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CLEANTECH VENTURE CAPITAL: THE IMPACT OF THE PARIS AGREEMENT

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ABSTRACT

This paper aims to investigate the impact of the Paris Agreement (PA) on the allocation of capital from venture capital (VC) firms towards cleantech startups. The study analyzed over 12,000 investments in 2,021 cleantech startups and compared them to a control sample of over 300,000 investments in non-cleantech startups. This paper constructed five hypotheses to answer the research question and used Difference-in-Differences regressions, multilevel analyses, and multinomial regressions to test these hypotheses. The results showed that the PA had a negative impact on cleantech investments, and private VC firms and smaller syndicates invested more in cleantech. Additionally, the study found that VC exits were more successful for VC firms that invested in cleantech. However, the robustness checks implicated that investments made in the US were responsible for the negative impact of the PA that was found. The findings provide interesting insights into the factors influencing the allocation of VC funds towards cleantech startups.

Keywords: Venture Capital, cleantech, Paris Agreement, VC characteristics, VC investments

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LIST OF ABBREVIATIONS

ATE	Average treatment effect
CVC	Corporate venture capital
DiD	Difference-in-differences
GP	General partner
ICC	Intraclass correlation coefficient
LRTest	Likelihood Ratio Test
M&A	Mergers and acquisitions
MLME	Multilevel mixed effects
NAV	Net asset value
PA	Paris Agreement
PE	Private Equity
PMI	Post-merger integration
R&D	Research and development
VC	Venture Capital
YoY	Year-on-year

1 Introduction

1.1 Research question

The U.N. Secretary-General, António Guterres called a study from the climate panel: "A code red for humanity." Experts have described that there is no doubt that the planet's climate system has been harmed by human activity. Negative effects have been observed on every continent and still no effective strategies to stop these have been implemented (Meredith, 2021). Businesses throughout the globe are now adjusting to the transformation of the global energy industry, which is transitioning from fossil fuels to renewable energy sources (S&P Global, 2020). The *Renewables Global Status Report* (2021) highlights that oil, gas, and coal consumption has barely changed over the past decade. Energy incumbents[1] have invested next to nothing in renewable energies. The surge of energy incumbents with net-zero emission goals for 2050 may sound encouraging, but it looks to be merely another type of greenwashing[2] (Kumar, 2021).

Shareholders of fossil fuel companies have seen a 7% underperformance compared to the S&P 500 during the last 15 years. This indicates that the conventional energy industry has been facing pressure from its investors for some time. McKinsey's analysis shows that worldwide investments in the sector have surpassed $10 trillion during this period. However, these excessive investments have made it challenging to achieve profitable returns compared to the past (Beck et al., 2021). This implies that the industry is struggling to generate value from its investments due to declining margins.

Private equity (PE) spent approximately $24 billion on renewables in 2020, a fourfold increase from 2019. PE accounted for 50% of all private investments in renewable energy in the United States when it totaled $55 billion (American Investment Council, 2021). This is a positive trend in the fight against global warming. If the companies receiving these investments would be able to use them for the better, then maybe they stand a chance against global warming.

[1] Energy incumbents are large, established companies that dominate the traditional energy sector, including fossil fuel extraction, production, and distribution. They have significant market share and political influence and may face challenges in adapting to the changing energy landscape, including the transition to cleaner and more sustainable forms of energy.
[2] Greenwashing is a marketing strategy where companies make misleading or false environmental claims about their products or services to appeal to eco-conscious consumers, without actually implementing meaningful sustainability practices.

Cleantech refers to technologies and products that are designed to be environmentally friendly and sustainable, to reduce negative impacts on the environment. This term encompasses a wide range of industries, including renewable energy, energy efficiency, water conservation, waste management, and sustainable transportation, among others. The goal of cleantech is to provide environmentally sound alternatives to traditional technologies and practices that have contributed to environmental degradation. Cleantech is often seen as a key solution for mitigating the effects of climate change and promoting a more sustainable future (Pernick & Wilder, 2007).

The Paris Agreement (PA) is an international treaty signed by countries at the 21st Conference of the Parties of the United Nations Framework Convention on Climate Change in 2015. The main goal of the PA is to limit global temperature rise to well below 2 degrees Celsius above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 degrees Celsius. To achieve this, countries agreed to regularly report on their emissions and to take steps to reduce their carbon footprint.

Although private capital allocation towards the energy transition is crucial, research on this topic is currently lacking. Several authors researched cleantech investments regarding the performance and risks involved, but nothing has been written on which factors determine the allocation of funds to cleantech companies since the PA. However, this would be interesting to research because it would indicate whether our efforts to minimize global warming are making an impact. Based on the above, the following research question is formulated:

"How has the PA influenced the distribution of capital from venture capital (VC) firms toward cleantech startups?"

From 2002 to 2006, cleantech went from being a small niche to a "hot" investment sector. While originally driven by a handful of specialized VC investors, cleantech gained popularity in the VC community around 2006, according to prominent VC investor John Doerr it "could be the largest economic opportunity of the 21st century. It is an unprecedented challenge that demands great innovation, speed, and scale."

1.2 Relevance

Renewable energy projects and resources are being supported by energy incumbents through various methods. They play a significant role in this field, bringing their resources and expertise to the development of sustainable energy solutions. However, the results of their initiatives have been inconsistent, and their strategies are continually evolving (Zhong & Bazilian, 2018).

Energy incumbents are positioning themselves as future providers of renewable energy. According to findings, most energy incumbents have invested heavily in renewable resources. There is a correlation between a decrease in oil reserves and an increase in renewable energy efforts, suggesting that energy incumbents with fewer oil reserves tend to transition to renewables faster than those with larger reserves (Pickl, 2019).

This study aims to identify where future funding should be allocated and which government policies should be prioritized by examining the factors that drive cleantech investment.

The world cannot effectively tackle climate change without advanced energy technology. This research will uncover what motivates investors to invest in cleantech.

The following chapter of the paper reviews previous studies to provide an overview of existing theories, and research methods, and identify gaps in prior work. Based on the literature review, hypotheses are formed and expectations for this study are established. The sample selection and analysis methods are then discussed. Key findings are presented in the results section, followed by a discussion of the relevance, significance, and implications of the results. Finally, the research question is answered, and a discussion of this paper is provided in the conclusion and discussion section.

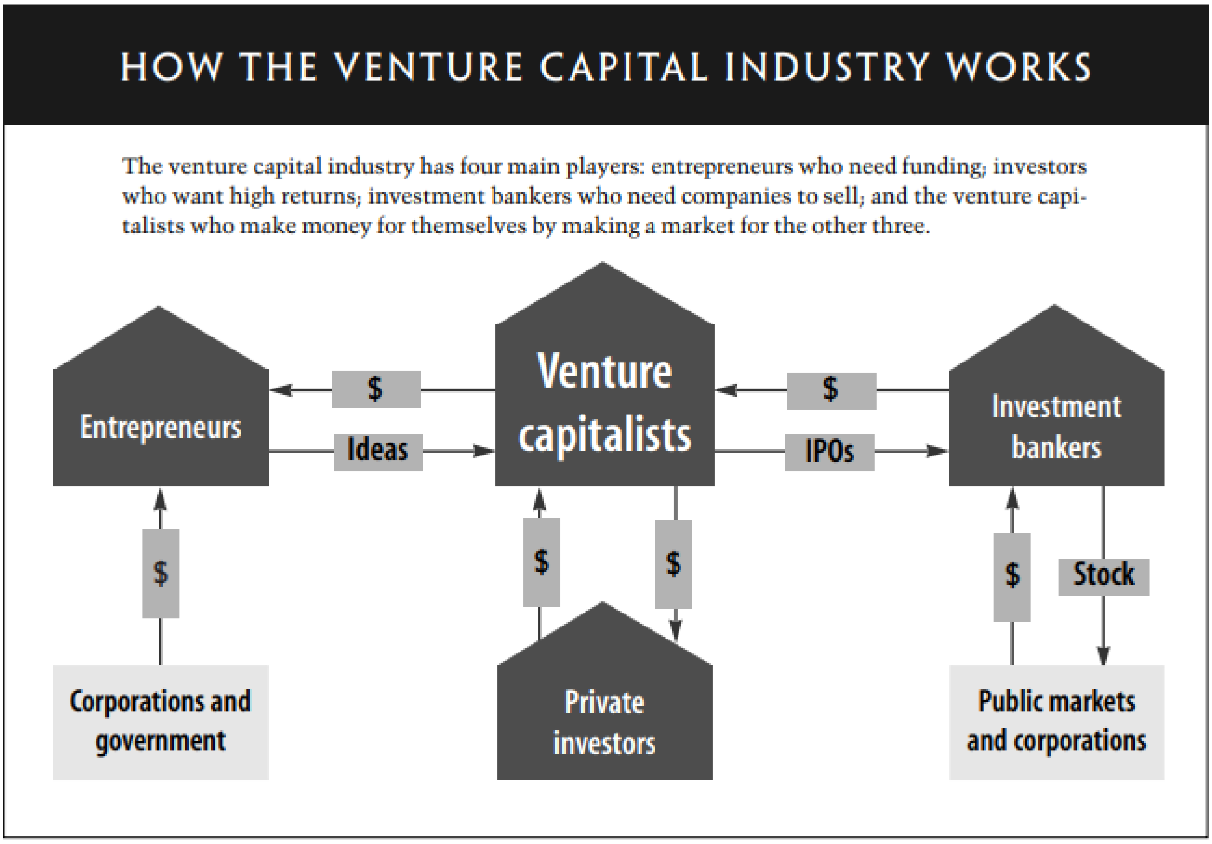
2 Literature review

The literature review provides a thorough analysis of VC innovation, returns, funding rounds, corporate VC, post-merger integration (PMI), and cleantech. As a result, gaps in the academic field are uncovered. Relevant findings, models, and theories are provided to form the hypotheses used to answer the research question.

