After	Before	After
Fukushima (11. 3. 2011)	22,555	28,629	4,972	7,345	1,866	2,369
out of which clean tech	*607*	*369*	*241*	*161*	*79*	*71*
Paris Agreement (12. 12. 2015)	35,410	15,774	8,658	9,916	3,366	3,110
out of which clean tech	*829*	*147*	*109*	*90*	*33*	*25*

large number of observations. Our results remain consistent and robust, as detailed in Appendix A.5.

We study three time windows: A) the full dataset, B) a three–year window, and C) a one–year window prior and after the exogenous demand shock. The tighter windows are more targeted but have fewer observations as shown in Table 8.

This methodology serves multiple purposes. First, we examine both short–term and long–term impacts. Second, we account for the potentially differential or diminishing impact of exogenous demand shocks and related policies over time. Third, we proxy for lagged time effects of early–stage companies to develop technologies and business models in response to these shocks, and for early–stage investors to recognize and react to those changes.

To account for outliers, we use Cook's distance to identify data points that have a significant impact on the estimates of the regression coefficients, and thus on the overall fit of the models. Cook's distance quantifies the impact of individual data points on the estimated coefficients and overall model fit. We use an established threshold for identifying influential data points set at 4/n (Snijders and Bosker, 2011). We find no data points in our dataset exceeding the applied Cook's distance threshold. Thus, we find no indication of influential outliers in our regression models.

7 Discussion

Based on our empirical results, we present evidence not supporting the assertion that positive exogenous demand shocks for clean technologies significantly and systematically influence early–stage funding, success rates, or exits of clean tech companies. This outcome is somewhat unexpected, given the extensive body of literature suggesting investors are not passive actors in the market and actively respond to external factors, such as shifts in demand conditions for clean technologies. However, previous research was largely focused on public markets where investment processes and information flow differ significantly from private markets.

Referring to the slim body of private market research, our findings do not align with those of van den Heuvel and Popp (2022), who discovered, following a negative demand shock, early–stage investors tend to allocate a smaller share of their portfolio to clean energy companies. Additionally, in their analysis, clean energy startups securing Series A funding after the negative demand shock tend to outperform those funded before the shock. Van den Heuvel and Popp (2022) focus on a negative exogenous demand shock. Hence, investors might only react to negative exogenous demand shocks and not to positive ones. Nevertheless, given the evidence from public markets, this seems unlikely. Therefore, we find no compelling reasons why their findings should not be transferred robustly to positive exogenous demand shocks. However, van den Heuvel and Popp (2022) restrict their study to a time window of six to nine months around the demand shock event, resulting in a small sample size of 34 explicitly clean energy startups. This raises concerns about the robustness of their findings. Further, the study uses a single case study of an exogenous demand shock, which may limit the power of statistical inferences.

To further support our results, we formulate several hypothesis exploring why exogenous shocks in demand for clean technologies might not significantly affect early–stage funding, success rates, or exits of clean tech companies.

7.1 Funding of clean tech startups

Regarding Hypothesis 1, we aim to assess why exogenous demand shocks for clean technologies might not impact the willingness of investors to fund early–stage clean tech companies. We hypothesize this might be due to the presence of other factors exerting a strong, potentially overshadowing, influence on early–stage investment decisions. Drawing from previous research and observed patterns in our dataset, we present several alternative hypotheses potentially serving as an explanation for our empirical results.

7.1.1 Return, risk and exit characteristics

Hypothesis I Early–stage clean tech companies may possess return, risk, and exit characteristics that deter early–stage investor interest irrespective of exogenous demand shocks for clean technologies.

First, as addressed in our literature review, it is commonly mentioned early–stage clean tech companies generally may possess return, risk, and exit characteristics that deter early–stage investor interest irrespective of exogenous demand shocks. To justify the decisions they make, early–stage investors must have confidence they will earn a good return. Hargadon and Kenney (2012) maintain this is the Achilles' heel of clean tech investment. The category must hold its own against the other categories in which early–stage investors can invest. For early–stage investors, successful investments are those from which they have profitably exited in a reasonable time frame and achieved a significant capital gain (Zider, 1998). Following, early–stage investment return is a product of three variables: (1) the purchasing price (including dilution) the investor paid for the venture investment, (2) the sales price the investor gains from exiting the venture investment, and (3) the time between the investment and the exit (Wüstenhagen and Teppo, 2013). Adding to the existing literature, to assess the suitability of the VC model for financing early–stage clean tech companies, we look at four sub–hypotheses:

Sub–hypothesis A Early–stage clean tech companies have fewer significant capital gain outcomes compared to other early–stage companies, affecting the potential for high returns in early–stage investments.

To assess the likelihood of significant capital gain outcomes in the context of early–stage companies, we employ the likelihood of achieving at least a 5x return on investment as a proxy for the potential of substantial returns. Specifically, we explore the influence of a binary variable, denoted as Clean tech, which indicates whether a given early–stage funding round is designated for a clean tech company (1) or not (0), on the likelihood of achieving at least a 5x return on investment. Our sub–hypothesis posits a negative coefficient for Clean tech, signifying a lower likelihood of early–stage clean tech companies achieving at least a 5x return.

In Panel A of Regression 3 (Table 4), contrary to our initial hypothesis, Clean tech has a positive coefficient. However, the coefficient does not attain statistical significance at 10% level. Following, our findings do not provide evidence to support the notion that early–stage clean tech funding rounds exhibit a reduced frequency of significant capital gain outcomes compared to their counterparts of other early–stage funding rounds.

To account for the asymmetric nature of *ex post* VC returns, we undertake an additional comparative analysis. Specifically, we examine the proportion of investments that yield returns of at least 10x the initial investment and those achieving the benchmark of at least 100x the original investment for early–stage investors.

Within our dataset, we observe 2.46% of early–stage clean tech funding rounds yield returns of at least 10x the initial investment, while 0.10% return at least 100x the initial investment for early–stage investors. In contrast, other early–stage funding rounds in our sample return at least 10x the initial investment in 1.44% of cases and return at least 100x the initial investment in 0.18% of cases. Conducting Pearson's Chi–squared test, we find the differences are both significant at 0.01% and 5% level respectively. An overview of the contingency tables is displayed in Appendix A.6. The attainment of returns reaching 100x the initial investment is a notably rare occurrence, often described as the pinnacle of early–stage investment success, or the "home run". Following, the Chi–square test results for 100x returns may not be reliable. This is particularly evident as only 89 instances of such "home runs" are discernible within our dataset, with merely one instance recorded for an early–stage clean tech funding round (Appendix A.6). The occurrence of just one additional early–stage clean tech funding round achieving returns of at least 100x the initial investment would bring the share in line with other early–stage funding rounds and render it indistinct. To attain higher confidence in our comparative analysis, building on the perspective advocated by Hargadon and Kenney (2012), we assert the notion of "home runs" can be suitably extended to "winning bets" which encompasses early–stage investments yielding at least 10x their initial commitment.

Following, overall, our analysis of the likelihood of achieving at least a 5x or 10x return does not provide compelling evidence to support the notion that early–stage clean tech funding rounds exhibit a reduced frequency of significant capital gain outcomes compared to their counterparts in the broader early–stage business landscape. While the comparative analysis of achieving returns of at least 100x confirms our initial hypothesis, we need to interpret these results cautiously due to the notably rare occurrence of these return events.

Sub–hypothesis B Early–stage clean tech companies experience weaker exit opportunities compared to other early–stage companies, resulting in a lower rate of exits and IPOs.

To assess exit opportunities, we look at the likelihood of exit outcomes for early–stage clean tech companies compared to other early–stage companies. Specifically, we explore the influence of a binary variable, denoted as Clean tech, which indicates whether a given early–stage funding round is designated for a clean tech enterprise (1) or not (0) on the probability of achieving an exit and going public via an IPO. We predict a negative coefficient for Clean tech, signifying weaker exit opportunities for early–stage clean tech companies.

Looking into the probability of achieving an exit, in Panel A of Regression 3 (Table 4), we observe a negative coefficient for Clean tech. The coefficient is significant at 0.01% level. Following, our findings provide strong evidence to support the notion that early–stage clean tech companies exhibit a reduced frequency of exit outcomes compared to other early–stage companies. Looking into the probability of going public via an IPO, in Panel A of Regression 3 (Table 4), we see a positive coefficient for Clean tech. The coefficient is significant at 5% level. Following, our findings provide evidence against the notion that early–stage clean tech companies exhibit a reduced frequency of IPO outcomes compared to other early–stage companies.

The differentiation in exit patterns might be ascribed to the historical reluctance of incumbents within the energy and utility sectors to engage in the acquisition of clean tech startups (Nanda et al., 2014; Gaddy et al., 2017). Weyant (2011) attributes the reluctance to the strong financial incentives of existing companies in the clean tech sector to delay the adoption of new technologies as they benefit from substantial investments already made in infrastructure for their existing products. This tendency is particularly pronounced in (implicitly) oligopolistic industries like oil and gas and electric generation equipment manufacturing as well as imperfectly regulated industries like electric and gas utilities. Similar exit patterns were observed in the early stages of the biotechnology sector. Pharmaceutical companies only actively started acquiring biotechnology startups when these startups began to actively compete with the pharmaceutical industry (Ghosh and Nanda, 2010).

Generally, our findings support the notion of a lower probability to achieve an exit outcome for early–stage clean tech companies compared to other early–stage companies. However, early–stage clean tech companies exhibit a significantly higher probability of achieving IPO outcomes. This is in line with our findings earlier showing no support to the notion that early–stage clean tech funding rounds exhibit a reduced frequency of significant capital gain outcomes as, in general, trade sales do not produce as big of a capital gain as IPOs (Bygrave et al., 2014).

Sub–hypothesis C Early–stage clean tech companies have a longer time–to–exit compared to other early–stage companies, making them unattractive for early–stage investors looking for a high Internal Rate of Return (IRR).

To assess the potentially longer time–to–exit of early–stage clean tech companies compared to other early–stage companies, we undertake a comparative analysis. Specifically, we look at the average and median time–to–exit. We define time–to–exit as the time from receiving the respective early–stage funding round to achieving a successful exit outcome. We find early–stage clean tech companies have an average time–to–exit of 5.87 years compared to 5.57 years for other early–stage companies. This comparative observation is similarly pronounced for the median of 5.17 and 4.76 years to exit respectively (Appendix A.7). However, based on the Welch two sample t–test, we fail to reject the null hypothesis of no difference in the means of time–to–exit (Appendix A.7). This indicates there is no statistically significant difference in the mean time–to–exit between early–stage clean tech companies and other early–stage companies.

Overall, while the comparative analysis is in line with our initial hypothesis, indicating a longer time–to–exit for early–stage clean tech companies, the difference is not statistically significant.

Sub–hypothesis D Early–stage clean tech companies are more capital–intensive compared to other early–stage companies, making them unattractive for capital efficiency focused early–stage investors.

To assess the potentially higher capital–intensity of early–stage clean tech companies compared to other early–stage companies, we undertake a comparative analysis. Specifically, we look at the average (median) total funding raised (TFR) for both, the full dataset and companies with successful exit outcomes.

Early–stage clean tech companies raise on average \$28.26m (\$5.17m) in total funding. Opposed to our hypothesis, this is lower than the average and median \$38.62m (\$7.07m) of other early–stage companies in the sample (Appendix A.8). Accounting for the non–normal distribution of total funding raised, we use the Wilcoxon rank-sum test to compare the mean of clean tech and other early–stage companies. The p–value is significant at 0.01% underscoring the observed difference between the two groups (Appendix A.8). However, this might be due to the lower probability of early–stage clean tech companies to receive follow on funding (Table 4). Surprisingly, we find a similar pattern for successfully exited companies. Early–stage clean tech companies on average raise \$52.45m (\$14.91m) until achieving a successful exit while other early–stage companies raise \$66.92m (\$15.06m). However, using the Wilcoxon rank-sum test, the difference is not significant (Appendix A.8). Nevertheless, the comparative analysis contradicts our initial hypothesis. We observe significantly less total funding raised by early–stage clean tech companies for the full dataset and find no indication of a higher capital–intensity for successfully exited clean tech companies.