2.1 Venture capital

VC plays a critical role in financing innovation, serving as a bridge between sources of funding such as companies, governments, and personal networks, and more conventional financing for companies (Zider, 1998). As shown in Figure 1, VCs provide a fund where large investors can participate and aim to generate high returns over a predetermined period by investing in innovative startups in thriving industries (Zider, 1998).

Figure 1: How VC works



Source: (Zider, 1998).

VCs continually evaluate their investments and if negative returns are discovered, they may discontinue their involvement in the project. Public companies tend to attract more investments and financing rounds compared to private companies and young firms often receive limited funding during a single investment round. As a company's future investment prospects have a significant impact on its value, multiple investment rounds are typically secured over time (Gompers, 1995).

Studies have shown that older and larger VC firms tend to have more performance-based pay compared to their younger or smaller counterparts. For instance, Gompers & Lerner (1999) found that the oldest and largest venture firms receive around 1% more capital gains, which can increase overall compensation by over 4% if the fund is successful. However, the study did not find a correlation between incentive pay and fund performance. It is worth noting that "performance-based pay" refers to compensation that is tied to the performance of the fund, rather than a fixed salary.

The general economic climate also plays a crucial role in affecting the limitations of limited partnerships for venture financing. During times of economic growth, venture financing funds tend to attract more capital, and fund managers receive higher salaries with fewer restrictions (Gompers & Lerner, 1996).

Barber & Yasuda (2017) find that when seeking funds for a follow-on fund, general partners (GPs) in PE disclose the results of their previous fund. The interim performance has a significant impact on the outcome of fundraising. The effect is particularly pronounced for GPs with a poor reputation and successful exits. In response, GPs use one of two strategies - exit ventures and raise capital or control net asset value (NAV) - to align their fundraising with times of peak performance. Funds with high exit rates tend to see the highest performance peaks, while poor reputation GPs with low realization rates tend to see performance peaks and declines following fundraising.

In summary, VC plays a critical role in financing innovation, and performance-based pay and the general economic climate can affect the success of VC firms. Additionally, fundraising outcomes can be influenced by the interim performance of a previous fund and GPs may use specific strategies to align fundraising with peak performance.

2.1.1 Innovation

VC has become a crucial source of funding for innovative startups in recent decades. The study by Gompers & Lerner (2001) highlights the significant growth of the VC industry, with investments increasing from less than $100 million to more than $20 billion per year between 1970 and 1999. This growth has been fueled by the important role that VC firms play in fostering innovation and supporting the growth of new companies.

One way that VC firms contribute to the success of startups is by providing more than just financing. As Kerr & Nanda (2015) note, VC firms often offer valuable advice, connections, and expertise to help companies grow and succeed. This support can be especially important for startups that are developing new and complex technologies, as the expertise of VC investors can help these companies navigate technical challenges and market uncertainties.

Sorensen (2007) explores the impact of "smart money" in the VC industry, finding that the quality of the VC firm can have a significant impact on the success of the startup. Specifically, Sorensen's research shows that VC firms with a strong track record of successful investments and expertise in the relevant industry are more likely to invest in startups that ultimately perform well.

Hall & Lerner (2010) provide further evidence of the importance of VC in funding research and development (R&D) and promoting innovation. Their research highlights the role of VC in financing high-risk, high-reward R&D projects that might not receive funding from other sources. By providing financing for these projects, VC firms can help spur innovation and drive economic growth.

Finally, Cumming & Johan (2009) provide an international perspective on the VC industry, exploring the different forms of VC contracting and how VC firms operate in different countries. This research highlights the importance of regulatory and legal frameworks in shaping the VC industry and promoting innovation.

In conclusion, these studies collectively suggest that the VC industry plays a critical role in fostering innovation and supporting the growth of new companies. By providing not just financing but also advice, expertise, and connections, VC firms can help startups navigate technical and market challenges, fund high-risk R&D projects, and ultimately drive economic growth. The quality of the VC firm, the regulatory and legal environment, and the expertise of the investors are all key factors that shape the impact of VC on innovation.

2.1.2 Returns

This paper provides an overview of the expectations and perceptions of large institutional investors in VC and the empirical evidence on VC returns.

According to Zider (1998), large institutional investors expect a 25-35% annual return on investment in VC, driven by the reputation of the VC firm and its partners, rather than individual investments. Puri & Zarutskie (2012) found that portfolio firms of VC investors are more likely to go public, get acquired, or succeed, supporting the argument that VC investments lead to better outcomes compared to a control group. Cressy et al. (2007) found that PE-backed firms achieved 4.5% higher profitability compared to their peers in the three years after a leveraged buyout. This supports the Jensen hypothesis that PE firms provide better governance, leading to better performance, and the advantages-of-specialization hypothesis, which states that PE firms that focus on a specific industry have an even greater performance advantage. The findings of Cressy et al. (2007) also suggest that effective investment selection and corporate finance practices are crucial for success in PE-backed firms.

Overall, the literature reviewed suggests that VC investments can lead to attractive returns for institutional investors, driven by factors such as the reputation of the VC firm and its partners, effective investment selection and corporate finance practices, and the advantages of specialization in PE.

2.1.3 Funding rounds

It is ideal to seek funding from VCs only when enterprises encounter an uncertain but high-reward project with substantial profits when the outcome is favorable (Metrick & Yasuda, 2011). VC can participate in such a project, which allows the company to share the risks and use certain knowledge that a VC has to offer. VCs have experience with these kinds of projects and could add value to the company.

Investments made by VC firms are frequently staged rather than a large sum made upfront because VCs want to monitor their initial investment before committing a large amount of capital. They monitor this initial investment based on some performance measures and based on the interim performance they can choose to invest more of their funds or abandon the project. Staged financing is a popular form of VC investment because it mitigates moral hazards and decreases risks (Wang & Zhou, 2004). Koçkesen & Ozerturk (2002) add another advantage for VC firms. The VC can get an informational advantage over uninformed outsiders which makes staging the ideal financing mechanism. A "lock-in" will occur because the VC can further its investment on better terms than uninformed competitors. Also, staged financing and syndication add value to the company receiving the investment as it allows them to raise capital in a controlled and structured manner, while also providing accountability and access to expertise (Smolarski & Kut, 2011). However, there is also a drawback with staged financing. Entrepreneurs get an incentive to underinvest in future earnings and to overinvest in the upcoming years to keep the VC satisfied (Yung, 2019). Which will lead to bad performance and losses for investors in the long term.

Young companies are often characterized by uncertainty and informational asymmetries, especially in the technology sector. When a company receives capital from a VC, the management may take excessive risks since he or she does not suffer the full cost of these expenditures. This is an example of the moral hazard problem (Jensen & Meckling, 1976). Staged cash injection may be a venture capitalist's best control technique. Staged capital injection "leashes" the owner/manager and decreases bad-decision losses. As the firm grows, the VC may extend financing and lower reevaluation frequency (Sahlman, 1990).

The literature summarizes the benefits and drawbacks of VC funding rounds for startups and young companies. The authors discuss how staged financing is a popular form of VC investment due to its ability to mitigate moral hazards and reduce risks, while also providing an informational advantage to the VC firm. However, they also mention that this form of financing may incentivize entrepreneurs to underinvest in future earnings and overinvest in the present to keep the VC satisfied. Additionally, the authors mention the moral hazard problem of management taking excessive risks with VC funds and how staged financing may help to mitigate this problem. Overall, the literature provides an insightful overview of the advantages and limitations of VC funding rounds.

2.1.4 Corporate venture capital

The literature on corporate venture capital (CVC) highlights the unique advantages and challenges that CVCs face compared to private, independent VCs. Hellmann (2002) introduces the concept of strategic venture investing, where CVCs aim to gain strategic advantages from synergies with their primary business. The decision for entrepreneurs to accept funding from a CVC or an independent VC may depend on the potential synergies between the startup and the CVC's existing business, as well as the potential trade-offs (Hellmann, 2002).

Norbäck & Persson (2009) and Riyanto & Schwienbacher (2006) both examine the decision of whether to accept funding from a CVC or an independent VC, taking into account incumbent and entrant competition, and complementarity between the CVC and the startup. Fulghieri & Sevilir (2009) include product market competitiveness in their model, suggesting that CVC investment may be advantageous in highly competitive markets where innovation is key.

Chemmanur, Loutskina, & Tian (2014) find that CVCs invest in younger, early-stage startups and less mature, R&D-intensive sectors compared to independent VCs. CVCs also tend to invest at higher valuations and are more tolerant of failure. Furthermore, CVC-backed companies attract higher-quality underwriters, analysts, and institutional investors when taking firms public and tend to create more patents, indicating greater innovation.

Yang et al. (2009) examine the effects of experience intensity, variety, and experience in acquisitions on the capacity development of CVC investments. They find that CVCs benefit from greater sector variety and experience intensity, as well as a successful acquisition experience.

In conclusion, the literature highlights the unique advantages and trade-offs of CVC investment compared to independent VC investment, as well as the importance of experience and strategic considerations in CVC investment decision-making.