Based on our four sub–hypotheses, we only find mixed evidence supporting the notion that early–stage clean tech companies generally possess return, risk, and exit characteristics that deter early–stage VC investor interest irrespective of exogenous demand shocks. While we find significant evidence for a lower probability of exits, we also find significant evidence of a higher probability of IPOs which are generally proxies for bigger success outcomes (Bygrave et al., 2014). This is supported by comparative evidence on returns where we find some evidence of a higher probability of early–stage clean tech companies achieving 5x and 10x returns. This, however, does not hold for at least 100x returns, where, even if only based on a small sample size, we find a comparatively higher probability for other early–stage companies. Further, while we find some comparative evidence for a longer time–to–exit, it is not statistically significant. We find no indication of higher capital intensity.

7.1.2 Regional policies

Hypothesis II Early–stage clean tech investment may be more closely linked to enduring regional policies rather than to sudden exogenous demand shocks on clean technologies.

Second, the uncertain impact of exogenous demand shocks on the effectiveness of policies following the shock (Falkner, 2016) may dampen the willingness of early–stage investors to invest. Investors may wait for more concrete regulatory and policy changes before committing capital. Noailly et al. (2022), for example, find decreases in environmental policy stringency are associated with lower willingness from VCs to fund clean tech startups. However, Cumming et al. (2016) find no supporting evidence around countries espousing environmental sustainability having greater clean tech VC activity.

Based on Regression 1 (Table 2), we can observe the impact of the headquarter region (APAC, Europe, US) on the likelihood of an early–stage funding round being for a clean tech company. We utilize regional dummy variables, namely APAC, Europe, and US, to examine how these regions differ in their likelihood of an early–stage funding round being for a clean tech company, using "non–APAC", "non–Europe", and "non–US" as reference categories. All region coefficients are significant at 1% level. This indicates a significant difference in the share of early–stage funding rounds going to clean tech companies based on where their headquarter is located. The coefficient for APAC is negative, suggesting the APAC region has a lower share of early–stage funding rounds associated with clean tech startups compared to the non–APAC region. Both Europe and US also show negative coefficients. In comparing the regions, we observe the coefficient for US and APAC is more negative than the coefficient for Europe. This suggests US and APAC have a lower likelihood of early–stage funding rounds being for clean tech startups compared to Europe or vice versa that Europe seems to have a higher share of clean tech funding rounds. This might indicate a favorable ecosystem for clean technologies.

In Regression 2 (Table 3), we observe a somewhat different picture. When assessing the impact of the headquarter region on the early–stage equity investment size received by clean tech companies, only the APAC and US coefficients are significant at 10% level. Both coefficients are positive, implying a higher early–stage equity investment size received by clean tech companies compared to the respective reference category. In comparing the regions, we observe the coefficient for APAC is higher than the coefficient for US and Europe. Following, clean tech companies headquartered in the APAC region have a higher total early–stage equity round size received compared to the US and Europe. This might indicate a favourable ecosystem for clean technologies.

These observed regional disparities in early–stage funding for clean tech companies may not solely be attributed to persistent regional policies. Rather, they may be underpinned by a variety of multifaceted factors, including, among others, a robust startup ecosystem, opportunity costs for investors, capital availability, geographical suitability for clean tech endeavours, the presence of influential industry stakeholders, and the prevailing regulatory framework unique to each region. To provide more nuanced insights, we plot the share of early–stage clean tech funding on the country–based OECD Environmental Stringency Index (ESI). The OECD ESI, with its comprehensive assessment of environmental regulations and policies, offers a valuable measure to gauge the enduring commitment of nations to environmentally sustainable practices (Martínez-Zarzoso et al., 2019).

Figure 3 shows the share of early–stage funding rounds going to clean tech plotted to the country–based OECD ESI for US, Canada, and France. We choose these countries based on their sample size as the three countries with the highest number of early–stage clean tech funding rounds in our sample. While the Clean Tech Bubble 1.0 (2005–2011) with its distinctive boom–and–bust pattern is present in all plots, we observe no clear visual pattern indicating a link between the OECD ESI and the share of early–stage clean

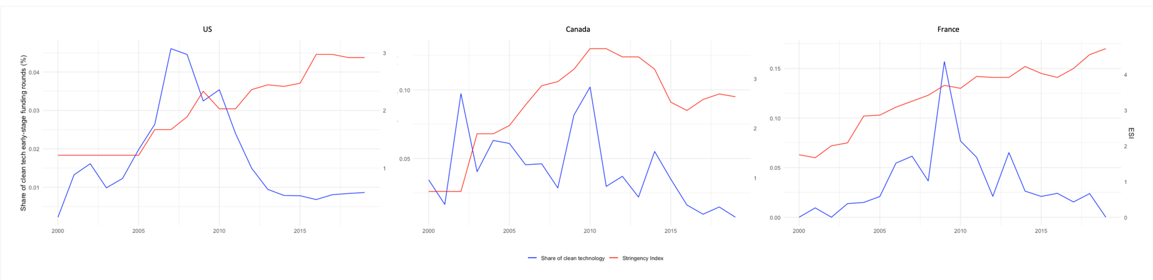

Figure 3: Share of early–stage clean tech funding rounds to OECD ESI
The figure shows the sample distribution share of early–stage funding rounds going to clean tech companies over time for the US, Canada, and France plotted to the respective country–based OECD ESI. The sample period is 2000–2019.

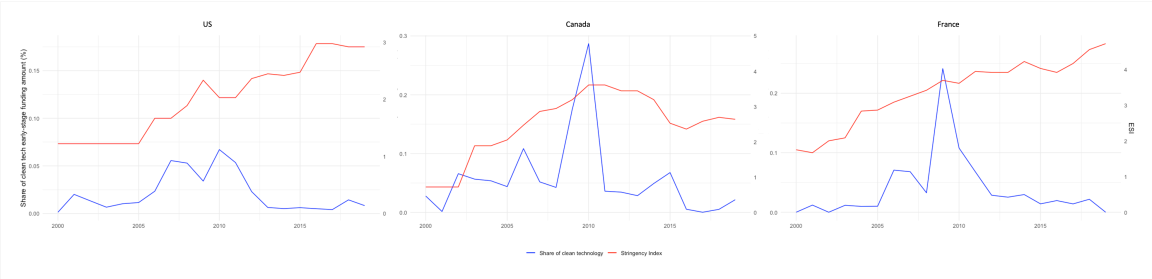

Figure 4: Share of early–stage clean tech funding amount to OECD ESI
The figure shows the sample distribution share of early–stage funding amount going to clean tech companies over time for the US, Canada, and France plotted to the respective country–based OECD ESI. The sample period is 2000–2019.

tech funding rounds. The correlation coefficients of –0.21 (US), –0.02 (Canada), and 0.25 (France) all confirm the visually observed negligible to weak correlation.

Figure 4 shows the share of total early–stage funding amount going to clean tech plotted to the country–based OECD ESI. Again, while the Clean Tech Bubble 1.0 (2005–2011) pattern is present in all plots, we observe no clear visual link between the OECD ESI and the share of early–stage funding amount to clean tech startups. The correlation coefficients of –0.12 (US), 0.33 (Canada), and 0.18 (France) all confirm the visually observed negligible to weak correlation.

Overall, we find mixed evidence for the impact of enduring regional policies on the willingness of early–stage investors to fund clean tech companies. While Europe seems to be a favourable environment for the share of early–stage funding rounds going to clean tech companies, the APAC region indicates to be a favourable environment for the early–stage equity round size received by clean tech companies. Scrutinizing this finding and acknowledging the multitude of factors at play in region variables, we find no visual support for a country–level link between enduring regional policies and the willingness of early–stage investors to invest in clean technologies. Considering the notably low (pseudo)–R^2 values of Regression 1 (Table 2) and 2 (Table 3), the headquarter region might only explain a small fraction of the variation in the likelihood of an early–stage funding round being for a clean tech company and the early–stage equity investment size received by clean tech companies.

7.1.3 Quantifiable pricing signals

Hypothesis III Early–stage clean tech investment may be more closely linked to quantifiable pricing signals on energy prices and commodities rather than to sudden exogenous demand shocks on clean technologies.

Third, quantifiable pricing signals on energy prices and commodities, rather than isolated shocks, may underpin early–stage clean tech investments. Instead of reacting to exogenous demand shocks, VC investors might wait until higher energy prices for non–clean energy, such as conventional fossil fuel energy, economically favour clean tech solutions.

Based on Regression 1 (Table 2), we can observe a significant positive impact of the oil price per barrel prevailing at the respective month (Oil price) on the likelihood of an early–stage funding round being for a clean tech company. The coefficient is significant at 0.01% level. Based on Regression 2 (Table 3), we can also observe a positive impact of

Oil price on the early–stage equity round size received by clean tech companies. However, the coefficient is only significant at 5% level in the Fukushima (2011) regression. In sum, we find a significant positive impact of the oil price on the likelihood of an early–stage funding round being for a clean tech company and some evidence for a positive impact of oil prices on the early–stage equity round size received by clean tech companies. This is in line with our hypothesis and suggests a significant link between oil prices and the willingness of investors to fund early–stage clean tech companies. It validates the findings of Cumming et al., 2016 showing oil price is the external factor that has the strongest impact on the decision of VC investors to invest in clean tech—more so than any other economic, legal or institutional variable.

To scrutinize this finding, we re–run Regression 1 and Regression 2, replacing Oil price with another quantifiable pricing signal. We assess governments penalize technologies with detrimental side effects to internalize external cost, for example by carbon pricing, economically favouring clean tech solutions (Michelfelder et al., 2022). Following, as shown for oil prices, we predict a positive impact of a higher carbon price on both the likelihood of an early–stage funding round being for a clean tech company and the early–stage equity round size received by clean tech companies.

We focus on European Union Allowance (EUA) prices based on the European Union Emissions Trading System (EU ETS) which is one of the world's largest and most established cap–and–trade programs for regulating carbon emissions, making it a robust and credible source of carbon pricing data (De Beule et al., 2022). Further, the EU ETS is designed to encourage emission reductions by putting a price on carbon, making it economically significant for companies operating within its jurisdiction. As EUA prices are only directly applicable to companies operating in the European Economic Area (EEA), we restrict our sample to early–stage companies headquartered in the EEA region.[2]

We observe a significant positive impact of the EUA price index prevailing at the respective month (Carbon price) on the likelihood of an early–stage funding round being for a clean tech company. The coefficient is significant at 1% (0.01%) level. In Regression 2, against our prediction, we observe a negative impact of Carbon price on the early–stage equity investment size received by clean tech companies. However, the coefficient is insignificant at 10% level. The full regression table can be found in Appendix A.9.

Overall, we find comprehensive evidence supporting the hypothesis that early–stage clean tech investment may be linked to quantifiable pricing signals on energy prices and commodities. Especially, we find a significant positive impact of the oil and carbon price on the likelihood of an early–stage funding round being for a clean tech company. Our findings suggest quantifiable pricing signals on energy prices and commodities might have a significant impact on the willingness of investors to fund early–stage clean tech companies. Still, considering the notably low (pseudo)–R^2 values of the regression models, oil and carbon prices might only explain a small fraction of the variation in the willingness of investors to fund clean tech startups.

[2] The European Economic Area (EEA) includes the EU member states, Iceland, Liechtenstein, and Norway.

7.1.4 Further hypotheses

Hypothesis IV Early–stage clean tech investment may be more closely linked to the broader economic environment rather than to sudden exogenous demand shocks on clean technologies.

Fourth, the broader economic environment, including factors like interest rates and the availability of early–stage capital, could affect investor decisions independently of demand shocks. To control for this, we include control variables for interest rate (Interest rate) and availability of early–stage capital (Fund supply and Average round size respectively). Based on the coefficients, the interest rate does neither have a significant impact on the likelihood of an early–stage funding round being for a clean tech company nor on the early–stage equity investment size received by clean tech companies. However, the coefficients of the proxies for the availability of early–stage capital are positive and significant at 0.01% level (Table 2; Table 3). This suggests a higher likelihood of an early–stage funding round being for a clean tech company and a higher early–stage equity round size received by clean tech companies if early–stage capital supply is high.

Overall, we find some support for the notion that clean tech investment is linked to the broader economic environment. Early–stage capital supply seems to significantly impact the willingness of investors to fund early–stage clean tech companies. Still, considering the notably low (pseudo)–R^2 values of Regression 1 and 2, early–stage capital supply might only explain a small fraction of the variation in willingness of investors to fund early–stage clean tech companies.

Hypothesis V Early–stage clean tech investment may be more closely linked to positive signals rather than to sudden exogenous demand shocks on clean technologies.