2.2 Post-merger integration

PMI is a critical factor in ensuring the success of an acquisition and realizing its full potential. Despite the high stakes involved, a significant number of mergers and acquisitions (M&A) fall short of expectations and fail to deliver value. According to a study by McKinsey, firms that effectively manage PMI tend to experience 6-12% higher growth rates than their peers (Doherty, Engert, & West, 2016).

The literature suggests that effective PMI involves a combination of planning, strategy development, the right team, and best practices. Additionally, companies with more acquisition experience tend to perform better in future M&A deals (Pennings, Barkema, & Douma, 1994). This is often referred to as learning-by-doing or experiential learning. Several studies have explored this relationship, but the results have been inconclusive, with some finding a positive effect, others finding a negative impact, and still, others finding no significant correlation (Barkema & Schijven, 2008a; Barkema & Schijven, 2008b; Pennings et al., 1994; Ellis et al., 2011; Barkema et al., 1996).

It is also suggested that companies that have experience with M&A and a larger scale can better weather the fluctuations in acquisition activity (Laamanen & Keil, 2008). On the other hand, an excessive rate of acquisitions, or an unfavorable history of prior deals, can negatively impact deal performance (Castellaneta & Zollo, 2015). These findings highlight the importance of careful consideration and effective management of PMI for M&A success.

2.3 Cleantech

Cleantech refers to the use of innovative technology and processes to reduce or eliminate negative environmental impacts, particularly in the areas of energy, transportation, and resource efficiency. This term can encompass a range of initiatives, including renewable energy sources, efficient recycling processes, and strategies to reduce the impact of fossil fuels (Pernick & Wilder, 2007).

Cleantech VC poses unique challenges due to its technical risks, such as scalability and exit criteria, and its requirements for substantial resources (Cumming, Henriques, & Sadorsky, 2016). The benefits of cleantech, such as reduced environmental harm and improved public health, are not fully captured by VCs. The authors found that oil prices have a greater impact on cleantech VC transactions than institutional, legal, or economic factors. Additionally, regions such as Europe with high carbon prices offer incentives for innovation to reduce the carbon footprint.

Gaddy et al. (2017) conducted a comprehensive analysis of the risk and return profile of cleantech investments, integrating data from hundreds of investments. The authors found that VC firms view cleantech as a risky and low-return investment class, with "deep technology" investments being the most resource-intensive and yielding the lowest returns. To foster new cleantech innovations, the authors call for greater support from politicians, companies, and investors.

Bürer & Wüstenhagen (2009) surveyed VC and PE firms to gauge their preferences for different regulations that encourage investment in cleantech. The authors found that feed-in taxes were the most effective renewable energy legislation, according to the investors surveyed.

VCs' inability to exit investments at the right time is a major barrier to energy innovation. Ghosh & Nanda (2010) compare this challenge to similar issues faced by the communications networking and biotechnology industries, which were eventually addressed by modifying the innovation environment. However, unlike other industries, the energy sector tends to have lower end-user demand for new technologies, and energy incumbents are often less motivated to adopt cleantech innovations due to their established dominant market position. The authors emphasize the need for government intervention to overcome these challenges. Cherry et al. (2010) use the BP oil disaster as a case study to explore the relationship between green marketing and corporate governance and to identify the factors that may motivate companies to engage in only superficial forms of corporate social responsibility, while still promoting their efforts to consumers and investors. The analysis sheds light on the underlying drivers of corporate behavior in this area and highlights the potential tension between corporate profits and genuine commitment to environmental and social responsibility.

Hart & Christensen (2002) argue that the key to advancing renewable energy technology will not come from the laboratory, but rather from the development and refinement of these technologies in real-world implementations through disruptive techniques.

Cohen & Winn (2007) posit that many of today's environmental problems stem from inefficiencies in the market, such as externalities, inefficient operations by companies, and insufficient information in the market and pricing. These market deficiencies create opportunities for innovative companies, promote more sustainable operations, and improve performance.

Polzin (2017) argues that the government can play a crucial role in redirecting private financing toward cleantech, by ending unproductive subsidies, supporting cleantech creation and distribution, balancing market forces, and clarifying the risks of fossil fuels. Financiers must educate themselves on cleantech and the new market for renewables.

Wüstenhagen et al. (2009) note that policymakers tend to favor established companies over startups in the field of revolutionary energy technologies. However, Wüstenhagen & Menichetti (2012) argue that diverse investors require policy segmentation.

Doblinger, Surana & Anadon (2019) propose and evaluate value-creation strategies for cleantech startups, highlighting the importance of government partners in providing resources and stimulating innovation. The authors stress the relevance of government partners in promoting cleantech innovation.

In conclusion, the literature reviewed highlights the challenges and opportunities associated with investing in cleantech and the role of government and private financing sources in promoting cleantech innovation. The literature argues that government intervention and support are crucial in addressing the technical and financial challenges of investing in cleantech and promoting a more sustainable future.

3 Hypotheses

This paper examines institutional factors affecting cleantech VC. The focus lies on the investments, syndicate size, and exits. Based on previous literature, five hypotheses can be formed.

Economic, political, and contractual regulations are examples of formal institutions that are crucial to cleantech VC activity because they lower transaction and opportunity costs. As a result, cleantech VC financing takes place in a more favorable business climate (Cumming, Henriques, & Sadorsky, 2016). To accomplish the objectives of the PA, the Mission Innovation Initiative[3] was brought to life. It is a global partnership of countries committed to accelerating the development and deployment of cleantech to address climate change. The initiative aims to double government investment in clean energy R&D over five years and to increase collaboration and knowledge-sharing between participating countries and the private sector. This leads to the first hypothesis of this paper:

Hypothesis 1: *Since the PA, VCs located in Mission Innovation countries have invested more in cleantech startups than before the PA.*

Investors in cleantech are more likely to be inexperienced because there are fewer exit opportunities (Schwienbacher, 2008). This lowers the number of investments in cleantech because the number of exit possibilities is reduced. Also, energy incumbents are less likely to invest in cleantech startups because they believe the startups will cannibalize their profits, which further reduces exit opportunities (Ghosh & Nanda, 2010). Inexperienced investors are more likely to invest in boom markets without experiencing a significant bust (Gompers & Lerner, 1999). Since the cleantech sector's popularity has increased since the PA, the second hypothesis is:

Hypothesis 2: *Since the PA, less-experienced VCs have invested more in cleantech startups than VCs that are more experienced.*

Investments by the energy incumbents tend to be perceived as 'greenwashing', which is a communication and marketing strategy to forge an ecologically responsible image among the public instead of making a real difference (Cherry & Sneirson, 2010). This causes them to

[3] For more information about the Mission Innovation Initiative, visit http://mission-innovation.net/.

stay away from cleantech investments, which reduces exit opportunities. Because energy incumbents stay away from cleantech investments, the third hypothesis of this paper is:

Hypothesis 3: *Corporate VCs have invested less in cleantech startups after the PA compared to Private VCs.*

Less experienced investors who are more likely to invest in cleantech may also have inadequate funds to finance the investment on their own (Reid, 1998). There are risks when investing in cleantech, so VCs would like to share these risks (Awounou-N’dri & Boufaden, 2020). At last, syndication is also beneficial when the deal flow is high and when VCs want to diversify their portfolio (Cumming, 2006). All these are arguments for syndicates to be bigger for cleantech investments when compared to non-cleantech investments. So, this results in the paper’s fourth hypothesis:

Hypothesis 4: *Syndicate size was larger for investments in cleantech startups compared to non-cleantech startups.*

Energy incumbents are not interested in acquiring cleantech companies as they are afraid these companies will cannibalize their profits. Fewer exit possibilities mean that there is a higher likelihood of inexperienced investors (Schwienbacher, 2008). Experience in VC is key to the success of their investments (Nahata, 2008). Inexperienced investors have never experienced a significant crash and because they lack this experience, they are more likely to invest in bull markets (Gompers & Lerner, 1999). This causes them to make significant losses after the bubble has burst (Nahata, 2008). Since the cleantech sector’s popularity has increased since the PA, the last hypothesis is:

Hypothesis 5: *Since the PA, cleantech VC exits have been less successful.*

4 Data and methodology

This chapter is divided into the sample construction and the methodology. In the sample construction, this paper provides the dependent, independent, and control variables to answer the hypotheses and research question and ends with descriptive statistics. The methodology follows an explanation of which regressions are used to answer all hypotheses.

4.1 Sample construction

This paper analyzes the influence of the PA on cleantech VC funding, the sample construction starts with the classification of cleantech. Cleantech is any good, resource, or activity that generates less pollution and uses fewer fossil fuels (Pernick & Wilder, 2007).

The cleantech VC investments are collected from Refinitiv Eikon, which contains PE data and capabilities powered by VentureXpert, the premier source for comprehensive information on this market[4]. The VentureXpert database is widely used by authors of renowned papers on VC (Kaplan & Schoar, 2005; Gompers & Lerner, 1999; Gulati & Higgins, 2003). Preqin is also a frequently used database in the academic literature, but it is not suitable for this paper because it generated insufficient data on cleantech VC investments. VentureXpert was preferred because it generated more observations for cleantech.