Fifth, based on signalling theory, we predict signals could significantly influence investor sentiment and confidence in the sector, even in the presence of demand shocks. We posit positive signals, such as success stories of clean tech companies, can instil confidence. These signals are crucial for investors to justify their decisions. The presence of successful exits could be a proxy for a positive signal showing the success of investors in the space. Hence, we predict the average number of clean tech exits in a respective year (Clean tech exits) has a positive impact on the willingness of investors to fund early–stage clean tech companies.

Based on Regression 1 (Table 2), we observe a positive impact of clean tech exits on the likelihood of an early–stage funding round being for a clean tech company, although the coefficient is only statistically significant at 10% level in the Paris (2015) regression. In Regression 2 (Table 3), both the coefficients of Clean tech exits and $\sqrt{\text{Clean tech exits}}$, are negative and non–significant.[3] This indicates no significant impact of clean tech exits on the early–stage equity investment size received by clean tech companies. Overall, our findings provide limited evidence of the impact of positive signals, as proxied by the average number of clean tech exits, on investor willingness to fund early–stage clean tech companies.

[3] $\sqrt{\text{Clean tech exits}}$ is employed to address the non–normality of count data and helps to stabilize variance and linearize the relationship in the OLS regression.

Hypothesis VI Investors might derive non–pecuniary utility from investing in early–stage clean tech companies and, following, are less influenced by exogenous demand shocks that could impact return expectations.

Sixth, Barber et al. (2021) show investors derive non–pecuniary utility from investing in dual–objective VC funds, thus sacrificing returns. Further, Heeb et al. (2023) find investors have a substantial willingness–to–pay for sustainable investments and experience positive emotions when choosing sustainable investments.

We argue this should also hold for early–stage clean tech investments often counted as impact investments (Giorgis et al., 2022). Taking the assets under management (AUM) of the UN Principles for Responsible Investment (PRI) signatories in a respective year (PRI AUM) as a proxy for investor interest in dual–objective investments, we predict a positive impact of PRI AUM on the willingness of investors to fund early–stage clean tech companies.[4]

In Regression 1 (Table 2), the coefficient is positive and significant at 0.01% level in the Fukushima (2011) regression. However, the coefficient turns negative when considering the Paris Agreement (2015) shock. Following, we cannot find a clearly directed impact of PRI AUM on the likelihood of an early–stage funding round being for a clean tech company when controlling for Paris (2015). Still, we interpret these results with caution based on the impact of the Paris Agreement (2015) on sustainable finance resulting in a high correlation coefficient of 0.843 between PRI AUM and Paris funding (Appendix A.10).

Hypothesis VII Early–stage investors might exhibit higher levels of risk aversion and information asymmetry when it comes to early–stage clean tech investments irrespective of the demand for clean technologies.

Lastly, the clean tech sector can be highly complex due to rapidly evolving technologies, regulatory uncertainties, and diverse subsectors (Marcus et al., 2013; Michelfelder et al., 2022). Information about early–stage clean tech companies and their technologies can be more difficult to obtain and evaluate compared to more established industries for VC investment. This could lead to strong information asymmetry. The information structures remind us of market for "lemons" (Akerlof, 1970). The seller (early–stage clean tech company) is better informed than the potential buyer (early–stage investors) about the value of the unit (equity) for sale. This might dampen the mutual benefit nature of trade (investment) and the ability to reach an agreement. Following, early–stage investors might prefer to allocate their resources to industries they are more familiar with and can more effectively overcome information asymmetries. While we cannot quantitatively assess investor risk aversion and information asymmetry based on the data available to us, this notion is supported by Michelfelder et al. (2022). Using a mixed–methods approach, they analyze investment decisions from 45 early–stage clean tech investors and venture investing experts to evaluate levers perceived by VC investors to positively influence the risk–return ratio for early–stage clean tech investments. They find clean tech sector specialisation, serving to overcome information asymmetries, and

[4] We acknowledge various potential proxies for dual–objective interest. We opt for an AUM–based approach over a survey–based approach due to robustness. We select PRI AUM for its data record, reporting, and high correlation (exceeding 0.93) with other widely–cited estimations by the Global Impact Investment Network (GIIN) and the Global Sustainable Investment Alliance (GSIA).

strategic syndication, serving to share risk and gain knowledge, as the two levers perceived most potent at the investor implementation level.

Overall, we find only partial support to the notion that early–stage clean tech companies generally possess return, risk, and exit characteristics that deter VC investor interest irrespective of demand for clean tech goods. Further, we cannot find a clearly directed, significant impact of enduring regional policies, positive signals, and investor interest in dual–objective investments on investor willingness to fund clean tech startups. While we find a clearly directed, significant impact of early–stage capital supply and quantifiable pricing signals on energy prices and commodities, they only explain a small fraction of the variation in the willingness of investors to fund clean tech startups.

7.2 Success rates of clean tech startups

Regarding Hypothesis 2, we aim to assess why exogenous demand shocks for clean technologies might not impact the likelihood of success for early–stage clean tech companies funded around the shock and why we cannot observe evidence of investors decreasing their quality threshold for clean tech startups.

First and foremost, based on our findings for Hypothesis 1, investors simply might not increase their willingness to invest into clean tech startups in response to exogenous demand shocks for clean tech. As we find no impact on the willingness to invest, this strongly points towards there might not be an impact on the quality threshold employed. Second, even if we assume investors are more willing to invest in clean tech startups following demand shocks, investors might simply not adjust their quality thresholds. A reluctance to change quality thresholds could have several reasons. Investors might have established routines and investment criteria which adhere to traditional quality thresholds because they have yielded results in the past. Further, investors might be influenced by cognitive biases, such as anchoring to past criteria or overconfidence in their evaluation methods. Additionally, even in the face of demand shocks, investors might maintain their risk aversion and continue to prioritize early–stage companies that align with their pre–shock risk profiles.

7.3 Clean tech exits

Regarding Hypothesis 3, we aim to assess why exogenous demand shocks for clean technologies might not impact clean tech exit activity. As for Hypothesis 1, we predict this might be due to the presence of other factors exerting a strong, potentially overshadowing, influence on clean tech exits.

Hypothesis VIII Clean tech companies might exhibit risk and return profiles that deter them an unattractive target for IPOs and acquisitions irrespective of exogenous demand shocks for clean technologies.

First, clean tech companies might not an attractive target for IPOs and acquisitions compared to other companies irrespective of exogenous demand shocks. Based on Regression 3 (Table 4), generally, our findings support the notion for acquisitions as we observe a lower probability of clean tech companies to achieve an exit outcome compared to non–clean tech companies. However, we also find clean tech companies exhibit a significantly higher probability of achieving IPO outcomes. Combined, we see mixed signals about the attractiveness of clean tech as exit targets.

Hypothesis IX Clean tech exits may be more closely linked to enduring regional policies rather than to sudden exogenous demand shocks on clean technologies.

Second, the uncertain impact of exogenous demand shocks on and the effectiveness of policies following the shock might dampen the exit and IPO environment of clean tech companies. Acquirers and IPO investors may wait for more concrete regulatory and policy changes before committing capital. Utilizing regional dummy variables in Regression 5 (Table 6), we observe a significant impact of the headquarter region (APAC, EU, US) on the likelihood of an exit outcome being for a clean tech company. All region coefficients are significant at 5% level. In comparing the regions, we observe the coefficients for US and Europe are more negative than the coefficient for APAC. This suggests APAC to have a higher share of clean tech exits. Following, the APAC region might have a favorable exit ecosystem for clean technologies. While it serves as a proxy for the impact of regions on the clean tech exit ecosystem, the observed regional disparities may not solely be attributed to persistent regional policies. Rather, they may be underpinned by a variety of multifaceted factors including, among others, a robust exit ecosystem, the share of non–clean tech exits, geographical suitability for clean tech endeavours, the presence of influential industry stakeholders, and the prevailing regulatory framework unique to each region.

Hypothesis X Clean tech exits may be more closely linked to quantifiable pricing signals on energy prices and commodities rather than to sudden exogenous demand shocks on clean technologies.

Third, quantifiable pricing signals on energy prices and commodities, rather than isolated shocks, may underpin clean tech exits. Instead of reacting to exogenous demand shocks, acquirers and IPO investors might wait until higher energy prices for non–clean energy economically favour clean tech solutions. Based on Regression 5 (Table 6), we can observe a positive impact of the oil price prevailing at the respective month (Oil price exit) on the likelihood of an exit outcome being for a clean tech company. However, the coefficient is not significant at 10% level.

Hypothesis XI Clean tech exits may be more closely linked to the broader economic environment rather than to sudden exogenous demand shocks on clean technologies.

Fourth, the broader economic environment, including factors like interest rates, the current state of the stock market, and the availability of alternative exit routes could affect the share of clean tech exits irrespective of demand shocks. In Regression 5 (Table 6), we include control variables for interest rate (Interest rate exit), stock market sentiment (MSCI price exit), and availability of alternative exit routes (SPAC count exit) prevailing at the time of exit. However, none of the coefficients is significant at 10% level. Still, based on the pattern observed in Figure 2, clean tech exits exhibit a strong correlation with the distribution of overall VC-backed exits over time, indicating a strong reliance on market sentiment.

Hypothesis XII Investors might derive non–pecuniary utility from acquiring and holding clean tech companies and, following, are less influenced by exogenous demand shocks that could impact return expectations.

Fifth, we take the AUM of the UN Principles for Responsible Investment signatories in the respective year of exit (PRI AUM exit) as a proxy for investor interest in dual–objective investments. We predict a positive impact of PRI AUM exit on the likelihood of an exit outcome being for a clean tech company. In Regression 5 (Table 6), in line with our prediction, we observe a positive coefficient. Still, the coefficient is insignificant at 10% level.

Overall, our findings partially support the notion that clean tech companies exhibit risk and return characteristics that deter them an unattractive target for acquisitions irrespective of exogenous demand shocks. Further, we find a strong correlation of clean tech exits to the distribution of overall VC–backed exits, indicating a reliance on market sentiment. However, we find no significant impact of the oil price, interest rate, stock market sentiment, availability of alternative exit routes, and AUM of the UN Principles for Responsible Investment on the likelihood of an exit outcome being for a clean tech company. While the headquarter region has a significant impact on the likelihood of an exit outcome being for a clean tech company, it can only explain a small fraction of the variation.

7.4 Limitations

In addition to the data limitations due to the nature of early–stage private capital data and the varying definitions applied to clean tech, there are some apparent challenges with the study–environment as a whole.

First, it is difficult to proxy for and completely isolate the effects of exogenous demand shocks. To counteract, we have taken several measures including control variables and robustness tests. We provide substantial evidence that both events we investigate, the Fukushima Nuclear Disaster (2011) and the signing of the Paris Agreement (2015), had a significant impact on global investor behaviour and policies driving the global demand for clean technologies. We account for regional variations and macroeconomic factors which might counteract the impact of exogenous shocks by utilizing various control variables. We conduct separate analyses on the subsample of clean energy companies and the subsample of startups headquartered in the APAC region, which are likely to be most affected by the Fukushima Nuclear Disaster (2011). Our results remain consistent and robust, as detailed in Appendix A.5 and Appendix A.11, respectively. Lastly, the inclusion of two shocks, one focused on regulatory mandates and one resulting from an adverse event, further strengthens the overall robustness of our study. Nevertheless, in interpreting the results, we must consider the potential overshadowing effects of the Clean Tech Bubble 1.0 with its distinctive boom–and–bust pattern (see Figure 1). This pattern significantly influenced investor sentiment (Gaddy et al., 2017; Giorgis et al., 2022), potentially counteracting the impact of the Fukushima (2011) demand shock and challenging the parallel trends assumption in our DiD estimations. To assess this, we plot the temporal dynamics concerning the probability of securing follow on funding, exit events, attaining IPOs, and realizing at least a 5x return on investment based on the year of early–stage funding received (Appendix A.11). We observe similar trend directions for early–stage clean tech companies and the control group of other early–

stage companies. While these patterns provides some relief, we cannot entirely dismiss the possibility of a potential breach, given the lack of perfect alignment in the trends. Future research could address potential issues with the parallel trends assumption by employing advanced matching methods. It may involve selecting control groups that are potentially more nuanced and similar to the treatment group based on observed characteristics. Additionally, one could explore synthetic control methods allowing to assign different weights to various control groups.