For this paper, data on VC investments made between 01/01/2003 to 31/12/2021 was retrieved. This time frame was selected because more VCs invested in cleantech since 2003. Before 2003, there was volatility and uncertainty in the market, with some failures and disappointing returns. This led to a period of retrenchment and skepticism around cleantech investment (Caprotti, 2012). Investments labeled as 'buyout/acquisition', 'real estate', and 'other' are not included in the analysis to guarantee that the focus is on VC transactions. VC investments are identified as 'cleantech' when the portfolio company's primary technology group is 'clean technology'. After applying these filters, this generates a final sample of 12,593 unique investments in 2,021 unique cleantech companies. Similar to this, a sample of 317,805 investments in 48,625 unique non-cleantech portfolio companies are included that cover all other industries. In total, the data consists of 330,398 investments in 50,646 unique portfolio companies. To analyze the success of the investments, this paper also adds VC exits to the sample. Eikon contains a database on VC exits that is similar to the VC investment database.

[4] For more information on Refinitiv Eikon and VentureXpert, visit https://www.refinitiv.com/en/products/eikon-trading-software/private-equity-data

By applying the same filters, the VC exits are collected from the database. The VC investments and exits are matched with the portfolio company's 'PermID'[5].

From the World Bank database[6], other macroeconomic statistics are retrieved about the portfolio company's country. First, the investments and exit year GDP are matched to the sample by merging the World Bank database with the VentureXpert database. This procedure was repeated for GDP per capita, GDP growth, and CO2 emissions (per capita).

A description of the sample is shown in Table 1. Panel B shows a sample distribution of the top 10 countries. The majority of the sample comes from the US with 203,184 observations (61.5%). On June 1st, 2017, President Donald Trump announced that the US would withdraw from the PA, dealing a significant setback to global efforts to address climate change and creating distance between the country and its closest international partners. The White House has signaled that it intends to adhere to the extensive withdrawal process specified in the agreement. As a result, the US continued to be a participant in the agreement for another three and a half more years (Colvin & Pace, 2017). Following the withdrawal on November 4th, 2020, and later rejoining under President Biden, the US was officially out of the PA for only 107 days. This means that the announcement of Trump on withdrawing from the PA has little impact on this research. In addition, China accounts for 24,021 observations (7.27%), and the remaining countries each account for less than 5% of the sample. Panel C presents the distribution of the sample by year. The number of observations grows consistently with two minor declines for the years 2011-2012 and 2015-16 and a larger decline of 34% over the years 2007-2009, because of the Financial Crisis (Mason & Harrison, 2015). Furthermore, panel D displays the sample distribution by industry, revealing that the technology industry is the most heavily represented (55.69%), followed by the healthcare industry (21.60%).

[5] PermID is a unique identifier assigned by Refinitiv to each entity in its financial database, enabling consistent and reliable data aggregation across disparate sources.
[6] The World Bank database is a comprehensive collection of data and statistics on global development, including information on countries, economies, social indicators, and the environment.

Table 1: Overview of the sample

Panel A: Sample distribution

Selection	Frequency
VC investments in cleantech	12,593
VC investments in other industries	317,805
Final sample – VC investments	330,398

Panel B: Sample distribution by country (top 10)[7]

Country	Frequency	Percentage
United States	203,184	61.5
China	24,021	7.27
Canada	16,356	4.95
United Kingdom	15,002	4.54
France	12,522	3.79
India	10,413	3.15
Germany	6,985	2.11
Israel	5,401	1.63
Japan	4,854	1.47
Australia	2,596	0.79

Panel C: Sample distribution by year

Year	Frequency	Percentage
2003	11,311	3.42
2004	12,472	3.77
2005	13,184	3.99
2006	14,728	4.46
2007	15,485	4.69
2008	14,637	4.43
2009	10,246	3.10
2010	12,335	3.73
2011	13,543	4.10
2012	12,563	3.80
2013	12,790	3.87
2014	13,862	4.20
2015	16,221	4.91
2016	15,774	4.77
2017	17,680	5.35
2018	21,309	6.45
2019	24,150	7.31
2020	28,504	8.63
2021	49,604	15.01

Panel D: Sample distribution by industry

Industry	Frequency	Percentage
Academic & Educational Services	2,313	0.70
Basic Materials	4,306	1.30
Consumer Cyclicals	18,342	5.55
Consumer Non-Cyclicals	10,233	3.10
Energy	3,295	1.00
Financials	7,892	2.39
Government Activity	86	0.03
Healthcare	71,357	21.60
Industrials	25,893	7.84
Institutions, Associations & Organizations	57	0.02
Real Estate	1,540	0.47
Technology	183,988	55.69
Utilities	1,096	0.33

[7] The investments were made in 128 different countries. Panel B displays only the top 10 countries where the investments were done, which covers a large part of the whole sample.

4.1.1 Dependent variable – Investment

This study examines the impact of the PA on VC investments in cleantech. VC investment serves as the dependent variable *Investment* in this paper. The VentureXpert database is utilized to determine the per-round *Investment* in a portfolio company. The database provides a separate number for every investment made by a VC firm in a portfolio company and there may be multiple investments by different VCs in a single investment round. *Investment* can be divided in two subsets to answer Hypotheses 1-3, namely 'cleantech' and 'non-cleantech'. When a portfolio company's primary technology group involves 'clean technology', the investments made by VCs are classified as 'cleantech'. Otherwise, the investments made by VCs are classifies as 'non-cleantech'. Any reported *Investment* that is negative or zero is omitted from the sample, as it is not a valid data point. Since *Investment* is a highly skewed variable, the study transforms it into a normalized variable by using the natural logarithm of this variable (*ln(Investment)*).

4.1.2 Dependent variable – Syndicate size

Syndicate size represents the number of investors in an investment round (Lerner, 1994; Terjesen et al., 2013). Syndication enables backers to invest alongside recognized investors (leaders) in the top firms. *Syndicate size* is a fundamental attribute impacting performance, a syndicate could supply its portfolio startup with more diverse resources (Kim & Park, 2021). This paper uses *Syndicate size* as a dependent variable because it is of interest how many VC firms participate in one investment round to answer Hypothesis 4.

4.1.3 Dependent variable – Exit outcome

To analyze the performance of the investments, the *Exit outcome* variable is used as a proxy. This metric is often used as a proxy for VC performance (Hochberg, Ljungqvist, & Lu, 2007; Das et al. 2011). Similar to Cumming et al. (2017), the probability of a successful exit is approximated using a categorical variable. Possible exit outcomes are successful, unsuccessful, or still active. The investment is successful if the startup was acquired or did an IPO. If the startup was liquidated or had a secondary sale or buyback, the investment was unsuccessful. When there has not been an exit, the investment cannot yet be evaluated. This paper uses *Exit outcome* as a dependent variable because it is of interest whether or not the exit was successful or not to answer Hypothesis 5.

4.1.4 Independent variables

The main variable of interest is VC investments in cleantech portfolio companies after the PA. The PA was adopted in December 2015, so the dummy variable *PA* is created for the period after the PA. *PA* had a value of one if the year in which the VC invested is equal to or greater than 2016, otherwise, the value was zero. Another dummy variable was created namely *Cleantech*. This variable had a value of one when the portfolio company's primary technology group is 'clean technology', otherwise, the variable was zero. The main variable of interest is the interaction effect *PA * Cleantech* and hence is a binary variable.

4.1.5 Control variables

In addition to the primary independent variables, this paper contained several control variables relevant to the features of the startup, the investment, the VCs, and the market conditions (Terjesen, Patel, Fiet, & D'Souza, 2013). Below is a detailed description of the variables:

1. *Startup age*: The age in years of the portfolio company at the time of the VC investment. *Startup age* was added because it is a common control variable in other studies on VC investments (Block & Sandner, 2009; Pandey & Jang, 1996). These studies have shown that older, and more experienced startups obtain more funding from VCs and therefore, the paper expected a positive (+) effect of *Startup age* on *Investment*.
2. *Private VC fund:* A dummy variable that was equal to one when the fund investor type is an 'independent private partnership' and otherwise equal to zero.
3. *Corporate VC fund*: A dummy variable that was equal to one when the fund investor type is 'corporate or PE/venture fund' and otherwise equal to zero. This variable has been used by Cumming et al. (2016) and Cumming & Schwienbacher (2021). According to Ghosh & Nanda (2010), energy incumbents see cleantech as supplementary, so they underinvest in these startups. Therefore, this paper expects a negative (-) effect of *Corporate VC fund* on *Investment*.
4. *VC firm age:* The age in years of the VC firm at the time of the investment.

Following Gompers & Lerner (1999), market conditions are proxied by GDP, GDP per capita, and GDP growth:

5. *GDP:* GDP in billions of USD (in current prices) in the year of investment in the portfolio company's country.
6. *GDP per capita:* GDP per capita in USD (in current prices) in the year of investment of the portfolio company's country.

7. *GDP growth:* Annual percentages of year-on-year (YoY) changes in GDP[8] in the year of investment of the portfolio company's country.

4.1.6 Descriptive statistics

In Table 2, descriptive statistics of the complete sample, the cleantech sample, and the non-cleantech sample are provided. The size of the cleantech sample (12,593) is smaller than that of the control sample (317,805) because the control sample covers all sectors except cleantech, while the cleantech sample only covers the cleantech sector.

The mean *Investment* in a portfolio company is 27,903,290 USD for the entire sample. There was a difference between the mean *Investment* for the cleantech and non-cleantech samples, which are 26,192,829 USD and 27,971,067 USD, respectively. The variable for *Investment* contained some outliers, so for the regression analysis, the natural logarithm of *Investment* was used. The median *Syndicate size* in an investment round was 4. On average, a portfolio company was 5.6 years old when it received an investment. The cleantech companies were older, with an average startup age of 6.9 years, compared to non-cleantech companies, which had an average startup age of 5.6 years. Most investments were made in the early stage (38.3%) of the company, although there were significant differences between the investment stage for cleantech and non-cleantech companies. Cleantech companies received more investments in later stages, such as the expansion stage (37.6%) or later stage (30.0%), while non-cleantech companies received more investments in the early stage (38.8%). The possibility of an IPO was higher in the cleantech sample (37.8%) compared to the non-cleantech sample (29.4%). Non-cleantech portfolio companies had a higher possibility of a trade sale exit (67.7%) compared to cleantech companies (56.6%), and non-cleantech exits were also more successful (97.1%) compared to cleantech exits (94.4%).

The majority of investments (61.5%) were made in the US, followed by China (7.3%), Canada (5.0%), the UK (4.5%), and France (3.8%). Most investments were made by private VC firms (59.2%) and only a small portion (8.8%) were made by CVC firms. The average VC age was 23.9 years, but this was higher for VC firms that invested in cleantech companies (25.1 years).

To assess the impact of outliers on the descriptive statistics, the mean and median values were compared. When the mean was higher than the median, the variable was positively skewed, and when the mean was lower, the variable was negatively skewed. The mean

[8] At market prices that are based on constant local currency.

Investment (27,903,290 USD) was significantly higher than the median (8,000,100 USD), which indicated positive skewness, and therefore, the natural logarithm of investment was used for the analysis. On the other hand, the mean and median values for startup age were comparable to each other, with a mean of 5.6 years and a median of 4.5 years, which indicated a normal distribution. The mean and median values for the GDP market control variables were also close to each other, implying that outliers did not significantly influence the mean.

Table 2: Summary statistics for the full sample and sub-samples

This table summarizes the full sample's statistics. It includes separate columns for cleantech and non-cleantech samples on the right. The results of the mean comparison test are shown in the last column. The number of observations is noted at the bottom for each sample except for the exit variables, which have fewer observations due to the incompleteness of the data.

	Full sample			Cleantech sample only	Non-cleantech sample only	Diff. mean test
Variable	Mean	Median	Std. dev	Mean	Mean	p-value
PA (dummy)	.475	0	0.499	.267	.484	0.0000
Cleantech (dummy)	.038	0	0.191	1	0	-
Investment (x1000 USD)	27903.290	8000.1	102040.610	26192.829	27971.067	0.055
ln(investment)	8.938	8.987	1.630	8.829	8.943	0.000
Syndicate size	4.710	4	3.162	4.236	4.729	0.000
Startup age (in years)	5.636	4.49	6.200	6.907	5.586	0.000
Seed stage (dummy)	.052	0	0.222	.062	.052	0.000
Early stage (dummy)	.383	0	0.486	.262	.388	0.000
Expansion stage (dummy)	.337	0	0.473	.376	.335	0.000
Later stage (dummy)	.228	0	0.420	.300	.225	0.000
IPO-exit (dummy)	.296	0	0.457	.378	.294	0.000
Trade sale exit (dummy)	.673	1	0.469	.566	.677	0.000
Successful exit (dummy)	.970	1	0.172	.944	.971	0.000
Write off (dummy)	.030	0	0.172	.056	.029	0.000
USA (dummy)	.615	1	0.487	.565	.617	0.000
China (dummy)	.073	0	0.260	.061	.073	0.000
Canada (dummy)	.050	0	0.217	.106	.047	0.000
United Kingdom (dummy)	.045	0	0.208	.056	.045	0.000
France (dummy)	.038	0	0.191	.057	.037	0.000
Private VC fund (dummy)	.592	1	0.491	.533	.594	0.000
Corporate VC fund (dummy)	.088	0	0.284	.092	.088	0.103
VC firm age (in years)	23.907	17	19.931	25.103	23.860	0.000
GDP (in USD)	12211.443	14474.227	7681.750	10432.473	12281.935	0.000
GDP per capita (in USD)	46226.387	48570.046	18278.511	45498.162	46255.243	0.000
GDP growth	2.597	2.291	3.165	2.407	2.604	0.000
No. obs.	330,398			12,593	317,805	

4.2 Methodology

To examine the impact of the PA on VC investments in the cleantech sector, this paper utilized a combination of the difference-in-differences (DiD) method and multilevel analysis. Additionally, this paper investigated the influence of syndicate size through Poisson regressions. Finally, this paper analyzed the success of the investments by examining exits using multinomial regressions.

4.2.1 DiD analysis on investments

Environmental governance, policy effect assessment, investment performance studies, and medical research all employ the DiD framework. This study uses the DiD approach to evaluate the influence of the PA on VC investments in cleantech companies. The impact is examined by comparing cleantech investments (treatment group) with non-cleantech investments (control group) (Roberts & Whited, 2013; Lechner, 2011).

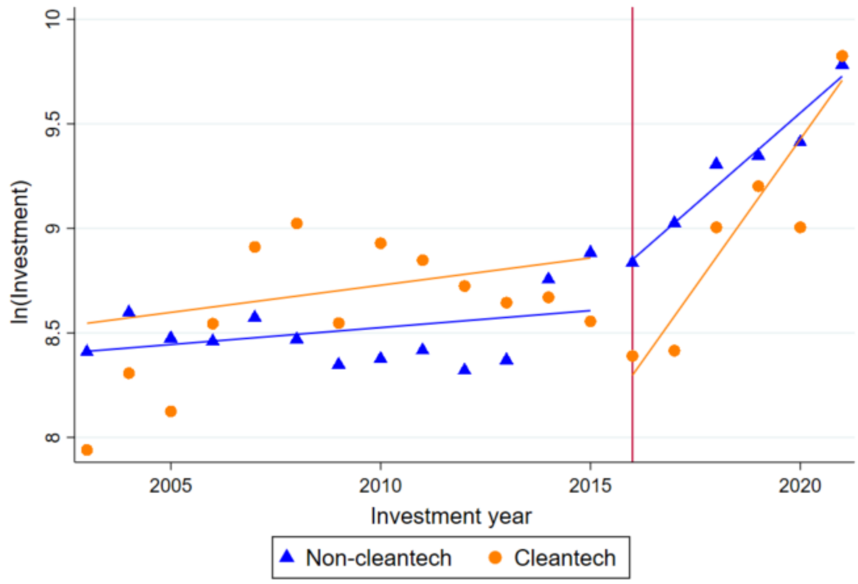
The DiD method is a suitable choice for this particular study because it allows for the estimation of the causal effect of an intervention (in this case, the PA) on an outcome variable (VC investment in cleantech companies). The DiD method takes advantage of the fact that the treatment group (cleantech companies) and the control group (non-cleantech companies) have different levels of exposure to the intervention (the PA) and enables the comparison of the changes in the outcome variable between the two groups over time.

One of the key advantages of the DiD method is that it can account for differences between the treatment and control groups that are not related to the intervention. This helps to address the issue of omitted variable bias, which occurs when important factors affecting the outcome variable are not included in the analysis. The DiD method also allows for the estimation of the average treatment effect (ATE) in a controlled manner, which provides a more accurate estimate of the effect of the intervention (Lechner, 2011).

The parallel trends and common shock assumptions form the foundation of the DiD method (Dimick & Ryan, 2014; Angrist & Pischke, 2008). The parallel trends assumption states that the trend in the outcome variable of the treatment and control groups before treatment is the same or comparable. To test the parallel trends assumption, this paper analyzes graphs of the outcome variable across time (Dimick & Ryan, 2014). If the assumption is false, the DiD approach is biased.

Figure 2 shows the *ln(Investment)* against the investment year for both the control and treatment groups. Before 2016, investments in cleantech and non-cleantech showed similar trends. The cleantech investments show similar variation as the non-cleantech investments and the plotted lines before 2016 of both groups match. After the PA in December 2015, the investments made in both groups differ from each other. Since 2016, cleantech investments increase more YoY than non-cleantech investments. When comparing the treatment and control groups over time, they displayed parallel trends before 2016. Based on the graph in Figure 2, this paper assumed the parallel trends assumption holds. As the parallel trends assumption holds, there is no need to use matching methods (Ryan, Kontopantelis, Linden, & Burgess Jr, 2019).

Figure 2: Parallel trends



Note: Visual depiction of the parallel trends assumption. The vertical line indicates 2016.

Secondly, the common shocks assumption needs to hold for the DiD method to be valid. The common shocks assumption states that any unanticipated events or factors affecting the outcome variable should have the same effect on both the treatment group and the control group. Shocks in economics are unexpected or unanticipated events that disrupt a system (Dimick & Ryan, 2014). The correctness of this assumption cannot be verified analytically, however, if the parallel trends assumption is true, which means that there are no significant variations in *Investment* before the PA, one may suppose that additional pertinent shocks would have had the same effect on both groups.

The panel data contains observations on different industries and different stages of financing over the time period 2003-2021. The DiD regressions are used to analyze the effect of the PA on VC investments. For all the regressions the standard errors are clustered by year of investment. Clustering standard errors by year of investment reduces bias from repeated observations in the investment year. The use of fixed effects helps control for common impacts that may not be captured across the industry, stage of investment, and country. It is designed to capture, among other things, possible variations in economies of scale and scope among countries, as well as differences in time-invariant business laws, degree of corruption, and misreporting methods across governments (Djankov et al., 2002; Johan and Zhang, 2015). This paper uses industry, stage of investment, and country fixed effects because this leads to the highest R-squared in the models.