Second, the (pseudo–)R^2 in our analyses were low, meaning our models are far from exhaustive. In this complex setting, many factors play a role explaining early–stage investment decisions and company exits. Our models capture only few of them. We ascribe this to our adoption of an aggregate perspective to early–stage investing, despite many critical determinants operating at the individual level. Based on looking at the type–aggregate view of early–stage companies, we mask the heterogeneity of these. Early–stage companies may have varying responses to exogenous demand shocks and some may be better positioned to capitalize on these factors, while others may not adapt as effectively. Ghosh and Nanda (2010) recognize clean tech's suitability for early–stage funding is not uniform but varies depending on the specific sub–sectors and venture characteristics. Further, as highlighted by Michelfelder et al. (2022), the most important levers perceived by VC investors to positively influence the perceived risk–return ratio for early–stage clean tech investments are almost exclusively to be implemented at company level. These levers include a recurring revenue model, performance and application focus, regulatory independence, and use of proven parts (Michelfelder et al., 2022). Further, based on looking at the aggregate view of early–stage investors, we mask the heterogeneity of investors. Different early–stage investors may not respond in the same way to exogenous demand shocks, and these differences can be masked in aggregate analysis. For example, the knowledge and expertise of early–stage investors in the clean tech sector might vary. Investors with a strong understanding of the industry might be more willing to invest following a positive exogenous demand shock, while those less familiar with the sector might be more cautious. Cole et al. (2022) find, relative to traditional venture investors, impact investors – private investors who seek to generate simultaneously attractive financial and social returns – select companies that are less likely to reach exits and take longer to do so, which is consistent with greater risk tolerance and longer time horizons. Venture impact investors are also more likely to invest in "pioneer companies" – the first 30 or 40 companies in new industries (Cole et al., 2022).

Third, while we include a comparatively large sample based on a twenty–year time frame, the share of clean tech companies that receive early–stage funding is still considerably small compared overall early–stage funding. This could potentially reduce the robustness of our findings.

Fourth, some variables of interest are not directly observable. We account for these by proxy variables. Proxies, while cautiously chosen, might not fully capture or represent the variable of interest. This is specifically an issue in Hypothesis 2 where we proxy the quality threshold of investors for a specific early–stage funding round with an *ex post* success measure. However, success as an *ex post* measure is dependent on a myriad of factors that might, for example, not have been known at the point in time when the investment decision quality threshold was applied.

Fifth, our analysis reveals clean tech startups exhibit an average time-to-exit of 5.87 years, which exceeds the conventional three to five year horizon commonly associated with VC investments (Gompers and Lerner, 1998). Following, based on our early–stage funding round dataset concluding 1st of July 2020 and exit data collected until 20th of September 2023, clean tech startups that received early–stage funding between the 20th of March 2017 and 1st of July 2020 had less time–to–exit than the average clean tech exit took in our dataset. This does not pose a significant concern to our results in Regressions 3 (Table 4) and 4 (Table 5), primarily due to the absence of a statistically significant difference in time–to–exit to our control group. Furthermore, we discern no substantial surge or decline in the proportion of early–stage clean tech funding rounds during the period commencing on 20th of March 2017. Nevertheless, when interpreting the event dummies (Fukushima funding; Paris funding) for Hypothesis 2 in isolation, particularly within the broader dataset and three-year window panels, a cautious approach is advisable.

7.5 Implications

Private sector investments in clean tech are an important driver of innovation but depend on an array of variables like risk, expected performance, cost of capital and a range of industry and economy indicators. Our results indicate positive exogenous demand shocks might not have a clearly directed impact on early–stage funding, success rates, or exits of clean tech companies. Following, induced exogenous demand shocks might not be an efficient model for policymakers to drive investment in clean tech innovation.

Rather, quantifiable pricing signals such as high oil and carbon prices seem to be important for the willingness of investors to fund clean technologies. Policymakers might want to focus on robust carbon pricing and penalizing fossil fuel energy to funnel investment more effectively into clean tech startups. Further, we find evidence for a low rate of acquisitions of clean tech companies compared to non–clean tech companies. Since trade sales are an important puzzle of early–stage investor returns (Ghosh and Nanda, 2010), building a more encouraging environment for acquisitions of clean tech companies might be an additional lever to drive investment in clean tech innovation. Further, based on our results, encouraging overall early–stage capital supply could be a driver for the willingness of investors to fund early–stage clean tech companies.

We expect the aforementioned policy approaches to show prospects for increasing VC funding of clean tech startups as we do not find an apparent mismatch of the suitability of the VC model for clean tech financing. *Ex post* risk and return profiles of clean tech startups seem to be mostly in line with other early–stage investments. Further, we find no significant evidence for higher capital intensity or longer time–to–exit for early–stage clean tech companies. Pending the aforementioned policy approaches, early–stage VC investors, therefore, should generally be willing to invest in clean tech startups.

Importantly, based on the notably low (pseudo)–R^2 across our regressions, the highlighted approaches might only influence a small fraction of the variation in willingness of investors to fund clean tech startups. While there is potential for policymakers to drive funding to clean tech innovation based on the outlined aggregate–view initiatives, significant levers are likely to remain on more micro level due the heterogeneity of companies and investors.

8 Conclusion

In this study, building on the notion that investors are not passive players in the market but actively respond to changes in demand conditions, we research the impact of the Fukushima Nuclear Disaster (2011) and the signing of the Paris Agreement (2015) on early–stage funding, success rates, and exits for clean tech companies.

To assess the impact on early–stage funding, we run two regression models across several time windows around both shocks. We proxy the willingness of investors to invest in clean tech startups by the likelihood of an early–stage funding round being for a clean tech company and the early–stage equity round size for clean tech companies. We do not find a significant positive influence of the exogenous demand shocks on investor willingness to invest. Instead, in testing alternative hypothesis, we find willingness to invest is significantly influenced by quantifiable pricing signals such as high oil and carbon prices as well as overall early–stage capital supply. We only find mixed evidence supporting the common notion that clean tech startups generally possess return, risk, and exit characteristics that deter early–stage investor interest irrespective of exogenous demand shocks. While we find significant evidence for a lower probability of exits, we also find significant evidence of a higher probability of IPOs and comparative evidence of a higher probability of achieving at least 5x and 10x returns for early–stage clean tech companies compared to other early–stage companies. Further, we do not find significant evidence for a longer time–to–exit or higher capital–intensity for clean tech startups.

Based on difference–in–differences estimations, we assess the impact on success rates of clean tech companies that received early-stage funding in the period prior to and after the shocks. We proxy for success with the probability of achieving follow on funding, an exit event, an IPO, or an outsized return. We do not find a significant impact of the exogenous demand shocks on success rates.

To evaluate the impact on exits, we run two regression models around both shocks. We do not find a significant impact of the exogenous demand shocks on the likelihood of exits being associated with clean tech companies and the Cash-on-Cash multiple outcomes for clean tech companies. Instead, we observe a generally lower probability of clean tech companies to achieve an exit outcome compared to non–clean tech companies and a strong correlation of clean tech exits to the distribution of overall VC-backed exits over time. We predict this could potentially overshadow the impact of the exogenous demand shocks.

These results hold important implications for investors and policymakers to construct efficient models to fund and enhance the flow of funding to clean tech innovation. However, the (pseudo–)R^2 in our analyses are low. This means the aforementioned levers are far from exhaustive. We attribute this mainly to taking an aggregate view to early–stage investing while a lot of decisive factors happen on the individual or micro level. Future research might take a more granular view of early–stage companies and investor decision–making, unmasking the heterogeneity of these actors. Moreover, given the recent resurgence in clean tech investments, upcoming studies may seize the opportunity to integrate significantly larger datasets. Replication studies might consider addressing potential issues with the parallel trends assumption in our DiD estimations through the application of advanced matching and synthetic control methods. Lastly, a prospective avenue involves analyzing additional (future) exogenous demand shocks. Such inquiries could illuminate the impacts arising from regulatory driven and adverse event demand shocks and enable a deeper investigation into region–specific dynamics.

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A Appendix

A.1 Firm classifications

Table 9: Clean tech classifications

Table 9 reports the sample distribution of unique early–stage funding rounds with regard to TRBC industry classification from January 2000 to July 2020.

Classification	TRBC ID	TRBC Level	#
Clean Technology			**976**
Environmental Organizations	6110103010	Activity	2
Environmental Services & Equipment	52203010	Industry	309
Carbon Capture & Storage	5220301015	Activity	1
Environmental Consultancy Services	5220301013	Activity	9
Environmental R&D Services & Biotechnology	5220301014	Activity	11
Environmental Services & Equipment (NEC)	5220301010	Activity	81
Purification & Treatment Equipment	5220301011	Activity	46
Waste Management, Disposal & Recycling Services	5220301012	Activity	161
Clean Energy			**665**
Batteries & Uninterruptable Power Supplies	5210203011	Activity	153
Electric Utilities	59101010	Industry	125
Renewable Energy	5020	Bus. Sec.	387
Biodiesel	5020102011	Activity	3
Biomass & Biogas Fuels	5020102014	Activity	6
Biomass Power Energy Equipment	5020101015	Activity	4
Ethanol Fuels	5020102015	Activity	6
Hydrogen Fuel	5020102015	Activity	3
Hydropower Equipment	5020101017	Activity	1
Photovoltaic Solar Systems & Equipment	5020101013	Activity	120
Renewable Energy Equipment & Services (NEC)	5020101010	Activity	166
Renewable Energy Services	5020101019	Activity	8
Renewable Fuels (NEC)	5020102010	Activity	17
Stationary Fuel Cells	5020101012	Activity	4
Thermal Solar Systems & Equipment	5020101014	Activity	10
Waste to Energy Systems & Equipment	5020101016	Activity	3
Wind Systems & Equipment	5020101011	Activity	36
Other			**50,208**

A.2 Dilution uncertainty bounds

Table 10: Dilution uncertainty bounds

Table 10 shows the number of observations for cash–on–cash (CoC) multiples depending on dilution per additional round of funding in our sample. Column 1 indicates the number of observations that return at least 5x the initial investment for early–stage investors. Column 2 indicates 10x and Column 3 100x returns to early–stage investors.

	5X	**10X**	**100X**
Panel A: 20% dilution			
Full Sample	1,266	745	89
Non-Clean Tech Early Stage Company (TD=0)	1,231	721	88
Clean-Tech Early Stage Company (TD=1)	35	24	1
	2.8%	*3.2%*	*1.1%*
Panel B: 10% dilution			
Full Sample	1,764	1,150	148
Non-Clean Tech Early Stage Company (TD=0)	1,725	1,118	146
Clean-Tech Early Stage Company (TD=1)	39	32	2
	2.2%	*2.8%*	*1.4%*
Panel C: 30% dilution			
Full Sample	843	444	49
Non-Clean Tech Early Stage Company (TD=0)	819	428	48
Clean-Tech Early Stage Company (TD=1)	24	16	1
	2.8%	*3.6%*	*2.0%*

A.3 VIF tables

Table 11: Regression 1: VIF

	Panel A		Panel B		Panel C	
	F	**P**	**F**	**P**	**F**	**P**
Fukushima funding	3.615	—	6.794	—	7.010	—
Paris funding	—	4.814	—	1.803	—	9.122
Clean tech exits	2.014	1.986	1.754	3.369	—	4.720
Fund supply	2.930	3.197	1.555	5.724	2.057	3.022
Interest rate	2.330	2.447	3.298	—	4.751	—
Oil price	1.833	2.097	3.654	1.742	5.254	1.874
PRI AUM	4.874	7.208	6.269	—	—	—
APAC	1.883	1.883	2.902	1.888	3.127	2.004
Europe	2.399	2.388	4.516	2.288	5.232	2.006
US	2.427	2.416	4.359	2.255	4.938	2.119
df	51,174	51,174	12,313	18,569	4,233	6,471

Table 12: Regression 2: VIF

	Panel A		Panel B		Panel C	
	F	**P**	**F**	**P**	**F**	**P**
Fukushima funding	2.119	—	4.876	—	8.546	—
Paris funding	—	5.462	—	4.792	—	9.874
Average round size	1.610	5.358	3.067	9.810	1.424	4.671
Interest rate	1.691	1.405	3.456	—	4.549	—
Oil price	2.007	1.685	3.703	1.777	5.961	2.334
APAC	1.896	1.890	2.966	1.876	3.170	2.065
Europe	2.520	2.514	4.643	2.321	5.302	2.191
US	2.516	2.505	4.453	2.254	4.958	2.323
$\sqrt{\textbf{Clean tech exits}}$	1.843	1.786	1.322	4.752	—	3.594
df	967	967	395	191	144	50