Hypothesis 1 stated that since the PA, VCs located in Mission Innovation countries have invested more in cleantech compared to before the PA. The method used to answer Hypothesis 1 is described below in Formula 1. The interaction term *PA * Cleantech* is the DiD estimator, which is the parameter of interest as it captures the causal effect of the treatment on the outcome variable by comparing the pre-post change in the treatment group to the change in the control group. Coefficient β_3 was expected to be positive following a one-sided t-test.

Secondly, Hypothesis 2 expected that since the PA, less-experienced VCs invested more in cleantech startups than VCs that are more experienced. This hypothesis is tested by comparing experienced and inexperienced subsets of the data. Formula 1 was used to test Hypothesis 2, where the variable of interest is the interaction term *Paris * Cleantech*. Coefficient β_3 was expected to be higher for the inexperienced subset compared to the experienced subset, which was tested with a one-sided t-test.

Lastly, Hypothesis 3 expected that CVCs invested less in cleantech companies after the PA compared to Private VCs. This hypothesis was tested by comparing the CVC and Private VC subsets of the data. Formula 1 was used to test Hypothesis 3, where the variable of interest was the interaction term *PA * Cleantech*. Coefficient β_3 was expected to be higher for the Private VC subset compared to the CVC subset, which was tested with a one-sided t-test. The DiD regression formula to answer Hypotheses 1, 2, and 3 was written as follows:

$$\begin{aligned} Investment_{i,t} = {} & \beta_0 + \beta_1 PA_{i,t} + \beta_2 Cleantech_{i,t} + \beta_3 (PA * Cleantech)_{i,t} \\ & + \beta_4 controls + industry\ fixed\ effects \\ & + investments\ stage\ fixed\ effects + country\ fixed\ effects \\ & + \varepsilon_{i,t} \end{aligned} \tag{1}$$

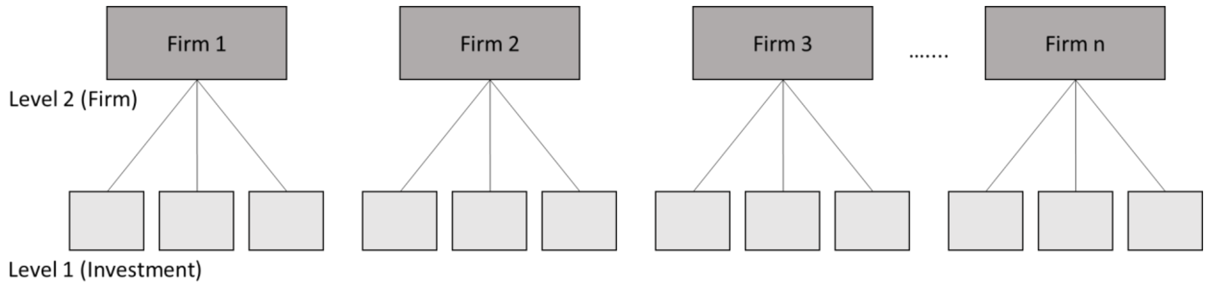
Where the index *'i'* denotes a unique investment round and where *'t'* denotes the investment date. β_1 measured the average change in *Investment* for the non-cleantech investments after the PA and β_2 measured the ATE for the cleantech investments before the PA. β_3 measured the difference in the pre-post change between the cleantech and non-cleantech investments. Controls represent *Startup age, Private VC, Corporate VC, VC firm age, GDP, GDP per capita,* and *GDP growth.* Industry, investment stage, and country fixed effects are included in the formula to help for common impacts that may not be captured across the industry, stage of investment, and country. The different investment stages are the seed, early, later, and expansion stages. The error term represents the variance in the dependent variable that cannot be accounted for by the independent variables. The standard errors are clustered by year of investment.

4.2.2 Multilevel analysis on investments

A multilevel mixed effects model, also known as a hierarchical linear model, is a type of statistical model used to analyze data with multiple levels of nested structure. It accounts for both within-group (i.e. "random") variation and between-group (i.e. "fixed") variation. The mixed effects aspect refers to the modeling of both fixed and random effects in the same model.

The Multilevel Mixed Effects (MLME) analysis of the data was structured in two levels: the investment level and the firm level. The independent variables *PA* and *Cleantech* and the dependent variable *Investment* were within the investment level. The variable *Startup age* and the GDP variables were within the firm level. Its hierarchical structure was distinguished by the nesting of investments inside the startups in which were invested. The two-level design is shown in Figure 3. To analyze a hierarchical dataset, the MLME model was used in this paper (Aguinis, Gottfredson, & Culpepper, 2013). The approach of this paper analyzed the effect of the level-1 direct effects and if those also depended on interaction effects across level-1 and level-2 (Aguinis et al., 2013).

Figure 3: MLME model representation



The first of the two levels, namely the investment level, to this approach is shown in Formula 2:

$$Investment_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + \varepsilon_{ij} \tag{2}$$

In the formula, the term x_{ij} stands for the independent variables *PA* and *cleantech*. These variables are investment characteristics. The intercept and the slope coefficients were represented by the terms β_{0j} and β_{1j} respectively. Finally, ε_{ij} stands for the investment-specific residual error (Aguinis et al., 2013). The individual *Investment* observations were indicated as i and the portfolio firm in which the VC invested as j. The level-2 formulas are then expressed as shown in Formulas 3 and 4:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} w_j + u_{0j} \tag{3}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} w_j + u_{1j} \tag{4}$$

In Formulas 3 and 4, w_j stands for the *Startup age* of firm j (Preacher, Curran, & Bauer, 2006). The formulas assess the influence of cross-firm variation.

The level-2 formulas (Formulas 3 and 4) were then added to the previous level-1 (Formula 2) (Preacher et al., 2006) in the following way:

$$Investment_{ij} = (\gamma_{00} + \gamma_{01} * w_j) + (\gamma_{10} + \gamma_{11} * w_j)x_{ij} + (u_{0j} + u_{1j} + x_{ij} + \varepsilon_{ij}) \tag{5}$$

In Formula 5, the dependent variable is *Investment,* w_j stands for *startup age* of firm *j* and the term x_{ij} stands for the independent variables *PA* and *Cleantech*.

According to Aguinas et al. (2013), the MLME approach needed to be split into three parts:

1. Null model and intraclass correlation coefficient (ICC)
2. Random intercept model with fixed predictors
3. Random intercept model with random predictors

4.2.2.1 Null model and ICC

The initial step involved conducting a null model and calculating the ICC. The purpose of this step was to determine if there was enough variation in the investment data between different firms (level-2 units) to warrant a multilevel analysis. The ICC was computed as depicted in Formula 6 below.

$$ICC = \frac{intercept\ variance}{residual + intercept\ variance} \tag{6}$$

The ICC was calculated as the ratio of the variance in the investments due to differences between companies to the total variance in the investments, as depicted in Formula 6. If the

ICC value was greater than 0.05, it suggested that a significant proportion of the variance in investment data was due to differences between companies, making a multilevel analysis necessary (Aguinis, Gottfredson, & Culpepper, 2013).

However, if the ICC value was less than 0.05, it meant that there was insufficient variation between companies to justify a multilevel analysis and a single-level analysis would be preferred instead (Heck, Thomas, & Tabata, 2013). In the next step, if the criteria are met, a random intercept model with a fixed slope was implemented to account for the variation in investments between companies.

4.2.2.2 Random intercept model with fixed predictors

If the ICC value was sufficient, a multilevel analysis could be conducted to examine the effect of the PA on VC investments in cleantech companies. This step involved testing if different values for the PA for each country could explain the variance in the VC investments made by different cleantech companies.

With a fixed slope, the analysis would determine if the variance in VC investments between companies could be explained by different intercepts, meaning different starting points for the PA values. This step was performed for all relevant investment data and the overall investment data.

4.2.2.3 Random intercept model with random predictors

After verifying if the random intercept model could account for the variance between investment groups, the analysis was further tested with a random slope. This step investigated whether the random slope could explain a portion of the variance, potentially leading to a better model fit than the one obtained in step 2.

The Likelihood Ratio Test (LRTest) was used to compare the results of both models and determine which one had the better fit for the data. It is a statistical test used to compare the fit of two nested models, one of which is a simplified version of the other. This test measured the amount of cross-firm variance explained by each model and output a Prob > chi2 value. If the value was significant, it indicated that the random slope model provided a better explanation of the data.

After performing all three steps of the analysis, the results were presented in Section 5.3.

4.2.3 Syndicate size

The paper used Poisson regressions with standard errors clustered by year of investment to analyze the effect of the PA on the syndicate size of cleantech investments. The Poisson distribution was used to model syndicate size because *Syndicate size* is a count variable. The dependent variable *Syndicate size* is the number of investors involved in the financing of a given round.

Hypothesis 4 stated that syndicate size was larger for investments in cleantech startups compared to non-cleantech startups. Formula 2 was used to test Hypothesis 4, where the variable of interest is *Cleantech*. Coefficient β_2 was expected to be positive following a one-sided t-test. Hypothesis 4 was tested using the following regression formula:

$$\begin{aligned} Syndicate\ size_{i,t} &= \beta_0 + \beta_1 PA_{i,t} + \beta_2 Cleantech_{i,t} + \beta_3 (PA * Cleantech)_{i,t} \\ &+ \beta_4 controls + industry\ fixed\ effects \\ &+ investments\ stage\ fixed\ effects + country\ fixed\ effects \\ &+ \varepsilon_{i,t} \end{aligned} \tag{7}$$

Controls represented *startup age, private VC, corporate VC, VC firm age, GDP, GDP per capita, and GDP growth*. Industry, investment stage, and country fixed effects are included. The investment stages were the seed, early, later, and expansion stages. The error term represented the variance in the dependent variable that could not be accounted for by the independent variables. The standard errors were clustered by year of investment. Where the index *'i'* denoted a unique investment round and where *'t'* denoted the investment date.

4.2.4 Exits

To investigate whether these investments were successful, this paper analyzed the exit outcome of these investments. Similar to Cumming et al. (2017), the probability of a successful exit was approximated using the categorical variable *Exit outcome*. Possible exit outcomes were successful, unsuccessful, or still active. The exit category was marked as successful when the startup was acquired or did an IPO. If the startup was liquidated or had a secondary sale or buyback, the exit was unsuccessful. When the investment was not exited yet, the startup was still active. A multinomial logistic regression was used to analyze the exit data because the dependent variable was a categorical variable that had three discrete outcomes. *Exit outcome* had a value of one when the exit was unsuccessful (secondary sale or buyback), two when the startup was still active and three when the exit was successful (startup was acquired or did an IPO).

Hypothesis 5 presumed that cleantech VC exits had been less successful after the PA. Formula 3 was used to test Hypothesis 5, where the variable of interest was the interaction term *PA * Cleantech*. The coefficient for *PA * Cleantech* was expected to be negative for a negative exit outcome and positive for a positive exit outcome following a one-sided t-test. To test whether Hypothesis *5* could be rejected or not, the following regression formula was used:

$$Exit\ outcome_{i,t} = f(PA_{i,t} + Cleantech_{i,t} + (PA * Cleantech)_{i,t} + controls + industry\ fixed\ effects) \quad (8)$$

Formula 8 is a multinomial logistic regression because the dependent variable is a categorical variable that had three discrete outcomes. The interaction effect of *PA* and *Cleantech* was the variable of interest as this represented the effect of the PA on the exit outcome of cleantech investments. Industry fixed effects were included, and the standard errors were clustered by investment year. The index *'i'* denoted a unique investment and *'t'* denoted the investment date.

5 Results

In this chapter, the findings are presented and discussed to answer the research question and hypotheses. Firstly, the impact of the PA on investments is examined in Table 3 using DiD regressions as a base scenario, without evaluating the differences as expected by Hypotheses 1-3. Subsequently, VC characteristics and Mission Innovation countries are analyzed using DiD regressions in Table 4, and robustness analyses on the effect of the PA on cleantech investments are reported in Table 5. After the DiD regressions, the multilevel analyses are conducted, and the results of every step were displayed in Tables 6-8. The DiD regressions and multilevel analyses are used to answer Hypotheses 1-3. Next, an analysis of VC syndicate size is conducted in Table 9 to address Hypothesis 4. Finally, Hypothesis 5 is tested by examining the exit success rate in Table 10. The variables *GDP* and *GDP per capita* were dropped from the sample based on the VIF tests[9] in Appendix A.

5.1 The impact of the PA on cleantech investments

In Table 3, the results of the DiD regressions on the effect of the PA on the (natural logarithm of) investments can be found. In Table 3, the paper examined cleantech investments compared to non-cleantech investments. Hence, the *PA * Cleantech* interaction term was the variable of interest. The effects found in Table 3 served as a base scenario without assessing any differences as stated by Hypotheses 1-3.

The cleantech investments decreased after the PA, which was not in line with the paper's predictions. Given that all other factors remain the same, investments in cleantech decreased by 4.81% and 4.89% after the PA in Models 3 and 4, compared to the average investments in the data.[10] In Models 5-6, the negative effect of the PA on cleantech investments was less strong and insignificant when only the early and seed stages were included. Lastly, when the early and seed stages were excluded, the negative effect of the PA was stronger and significant as investments in cleantech decreased by 5.86 and 6.01%, for Models 7 and 8 respectively.

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[9] The VIF (Variance Inflation Factor) test is a statistical method used to measure the multicollinearity (correlation) among the predictor variables in a regression model. The variables were dropped based on the VIF if its value was greater than 5.

[10] The effect was computed by dividing the coefficient by the corresponding coefficient in Table 2 (descriptive statistics). In this case, this resulted in -0.430 / 8.938 = -4.27%. This is the marginal effect that presents the results as differences in probabilities.

Table 3: DiD regressions on the impact of the PA on investments

DiD regression results with ln(*investment*) as the dependent variable. Models 1-4 show the results for the full sample, where Models 2 and 4 include industry fixed effects and Models 3 and 4 include the DiD effect of the PA on cleantech investments. Models 5 and 6 show the results of the early and seed stages and Models 7 and 8 show the results of the other investments without the early and seed stages. The standard errors were clustered by investment year.
*** p<0.01; ** p<0.05; * p<0.1.

	Full sample				Early/seed-stage rounds only		Early/seed-stage rounds excluded	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Startup characteristics:								
PA (dummy)	0.962***	0.986***	0.976***	0.999***	0.881***	0.921***	1.050***	1.059***
Cleantech startup (dummy)	0.118	0.200**	0.234***	0.320***	0.124	0.207**	0.281***	0.363***
PA * Cleantech	--	--	-0.430***	-0.437***	-0.174	-0.212	-0.537***	-0.524***
Startup age (in years)	-0.003	-0.003	-0.003	-0.003	0.159	0.012	-0.003	-0.002
VC fund conditions:								
Private VC fund (dummy)	0.482***	0.481***	0.481***	0.480***	0.590***	0.578***	0.405***	0.403***
Corporate VC fund (dummy)	0.702***	0.694***	0.702***	0.693***	0.798***	0.759***	0.625***	0.625***
VC firm age (in years)	0.005***	0.005***	0.005***	0.005***	0.007***	0.007***	0.003***	0.003***
Market conditions:								
GDP growth	0.031	0.032	0.031	0.023	0.030	0.032	0.032	0.033
Industry dummies	No	Yes	No	Yes	No	Yes	No	Yes
Stage dummies	Yes	Yes	Yes	Yes	Partial	Partial	Partial	Partial
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	330,398	330,398	330,398	330,398	143,795	143,795	186,603	186,603
R-squared	0.208	0.221	0.208	0.221	0.188	0.218	0.183	0.188
Adj. R-squared	0.208	0.221	0.208	0.221	0.187	0.218	0.183	0.188

Table 4 reports DiD regressions on the impact of the PA on investments with subsets of the data. Because of the presence of country-fixed effects, it was not possible to predict the effect of being part of the Mission Innovation initiative in one regression. The country-fixed effects cause the exclusion of the Mission Innovation variable because of its invariance over time and across countries. Hypothesis 1 stated that since the PA, VCs located in Mission Innovation countries have invested more in cleantech compared to before the PA. The cleantech investments decreased by 4.95% after the PA for countries part of the Mission Innovation initiative (Model 1), which was not in line with the expectation stated in Hypothesis 1. This effect was smaller but insignificant for non-Mission Innovation countries (Model 2).

Hypothesis 2 expected that since the PA, less-experienced VCs invested more in cleantech than VCs that are more experienced. The results in Models 5 and 6 showed that old VCs invested less in cleantech startups than young VCs after the PA, their investments decreased by 5.08% and 4.31% respectively. The young VCs were generally more inexperienced than old VCs, so these results were in line with Hypothesis 2.

Hypothesis 3 stated that CVCs invested less in cleantech companies after the PA compared to private VCs. In regression Models 3 and 4 the private VCs and CVCs were examined. Since the PA, private VC investments in cleantech reduced by 5.97% while corporate VC cleantech investments reduced by 5.28%. These results reject the third hypothesis, which expected that corporate VCs invested less in cleantech compared to private VCs.

Table 4: DiD regressions of data subsets on the impact of the PA on cleantech investments
Panel data analysis of subsets of the data with ln(*investment*) as the dependent variable. Model 1 uses data only including Mission Innovation countries. Model 2 uses data excluding Mission Innovation countries. Model 3 uses a subset of private VCs and Model 4 of corporate VCs. Model 5 uses a subset of young VCs and Model 6 of old VCs. A VC is labeled as "old" when the firm age is equal to or greater than 15 years. A VC is labeled as "young" when the firm age is less than 15 years. Standard errors are clustered by investment year. *** p<0.01; ** p<0.05; * p<0.1.

	Mission innovation countries	Non-mission innovation countries	Private VCs	Corporate VCs	Young VCs	Old VCs
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Startup characteristics:						
PA (dummy)	1.008***	0.855***	1.029***	1.046***	1.041***	1.008***
Cleantech startup (dummy)	0.328***	0.269	0.307***	0.305**	0.256***	0.369***
PA * Cleantech	-0.443***	-0.368	-0.534***	-0.472***	-0.385***	-0.454***
Startup age (in years)	-0.003	0.009	-0.006	0.016**	0.004	-0.005*
VC fund conditions:						
Private VC fund (dummy)	0.490***	0.342***	--	--	0.362***	0.546***
Corporate VC fund (dummy)	0.709***	0.506***	--	--	0.716***	0.633***
VC firm age (in years)	0.004***	0.005***	0.008***	0.000	0.018***	-0.000
Market conditions:						
GDP growth	0.032	0.037***	0.035	0.036	0.033	0.032
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Stage dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	308,613	21,785	195,634	29,179	147,857	182,541
R-squared	0.219	0.273	0.200	0.231	0.237	0.221
Adj. R-squared	0.219	0.269	0.199	0.228	0.236	0.220

5.2 Robustness checks

To ensure the quality of these results, robustness checks were performed to verify whether or not the regressions in Tables 3 and 4 are robust. The results of the robustness checks can be found in Table 5 below. Most of the investments were done in the US, so to check whether these results could also be found outside the US, the Mission Innovation countries without the US were analyzed. The subset excluding the US showed that the cleantech investments after the PA decreased by only 2.57% for Mission Innovation countries and 4.12% for non-Mission Innovation countries, although the effects were insignificant. The effect was weaker when the US was excluded, and the decrease was stronger for non-Mission Innovation countries. Based on these results, it seemed that most of the negative effects came from the US data.