Table 13: Regression 3: VIF

	F–FO	F–EX	F–IPO	F–5X	P–FO	P–EX	P–IPO	P–5X
	Panel A (full dataset window)							
Clean tech	1.628	1.352	1.273	1.378	1.183	1.078	1.084	1.108
Fukushima funding	3.185	2.719	2.710	2.608	—	—	—	—
FF × Clean tech	1.628	1.355	1.278	1.380	—	—	—	—
Paris funding	—	—	—	—	2.570	1.977	1.988	1.963
PF × Clean tech	—	—	—	—	1.181	1.077	1.085	1.113
Fund supply	2.095	1.954	1.989	1.785	2.677	2.216	2.140	2.124
Round size	1.019	1.087	1.099	1.135	1.019	1.085	1.100	1.147
Interest rate	3.000	2.778	2.556	2.386	1.550	1.595	1.563	1.403
Age at funding	1.013	1.015	1.024	1.018	1.014	1.016	1.023	1.019
Investment rounds	—	1.167	1.237	1.208	—	1.164	1.231	1.201
Total funding raised	—	1.192	1.208	1.254	—	1.178	1.194	1.260
APAC	3.128	2.409	4.682	5.393	3.129	2.401	4.677	5.384
Europe	3.081	2.990	3.694	3.343	3.079	2.990	3.695	3.341
US	3.605	3.683	5.457	6.439	3.605	3.681	5.461	6.433
df	51,173	51,171	51,171	51,171	51,173	51,171	51,171	51,171
	Panel B (3 year window)							
Clean tech	1.713	1.596	1.521	1.420	1.800	1.613	1.647	1.598
Fukushima funding	1.505	1.491	1.555	1.505	—	—	—	—
FF × Clean tech	1.718	1.598	1.530	1.410	—	—	—	—
Paris funding	—	—	—	—	2.944	3.047	2.806	3.111
PF × Clean tech	—	—	—	—	1.799	1.614	1.651	1.608
Fund supply	1.213	1.231	1.285	1.232	8.040	6.975	6.607	6.794
Round size	1.017	1.034	1.031	1.026	1.018	1.079	1.082	1.204
Interest rate	1.293	1.302	1.346	1.300	5.753	5.041	5.031	5.010
Age at funding	1.010	1.012	1.021	1.015	1.030	1.023	1.039	1.040
Investment rounds	—	1.251	1.324	1.256	—	1.215	1.165	1.170
Total funding raised	—	1.198	1.156	1.177	—	1.231	1.184	1.332
APAC	2.937	2.734	6.724	8.026	3.924	2.602	4.977	7.042
Europe	3.492	3.538	5.218	4.141	3.155	2.838	3.048	4.765
US	3.935	4.427	8.166	9.459	4.029	3.795	6.051	9.122
df	12,312	12,312	12,312	12,312	12,312	12,312	12,312	12,312
	Panel C (1 year window)							
Clean tech	1.954	1.812	1.988	1.016	1.758	1.404	1.556	1.423
Fukushima funding	4.493	4.681	4.492	4.581	—	—	—	—
FF × Clean tech	1.975	1.818	2.002	1.000	—	—	—	—
Paris funding	—	—	—	—	2.659	2.811	2.561	2.459
PF × Clean tech	—	—	—	—	1.756	1.396	1.546	1.392
Fund supply	1.537	1.584	1.643	1.602	2.654	2.805	2.535	2.428
Round size	1.027	1.048	1.050	1.047	1.011	1.085	1.086	1.332
Interest rate	4.684	4.919	4.740	4.830	—	—	—	—
Age at funding	1.020	1.022	1.032	1.031	1.045	1.033	1.057	1.081
Investment rounds	—	1.284	1.360	1.295	—	1.247	1.178	1.189
Total funding raised	—	1.209	1.164	1.183	—	1.288	1.207	1.483
APAC	3.204	2.833	4.795	5.161	4.150	2.487	3.517	6.578
Europe	4.058	3.563	3.483	3.327	3.135	2.619	2.888	4.778
US	4.407	4.440	5.500	6.143	4.050	3.494	4.663	8.870
df	4,230	4,228	4,228	4,228	6,469	6,467	6,467	6,467

Table 14: Regression 4: VIF

	Panel A		Panel B		Panel C	
	F	**P**	**F**	**P**	**F**	**P**
Clean tech	1.630	1.190	1.710	1.839	1.950	1.771
Fukushima funding	3.178	——	1.506	——	4.531	——
FF × Clean tech	1.630	——	1.713	——	1.968	——
Paris funding	——	2.564	——	2.953	——	2.611
FF × Clean tech	——	1.188	——	1.838	——	1.769
Fund supply	2.091	2.673	——	8.083	1.538	2.607
Round size	1.122	1.123	1.018	1.193	1.028	1.331
Interest rate	2.996	1.558	1.293	5.779	4.725	——
Age at funding	1.017	1.018	1.017	1.035	1.025	1.050
Investment rounds	1.163	1.160	1.186	1.186	1.238	1.253
Total funding raised	1.187	1.186	1.086	1.315	1.112	1.530
APAC	3.168	3.170	3.006	3.992	3.271	4.199
Europe	3.142	3.139	3.664	3.182	4.270	3.140
US	3.831	3.831	4.245	4.270	4.792	4.287
DF	51,171	51,171	12,310	18,564	4,228	6,467

Table 15: Regression 5: VIF

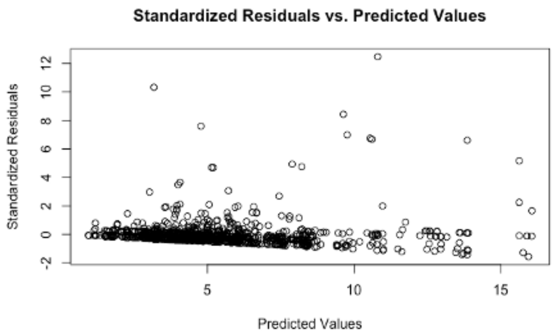
	Panel A		Panel B		Panel C	
	F	**P**	**F**	**P**	**F**	**P**
Fukushima exit	3.202	——	1.336	——	1.000	——
Paris exit	——	5.970	——	1.752	——	1.000
APAC	1.568	1.567	——	1.000	——	1.000
Europe	1.851	1.852	1.646	1.689	1.731	1.361
US	2.035	2.035	1.644	1.685	1.726	1.361
Interest rate exit	1.304	1.222	1.705	1.825	1.037	1.691
PRI AUM exit	4.014	6.870	4.293	7.541	1.177	4.257
MSCI price exit	——	——	——	7.877	——	4.997
Oil price exit	1.125	1.316	1.188	2.137	1.158	2.417
SPAC count exit	1.886	1.695	3.083	2.984	——	2.692
df	9,691	9,691	2,732	2,248	996	761

Table 16: Regression 6: VIF

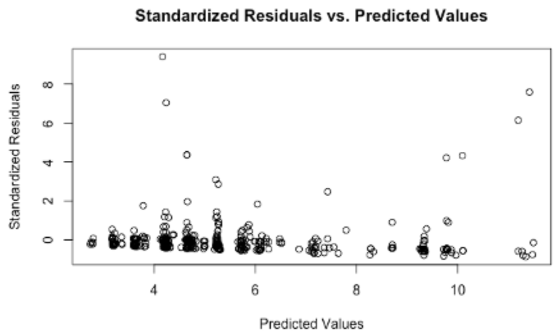
	F	**P**
Fukushima exit	3.360	——
Paris exit	——	2.584
CoC average exit	2.479	2.295
Interest rate exit	1.402	1.236
PRI AUM exit	5.602	——
Oil price exit	1.175	1.117
US	4.504	4.277
Europe	3.019	2.863
APAC	4.124	4.015
Total funding raised	1.629	1.655
Round size	1.246	1.211
Investment rounds	1.765	1.856
Fund supply	1.877	1.724
Age at funding	1.373	1.368
df	36	37

A.4 Heteroscedasticity

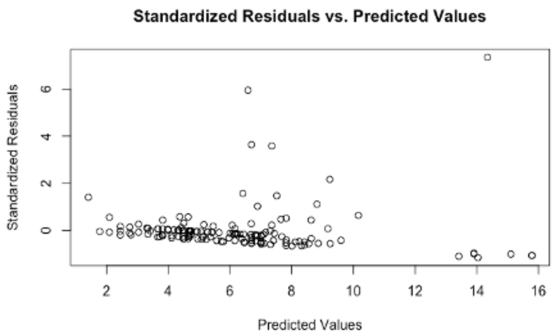
Figure 5: Regression 2: Scatter plots of independent variables and log–odds



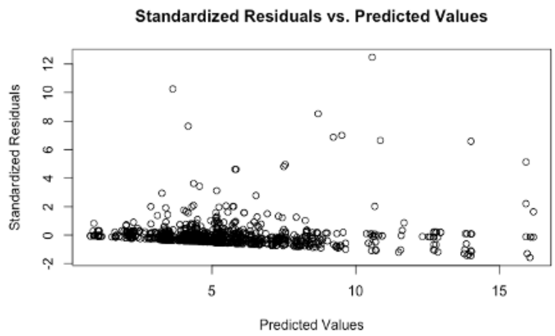
(a) Fukushima (2011) – Panel A



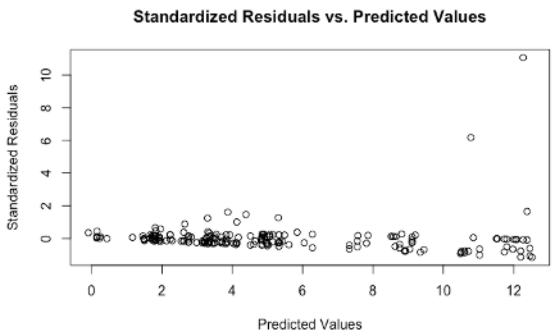
(b) Fukushima (2011) – Panel B



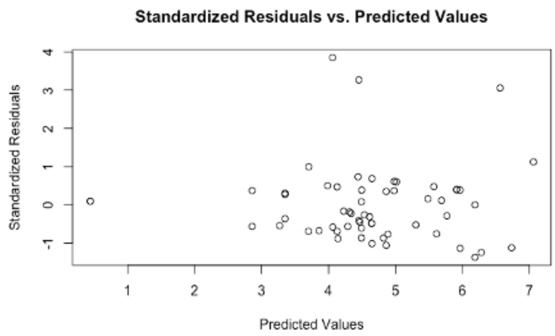
(c) Fukushima (2011) – Panel C



(d) Paris (2015) – Panel A

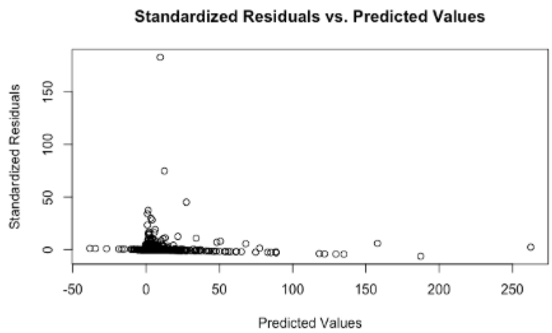


(e) Paris (2015) – Panel B

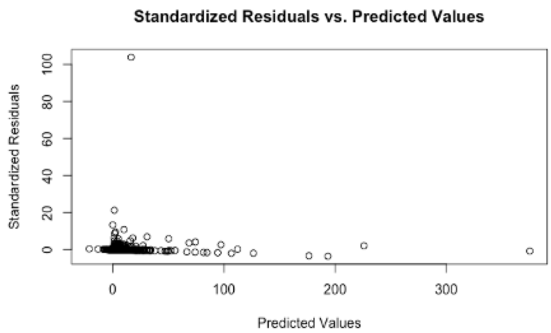


(f) Paris (2015) – Panel C

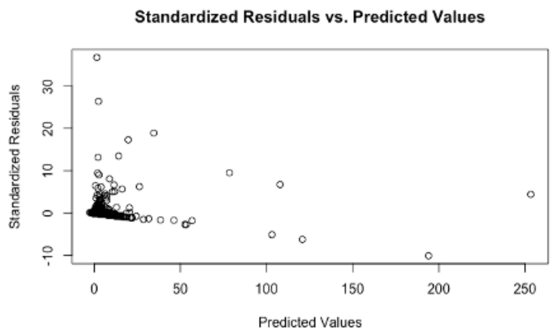
Figure 6: Regression 4: Scatter plots of independent variables and log–odds



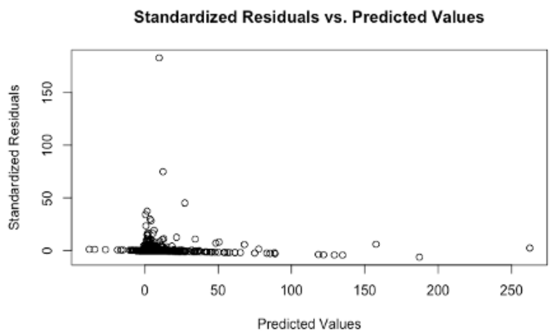
(a) Fukushima (2011) – Panel A



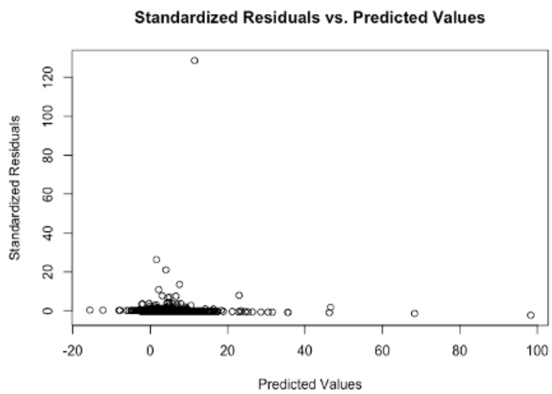
(b) Fukushima (2011) – Panel B



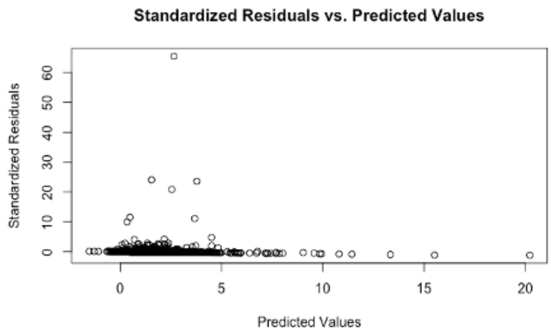
(c) Fukushima (2011) – Panel C



(d) Paris (2015) – Panel A

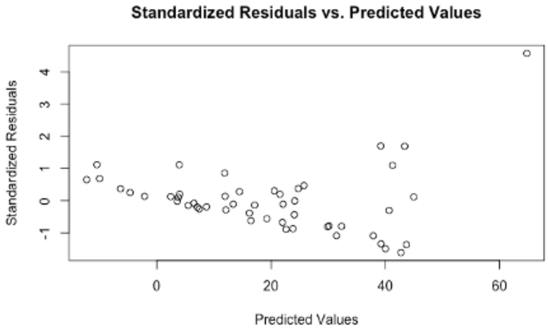


(e) Paris (2015) – Panel B

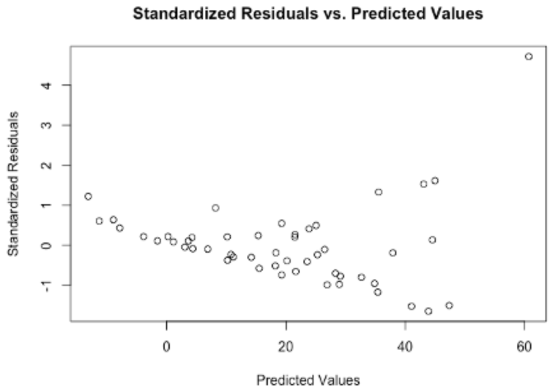


(f) Paris (2015) – Panel C

Figure 7: Regression 6: Scatter plots of independent variables and log–odds

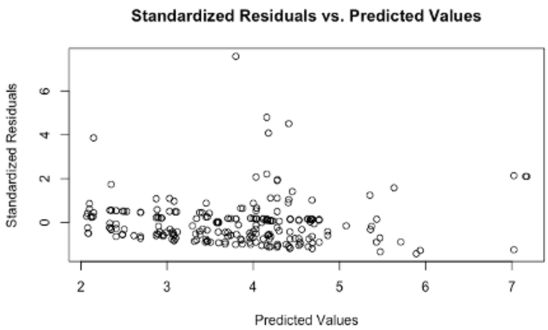


(a) Fukushima (2011)

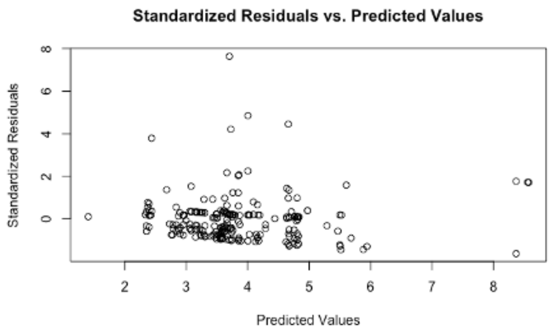


(b) Paris (2015)

Figure 8: Regression 2 (CP): Scatter plots of independent variables and log–odds

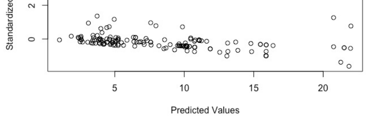


(a) Fukushima (2011) – Carbon Price

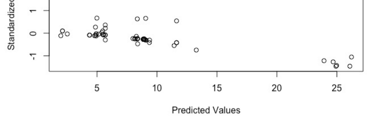


(b) Paris (2015) – Carbon Price

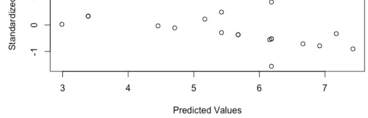
Figure 9: Regression 2 (APAC): Scatter plots of independent variables and log–odds



(a) Fukushima – Panel A



(b) Fukushima – Panel B



(c) Fukushima – Panel C

A.5 Clean energy robustness

Table 17: Regression 1: Clean energy robustness

Table 17 shows the results of Regression 1 re–run with the clean energy subsample instead of clean tech category of companies. The standard errors are reported in parentheses below. The sample period is 2000–2020. All independent variables are defined in subsection 5.2. Panel A comprises of the whole data set, Panel B comprises of a 3 year time window around the events, Panel C comprises of a 1 year time window around the events. *** 0.1% significance; ** 1% significance; * 5% significance; · 10% significance.

	Panel A	Panel B	Panel C
Intercept	−4.084 ***	−2.125 ***	−3.668 *
	(0.192)	(0.622)	(1.543)
Fukushima funding	−1.464 ***	−0.200	0.169
	(0.149)	(0.319)	(0.499)
Clean tech exit	0.007	0.009	—
	(0.018)	(0.036)	
Fund supply	0.000 ***	0.000	0.000
	(0.000)	(0.000)	(0.000)
Interest rate	−0.019	−0.354 *	2.557
	(0.029)	(0.164)	(4.009)
Oil price	0.014 ***	0.009 ·	−0.012
	(0.002)	(0.005)	(0.013)
PRI AUM	0.013 ***	−0.085 ***	—
	(0.003)	(0.022)	
APAC	−0.741 ***	0.026	−0.230
	(0.157)	(0.293)	(0.460)
Europe	−0.177	0.580 *	0.451
	(0.136)	(0.269)	(0.408)
US	−0.635 ***	−0.157	−0.404
	(0.133)	(0.271)	(0.417)
R^2_N	0.056	0.040	0.019
AIC	6,720	2,736	1,067
df	51,174	12,313	4,233
VIF (Fukushima funding)	3.362	7.028	7.050
VIF (Clean tech exits)	1.901	1.859	—
VIF (Fund supply)	2.860	1.679	2.069
VIF (Interest rate)	2.201	3.377	4.867
VIF (Oil price)	1.706	3.796	5.254
VIF (PRI AUM)	4.716	6.549	—
VIF (APAC)	1.999	3.318	2.846
VIF (Europe)	2.673	5.141	4.695
VIF (US)	2.771	4.990	4.404

A.6 Outsized return contingency tables

Table 18: Contingency table: 10X

Table 18 displays the contingency table of the independent samples of clean tech and non–clean tech early stage companies in terms of achieving at least a 10x return. The sample period is 2000–2023.

	10X	Non-10X	Sum
Non-Clean Tech Early Stage Company	721	49,488	50,209
Clean-Tech Early Stage Company	24	952	976
Sum	745	50,440	51,185

Table 19: Contingency table: 100X

Table 19 displays the contingency table of the independent samples of clean tech and non–clean tech early stage companies in terms of achieving at least a 100x return. The sample period is 2000–2023.

	100X	Non-100X	Sum
Non-Clean Tech Early Stage Company	88	50,121	50,209
Clean-Tech Early Stage Company	1	975	976
Sum	89	51,096	51,185

A.7 Time–to–exit

Table 20: Descriptive statistics: Time–to–exit

Table 20 displays the descriptive statistics of the independent samples of clean tech and non–clean tech early stage companies in terms of time–to–exit. The sample period is 2000–2023.

	n	Mean	sd	Median
Non-Clean Tech Early Stage Company	9,877	5.5698	3.7543	4.7583
Clean-Tech Early Stage Company	135	5.8661	3.7273	5.1694

Table 21: Welch's two sample t–test: Time–to–exit

Table 21 displays the results of Welch's two sample t–test comparing the independent samples of clean tech and non–clean tech early stage companies in terms of time–to–exit. The sample period is 2000–2023.

Test Statistic	0.9505
df	148.08
P-Value	0.3434
Confidence Interval (95%)	-0.3197 to 0.9122

A.8 Capital intensity

Table 22: Descriptive statistics: TFR full dataset

Table 22 displays the descriptive statistics of the independent samples of clean tech and non–clean tech early stage companies in terms of total funding raised (TFR). The sample period is 2000–2023.

	n	Mean	sd	Median
Non–Clean Tech Early Stage Company (TD=0)	50,208	38.6216	210.6846	7.0740
Clean–Tech Early Stage Company (TD=1)	976	28.2611	75.3964	5.1768

Table 23: Wilcoxon rank sum test: TFR full dataset

Table 23 displays the results of the Wilcoxon rank sum test comparing the independent samples of clean tech and non–clean tech early stage companies in terms of total funding raised (TFR). The sample period is 2000–2023.

Test Statistic	W = 22636534
P–Value	4.517e-05

Table 24: Descriptive statistics: TFR exited companies

Table 24 displays the descriptive statistics of the independent samples of clean tech and non–clean tech early stage companies for the subsample of exited companies in terms of total funding raised (TFR). The sample period is 2000–2023.

	n	Mean	sd	Median
Non–Clean Tech Early Stage Company	10,162	66.9208	362.6454	15.0566
Clean–Tech Early Stage Company	143	52.4492	85.1004	14.9050

Table 25: Wilcoxon rank sum test: TFR exited companies

Table 25 displays the results of the Wilcoxon rank sum test comparing the independent samples of clean tech and non–clean tech early stage companies for the subsample of exited companies in terms of total funding raised (TFR). The sample period is 2000–2023.

Test Statistic	W = 726612
P–Value	0.9994

A.9 Carbon price regressions

Table 26: Regression 1 & 2: Carbon price

Table 26 displays the results of Regression 1 and Regression 2 re–run with carbon price (Carbon price) instead of oil price (Oil price) for the subsample of EAA–headquartered companies. The sample period is 2000–2020. All independent variables are defined in the data section of the thesis. The standard errors are reported in parentheses below. *** 0.1% significance; ** 1% significance; * 5% significance; · 10% significance.

	Regression 1		Regression 2	
	Fukushima (2011)	Paris (2015)	Fukushima (2011)	Paris (2015)
Intercept	−2.981 ***	−3.031 ***	1.017	−1.277
	(0.215)	(0.217)	(1.191)	(1.462)
Fukushima funding	−0.469 *	—	−1.281 *	—
	(0.220)		(0.572)	
Paris funding	—	0.369	—	−4.037 **
		(0.376)		(1.551)
Clean tech exits	0.027	0.035	—	—
	(0.026)	(0.027)		
Fund supply	0.000 ***	0.000 ***	—	—
	(0.000)	(0.000)		
Interest rate	−0.107 *	−0.099 *	−0.044	0.023
	(0.049)	(0.050)	(0.153)	(0.140)
Carbon price	0.029 **	0.034 ***	−0.042	−0.051
	(0.011)	(0.010)	(0.037)	(0.037)
PRI AUM	0.001	−0.010 ·	—	—
	(0.006)	(0.006)		
Average round size	—	—	0.509 ***	0.950 ***
			(0.132)	(0.244)
$\sqrt{\text{Clean tech exits}}$	—	—	0.457	0.456
			(0.384)	(0.383)
R^2	—	—	0.061	0.068
$\bar{R}^2$	—	—	0.043	0.049
R^2_N	0.042	0.040	—	—
AIC	2,247	2,251	—	—
df	8,923	8,923	251	251
VIF (Fukushima funding)	2.779	—	1.436	—
VIF (Paris funding)	—	3.349	—	4.314
VIF (Clean tech exits)	1.615	1.721	—	—
VIF (Fund supply)	2.696	2.949	—	—
VIF (Interest rate)	2.010	2.070	1.437	1.224
VIF (Carbon price)	1.554	1.401	1.337	1.346
VIF (PRI AUM)	5.365	5.315	—	—
VIF (Average round size)	—	—	1.319	4.551
VIF ($\sqrt{\text{Clean tech exits}}$)	—	—	1.440	1.440

A.10 Correlation matrices

Table 27: Regression 1: Correlation matrix

	CT	FF	PF	CTE	FS	IR	OP	PRI	APA	EU	US
Clean tech	1.000										
Fukushima funding	– 0.051	1.000									
Paris funding	– 0.048	0.592	1.000								
Clean tech exits	0.037	0.356	– 0.067	1.000							
Fund supply	– 0.065	0.342	0.665	– 0.360	1.000						
Interest rate	– 0.008	– 0.624	– 0.204	– 0.631	0.278	1.000					
Oil price	0.039	0.404	– 0.137	0.634	– 0.264	– 0.466	1.000				
PRI AUM	– 0.046	0.843	0.843	0.228	0.556	– 0.484	0.150	1.000			
APAC	– 0.025	0.189	0.188	0.037	0.137	– 0.100	0.011	0.217	1.000		
Europe	0.039	– 0.086	– 0.082	0.006	– 0.088	0.010	– 0.001	– 0.099	– 0.299	1.000	
US	– 0.028	– 0.072	– 0.074	– 0.015	– 0.030	0.063	0.010	– 0.079	– 0.505	– 0.512	1.000
Observations	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*

Table 28: Regression 2: Correlation matrix

	RSCT	FF	PF	$\sqrt{\text{CTE}}$	ARS	IR	OP	APA	EU	US
Round size clean tech	1.000									
Fukushima funding	0.077	1.000								
Paris funding	0.183	0.592	1.000							
$\sqrt{\textbf{Clean tech exits}}$	0.024	0.462	0.103	1.000						
Average round size	0.219	0.465	0.866	– 0.055	1.000					
Interest rate	– 0.016	– 0.624	– 0.204	– 0.698	0.028	1.000				
Oil price	0.033	0.404	– 0.137	0.650	– 0.191	– 0.466	1.000			
APAC	0.129	0.189	0.188	0.068	0.169	– 0.100	0.011	1.000		
Europe	– 0.064	– 0.086	– 0.082	– 0.003	– 0.090	0.010	– 0.001	– 0.299	1.000	
US	0.033	– 0.072	– 0.074	– 0.030	– 0.053	0.063	0.010	– 0.505	– 0.512	1.000
Observations	*976*	*976*	*976*	*976*	*976*	*976*	*976*	*976*	*976*	*976*

Table 29: Regression 3: Correlation matrix

	FO	EX	IPO	5X	CT	FF	F×C	PF	P×C	FS	RS	IR	AF	IR	TFR	APA	EU	US
Follow on	1.000																	
Exit	0.190	1.000																
IPO	0.101	0.391	1.000															
5X return	0.090	0.319	0.440	1.000														
Clean tech	– 0.015	– 0.019	0.015	0.010	1.000													
Fuk. funding	– 0.007	– 0.222	– 0.080	– 0.037	– 0.051	1.000												
FF × CT	– 0.007	– 0.024	– 0.003	– 0.000	0.611	0.076	1.000											
Par. funding	0.011	– 0.199	– 0.066	– 0.055	– 0.048	0.592	0.017	1.000										
PF × CT	0.002	– 0.020	– 0.003	– 0.002	0.385	0.048	0.630	0.080	1.000									
Fund supply	– 0.004	– 0.140	– 0.048	– 0.055	– 0.065	0.342	0.001	0.665	0.054	1.000								
Round size	0.013	0.028	0.073	0.006	– 0.006	0.050	– 0.001	0.092	0.005	0.095	1.000							
Int. rate	0.003	0.122	0.041	– 0.003	– 0.008	– 0.624	– 0.053	– 0.204	– 0.015	0.278	0.003	1.000						
Age at fund.	– 0.054	– 0.005	0.010	– 0.017	0.047	– 0.005	0.037	0.027	0.019	– 0.011	0.012	– 0.026	1.000					
Inv. rounds	0.577	0.224	0.168	0.091	0.001	– 0.129	– 0.011	– 0.116	– 0.005	– 0.097	– 0.005	0.065	– 0.062	1.000				
Tot. fund. r.	0.127	0.068	0.154	0.130	– 0.007	0.046	– 0.004	0.027	– 0.001	0.013	0.307	– 0.038	– 0.027	0.239	1.000			
APAC	– 0.105	– 0.157	0.012	– 0.003	– 0.025	0.189	– 0.012	0.188	0.001	0.137	0.046	– 0.100	– 0.065	– 0.137	0.010	1.000		
Europe	– 0.127	– 0.080	– 0.033	– 0.051	0.039	– 0.086	0.029	– 0.082	0.007	– 0.088	– 0.023	0.010	0.051	– 0.150	– 0.048	– 0.299	1.000	
US	0.205	0.209	0.029	0.058	– 0.028	– 0.072	– 0.020	– 0.074	– 0.010	– 0.030	– 0.004	0.063	– 0.018	0.235	0.045	– 0.505	– 0.512	1.000
Observations	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*

Table 30: Regression 4: Correlation matrix

	COC	CT	FF	F×C	PF	P×C	FS	RS	IR	AaF	IR	TFR	APA	EU	US
CoC multiple	1.000														
Clean tech	– 0.001	1.000													
Fukushima funding	– 0.006	– 0.051	1.000												
FF × Clean tech	– 0.002	0.611	0.076	1.000											
Paris funding	– 0.018	– 0.048	0.592	0.017	1.000										
PF × Clean tech	– 0.001	0.385	0.048	0.630	0.080	1.000									
Fund supply	– 0.019	– 0.065	0.342	0.001	0.665	0.054	1.000								
Round size	– 0.003	– 0.006	0.050	– 0.001	0.092	0.005	0.095	1.000							
Interest rate	– 0.006	– 0.008	– 0.624	– 0.053	– 0.204	– 0.015	0.278	0.003	1.000						
Age at funding	– 0.006	0.047	– 0.005	0.037	0.027	0.019	– 0.011	0.012	– 0.026	1.000					
Investment rounds	0.032	0.001	– 0.129	– 0.011	– 0.116	– 0.005	– 0.097	– 0.005	0.065	– 0.062	1.000				
Total funding raised	0.086	– 0.007	0.046	– 0.004	0.027	– 0.001	0.013	0.307	– 0.038	– 0.027	0.239	1.000			
APAC	0.001	– 0.025	0.189	– 0.012	0.188	0.001	0.137	0.046	– 0.100	– 0.065	– 0.137	0.010	1.000		
Europe	– 0.012	0.039	– 0.086	0.029	– 0.082	0.007	– 0.088	– 0.023	0.010	0.051	– 0.150	– 0.048	– 0.299	1.000	
US	0.012	– 0.028	– 0.072	– 0.020	– 0.074	– 0.010	– 0.030	– 0.004	0.063	– 0.018	0.235	0.045	– 0.505	– 0.512	1.000
Observations	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*	*51,184*

Table 31: Regression 5: Correlation matrix

	CTE	FE	PE	IRE	PRI	MSCI	OPE	SPAC	APA	EU	US
Clean tech exit	1.000										
Fukushima exit	– 0.008	1.000									
Paris exit	– 0.011	0.599	1.000								
Interest rate exit	– 0.003	– 0.478	– 0.100	1.000							
PRI AUM exit	– 0.006	0.755	0.879	– 0.280	1.000						
MSCI price exit	– 0.002	0.642	0.816	– 0.099	0.941	1.000					
Oil price exit	0.016	0.275	– 0.193	– 0.198	0.043	0.095	1.000				
SPAC count exit	– 0.009	0.284	0.518	– 0.194	0.643	0.727	– 0.119	1.000			
APAC	0.014	0.040	0.040	– 0.002	0.053	0.054	0.034	0.006	1.000		
Europe	0.023	0.014	– 0.015	0.015	0.011	0.022	0.073	– 0.002	– 0.299	1.000	
US	– 0.058	0.008	0.008	– 0.039	– 0.009	– 0.025	– 0.043	0.001	– 0.505	– 0.512	1.000
Observations	*10,604*	*10,604*	*10,604*	*10,604*	*10,604*	*10,604*	*10,604*	*10,604*	*10,604*	*10,604*	*10,604*

Table 32: Regression 6: Correlation matrix

	COC	FE	PE	CaE	IRE	PRI	OPE	TFR	RS	IR	FS	AaF	APA	EU	US
CoC clean tech	1.000														
Fukushima exit	0.139	1.000													
Paris exit	0.011	0.599	1.000												
CoC average exit	0.195	0.499	0.552	1.000											
Interest rate exit	– 0.068	– 0.478	– 0.100	– 0.309	1.000										
PRI AUM exit	0.027	0.755	0.879	0.739	– 0.280	1.000									
Oil price exit	0.244	0.275	– 0.193	0.150	– 0.198	0.043	1.000								
Total funding raised	– 0.064	0.079	0.111	0.109	– 0.030	0.116	0.002	1.000							
Round size	– 0.204	0.026	0.061	0.061	– 0.009	0.058	– 0.027	0.307	1.000						
Investment rounds	– 0.241	0.094	0.080	0.055	– 0.053	0.092	0.067	0.239	– 0.005	1.000					
Fund supply	– 0.016	– 0.129	0.130	0.100	0.198	0.082	– 0.257	0.013	0.095	– 0.097	1.000				
Age at funding	– 0.137	– 0.006	0.009	0.005	0.015	0.011	– 0.020	– 0.027	0.012	– 0.062	– 0.011	1.000			
APAC	0.209	0.040	0.040	0.024	– 0.002	0.053	0.034	0.010	0.046	– 0.137	0.137	– 0.065	1.000		
Europe	– 0.164	0.014	– 0.015	0.013	0.015	0.011	0.073	– 0.048	– 0.023	– 0.150	– 0.088	0.051	– 0.299	1.000	
US	– 0.071	0.008	0.008	– 0.004	– 0.039	– 0.009	– 0.043	0.045	– 0.004	0.235	– 0.030	– 0.018	– 0.505	– 0.512	1.000
Observations	*50*	*50*	*50*	*50*	*50*	*50*	*50*	*50*	*50*	*50*	*50*	*50*	*50*	*50*	*50*

A.11 APAC robustness

Table 33: Regression 1 & 2: APAC robustness

Table 33 displays the results of Regressions 1 and 2 for Fukushima (2011) with data only from the APAC region. All independent variables are defined in the data section of the thesis. The sample period is 2000–2020. The standard errors are reported in parentheses below. ***0.1% significance; **1% significance; *5% significance; · 10% significance.

	Regression 1			Regression 2		
	Panel A (unlim.)	Panel B (3 year)	Panel C (1 year)	Panel A (unlim.)	Panel B (3 year)	Panel C (1 year)
Intercept	−3.949 ***	−0.998	1.328	−6.641	5.919	−15.130
	(0.358)	(1.256)	(3.248)	(5.521)	(41.176)	(14.750)
Fukushima funding	−1.955 ***	−0.703	−0.604	−6.860 *	−0.250	4.750
	(0.341)	(0.759)	(1.126)	(3.158)	(10.010)	(3.180)
Clean tech exits	0.027	−0.014	—	—	—	—
	(0.040)	(0.085)				
Fund supply	0.000	0.000	0.000	—	—	—
	(0.000)	(0.000)	(0.000)			
Interest rate	−0.046	−0.328	−6.981	−0.954	6.756	25.400
	(0.066)	(0.370)	(7.115)	(0.736)	(6.119)	(25.280)
Oil price	0.009 *	0.004	−0.048	0.109 *	0.002	—
	(0.004)	(0.010)	(0.034)	(0.051)	(0.181)	
PRI AUM	0.009	−0.074	—	—	—	—
	(0.007)	(0.052)				
Average round	—	—	—	2.081 ***	3.210	3.610
				(0.476)	(6.506)	(3.060)
$\sqrt{\text{Clean tech exits}}$	—	—	—	−0.342	−4.872	—
				(1.857)	(6.537)	
R^2	—	—	—	0.130	0.157	0.134
$\bar{R}^2$	—	—	—	0.100	0.078	−0.019
R^2_N	0.060	0.060	0.050	—	—	—
AIC	1,522	530.6	190.4	—	—	—
DF	11,667	2,182	718	144	54	17
VIF (FF)	4.140	6.838	5.735	2.113	4.696	3.759
VIF (CTE)	2.142	1.850	—	—	—	—
VIF (FS)	3.350	1.650	2.708	—	—	—
VIF (IR)	2.595	3.458	2.787	1.976	3.924	3.156
VIF (OP)	1.580	3.731	5.381	1.718	4.251	—
VIF (PRI)	5.877	6.928	—	—	—	—
VIF (AR)	—	—	—	1.827	3.898	1.424
VIF ($\sqrt{\text{CTE}}$)	—	—	—	2.149	1.352	—

A.12 Success metric plots

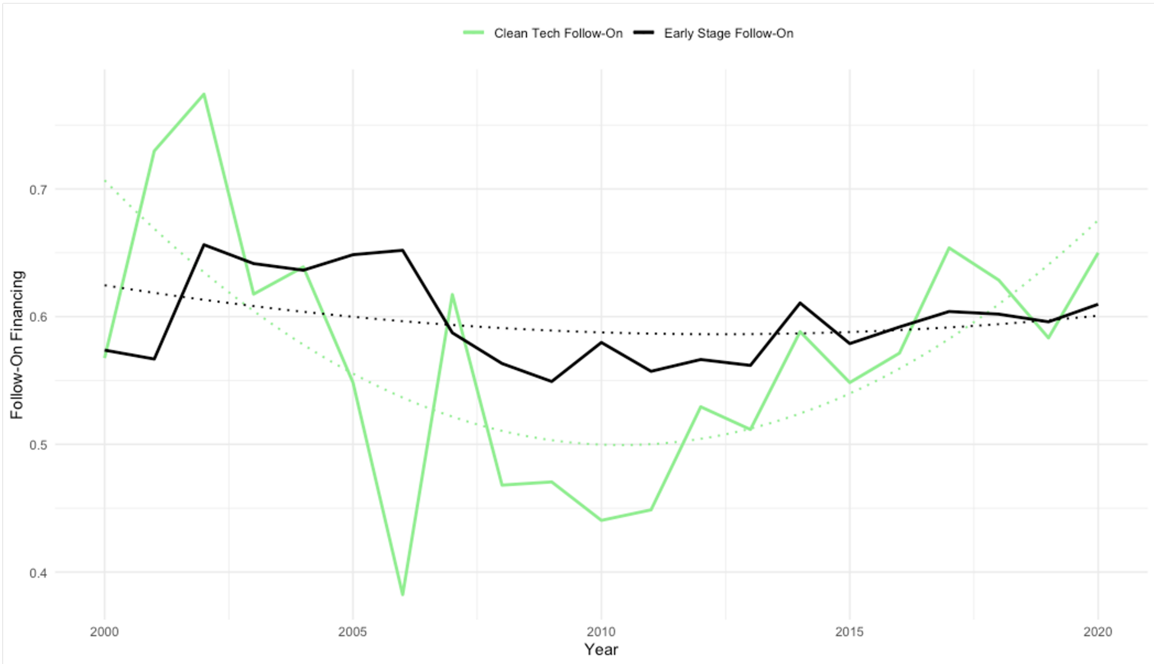


Figure 10: Likelihood of follow on financing by year of early–stage funding received
The figure shows the sample distribution of the likelihood of follow on financing by year of early–stage funding received over time for clean tech companies compared to other companies. The sample period is 2000–2020.

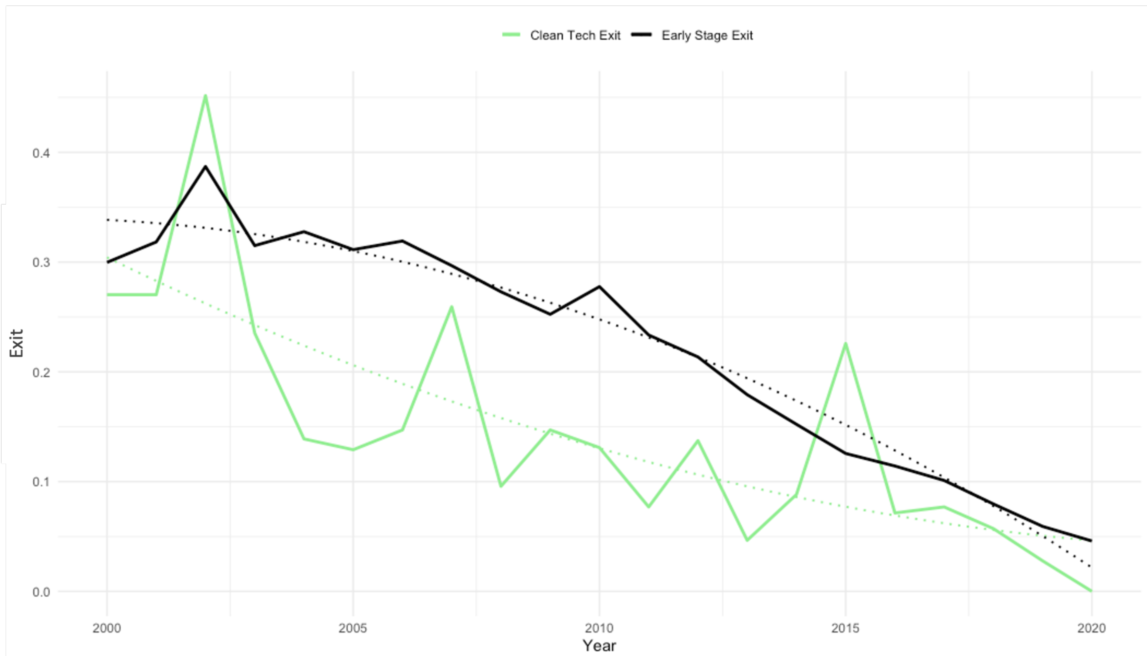


Figure 11: Likelihood of exit by year of early–stage funding received
The figure shows the sample distribution of the likelihood of exit by year of early–stage funding received over time for clean tech companies compared to other companies. The sample period is 2000–2020.

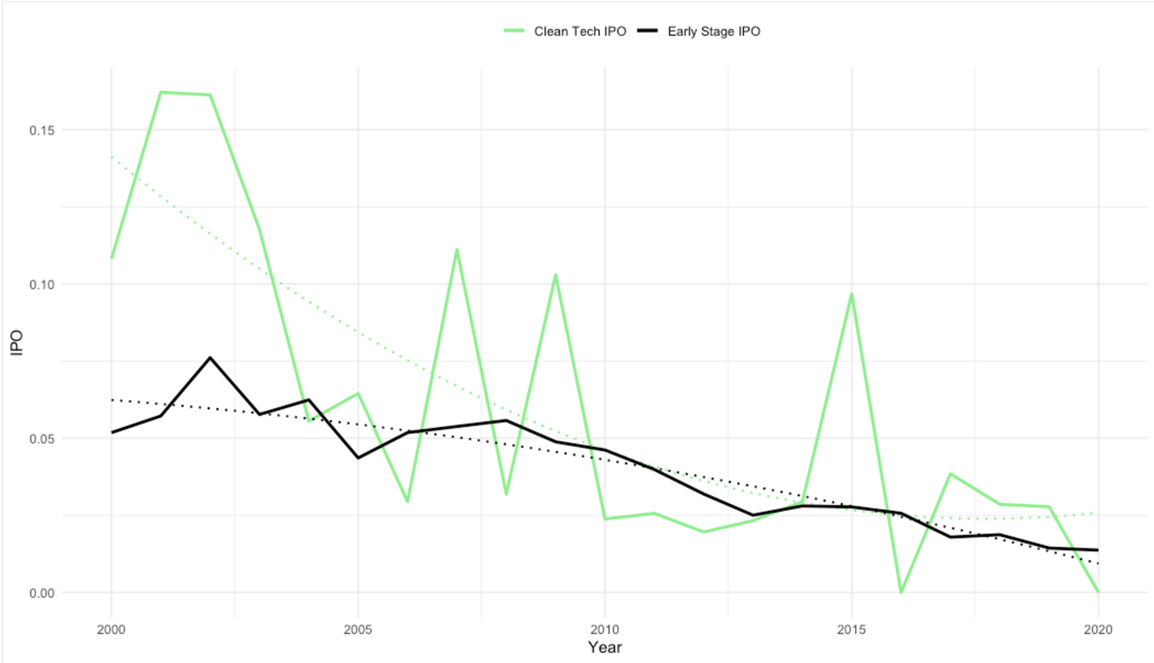


Figure 12: Likelihood of IPO by year of early–stage funding received
The figure shows the sample distribution of the likelihood of IPO by year of early–stage funding received over time for clean tech companies compared to other companies. The sample period is 2000–2020.

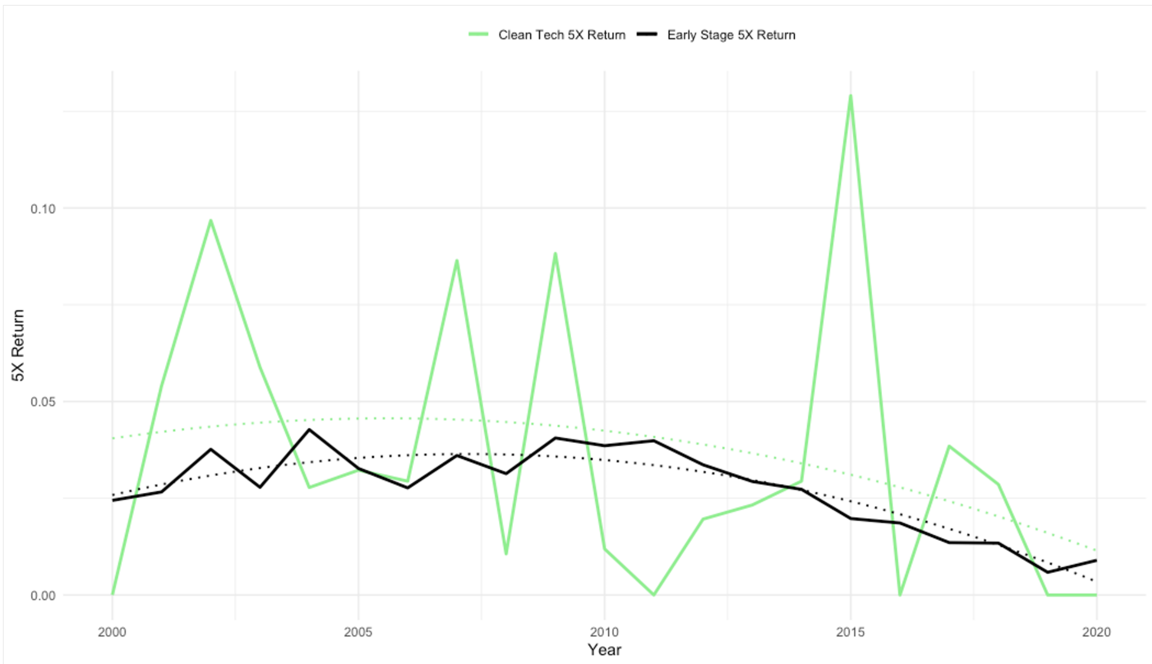


Figure 13: Likelihood of 5x return by year of early–stage funding received
The figure shows the sample distribution of the likelihood of 5x return by year of early–stage funding received over time for clean tech companies compared to other companies. The sample period is 2000–2020.