An alternative explanation for the decrease in cleantech investments is that it is not in the best interest of countries with high CO2 emissions to promote the allocation of VC funds to cleantech because their economy depends on energy incumbents. In Models 3 and 4, the cleantech investments after the PA decreased significantly more for countries with high CO2 emissions per capita compared to low CO2 emissions per capita countries, the investments reduced by 7.10% and 3.03% respectively. These results support the alternative hypothesis that fossil fuel-dependent countries did not prioritize cleantech investments.

Table 5: Robustness analyses

Robustness analyses on the effect of the PA on cleantech investments. Models 1 and 2 display the DiD regressions on the non-US subsample, where Model 1 analyzed Mission Innovation countries and Model 2 non-Mission Innovation countries. Models 3 and 4 show the DiD regressions on the high and low CO2 emission per capita subsamples respectively. Standard errors were clustered by investment year.
*** p <0.01, ** p<0.05, * p<0.1.

	Non-US ventures in Mission Innovation country	Non-US countries in non-Mission Innovation country	High CO2 emission per capita	Low CO2 emission per capita
Variable	(1)	(2)	(3)	(4)
Startup characteristics:				
PA (dummy)	0.957***	0.855***	0.739***	0.667***
Cleantech startup (dummy)	0.219***	0.269	0.376***	0.175**
PA * Cleantech	-0.230*	-0.368	-0.635***	-0.271***
Startup age (in years)	-0.003	0.009	-0.011***	-0.000
VC fund conditions:				
Private VC fund (dummy)	0.363***	0.342***	0.578***	0.248***
Corporate VC fund (dummy)	0.605***	0.506***	0.797***	0.502***
VC firm age (in years)	0.004***	0.005***	0.005***	0.004***
Market conditions:				
GDP growth	0.145	0.037***	0.047***	-0.026*
Industry dummies	Yes	Yes	Yes	Yes
Stage dummies	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes
No. obs.	105,429	21,785	185,242	66,368
R-squared	0.281	0.273	0.166	0.229
Adj. R-squared	0.281	0.269	0.165	0.227

5.3 Results of the multilevel analysis

To test the hypotheses of this study, it was necessary to utilize an MLME model due to the nested structure of the dataset. The first step was to assess if cross-firm differences could explain a sufficient amount of variance, for which the ICC value had to be calculated. If the ICC value met the criteria, a multilevel model could be conducted with a random intercept and a fixed slope in step 2. Finally, in step 3, the hypotheses were tested with a random intercept and random slope, and the results were compared to the second step using the LRTest.

5.3.1 Calculating the ICC

The initial step in the analysis involved evaluating the necessity for a multilevel model for the dataset. The null model was utilized to examine whether the observations should be grouped by firm, as detailed in Table 6. The results of the null model revealed a significant intercept of γ_{00} = 8.406 with cross-firm variance at τ_{00} = 2.078 and within-firm variance at σ^2 = 0.849.

The ICC calculation resulted in a value of 0.710, which indicated that 71% of the variance in ln(*investment*) could be explained by cross-firm variables. This value exceeded the recommended threshold of 5% (Aguinis et al., 2013), making it necessary to conduct a multilevel analysis.

Table 6: Null model (step 1)

Variable	Ln(*investment)*
Fixed part:	
Intercept (γ_{00})	8.406***
Variance components:	
(L2) intercept variance (τ_{00})	2.078***
(L1) residual (σ^2)	0.849***
ICC	0.710
No. obs.	330,398

****** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

5.3.2 Random intercept model with fixed predictors

Table 7 provides an overview of the results from the second step of the multilevel analysis of VC investments. The natural logarithm of *Investment* was analyzed to assess the impact of the PA on VC investments in cleantech with subsets of the data.

The model fit appeared to be strong, as evidenced by the prob > chi2 values, which are less than 0.01 for all models. Additionally, the Wald chi2 value was high for all models ranging between 4,074.66 and 37,305.14.

Both the *PA* and *Cleantech* had a significant effect on the investments in companies made by VC investors for all subsamples. Also, the interaction effect between *PA* and *Cleantech* had a significant negative effect on investments for all subsamples. So, the PA resulted in fewer VC investments in cleantech companies when compared to the non-cleantech VC investments.

Hypothesis 1 stated that since the PA, VCs located in Mission Innovation countries have invested more in cleantech compared to before the PA. Model 1 shows that investments in cleantech by VCs located in Mission Innovation countries decreased after the PA compared to before the PA ($\beta = -0.695$, $p < 0.01$). Investments in cleantech by VCs that were not located in Mission Innovation countries also decreased after the PA, but this effect was not as strong ($\beta = -0.492$, $p < 0.05$). These results were in line with the results from the DiD regressions and reject Hypothesis 1.

Hypothesis 2 expected that since the PA, less-experienced VCs invested more in cleantech than VCs that are more experienced. Models 5 and 6 report that young VCs invested less ($\beta = -0.636$, $p < 0.01$) in cleantech than old VCs after the PA ($\beta = -0.595$, $p < 0.01$). These results differed from the results from the DiD regressions. The Young VCs were generally more inexperienced than old VCs, so these results reject Hypothesis 2.

Hypothesis 3 stated that CVCs invested less in cleantech companies after the PA compared to private VCs. Models 3 and 4 report that CVCs invested less ($\beta = -0.658$, $p < 0.01$) in cleantech than private VCs after the PA ($\beta = -0.636$, $p < 0.01$). These results differed from the results from the DiD regressions and are in line with Hypothesis 3.

Table 7: Random intercept model with fixed predictors (step 2)
The dependent variable for this regression is *ln(Investment)*.

Variable	Mission innovation countries (1)	Non-mission innovation countries (2)	Private VCs (3)	Corporate VCs (4)	Young VCs (5)	Old VCs (6)
Startup characteristics:						
PA (dummy)	0.937***	1.014***	0.992***	0.779***	1.039***	0.888***
Cleantech startup (dummy)	0.257***	0.293*	0.264***	0.263***	0.210***	0.283***
PA * Cleantech	-0.695***	-0.492**	-0.636***	-0.658***	-0.636***	-0.595***
Startup age (in years)	0.054***	0.071	0.044***	0.088***	0.079***	0.031***
VC fund conditions:						
Private VC fund (dummy)	0.128***	0.056***	--	--	0.127***	0.193***
Corporate VC fund (dummy)	0.243***	0.141***	--	--	0.259***	0.300***
VC firm age (in years)	0.000	0.001**	0.002***	0.001***	0.007***	-0.001***
Market conditions:						
GDP growth	0.055***	0.038***	0.055***	0.054***	0.053***	0.054***
(L2) intercept variance (τ_{00})	2.052	2.444	1.687	1.479	1.811	1.778
(L1) residual (σ^2)	0.759	0.499	0.768	0.594	0.700	0.826
Wald chi2	37,305.14	4,074.66	22,449.58	4,492.44	23,543.73	18,429.79
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
No. obs.	308,613	21,785	195,634	29,179	147,857	182,541
Groups	46,105	4,565	42,057	14,233	40,508	41,785

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.3.3 Random intercept model with random predictors (step 3)

The third step of the MLME analysis assessed the effect of firm differences on the effect of the PA on VC investments in cleantech by including a random slope in the model. The results of this model are reported in Table 8. The regressions showed that the effect of the PA might vary by firm, with τ_{11} ranging between 1.593 and 2.029.

To determine if the model in step 3 with random slopes provided a better explanation of the effects in the multilevel analysis than the second model with fixed slopes, the LRTest was carried out. This test resulted in a low and significant Prob > chi2 value of 0.000 ($p<0.01$), indicating that the model with random slopes was a better fit than the model with fixed slopes.

The paper examined three hypotheses related to VC investment in cleantech companies before and after the PA. The first hypothesis predicted that VC investment in cleantech by VCs located in Mission Innovation countries increased after the PA. However, the findings indicate that such investments decreased after the PA, with a stronger effect for VCs located in Mission Innovation countries ($\beta = -0.458$, $p < 0.01$) than those not located in such countries ($\beta = -0.445$, $p < 0.1$). These results were in line with the results from the DiD regressions and reject Hypothesis 1.

The second hypothesis posited that less-experienced VCs invested more in cleantech than more-experienced VCs after the PA. Based on Models 5-6, Old VCs ($\beta = -0.485$, $p < 0.01$) invested less in cleantech after the PA compared to young VCs ($\beta = -0.468$, $p < 0.01$). These results are in line Hypothesis 2.

The third hypothesis suggested that CVC investors would invest less in cleantech compared to private VCs. However, the study found that CVCs invested more ($\beta = -0.433$, $p < 0.01$) in cleantech than private VCs ($\beta = -0.518$, $p < 0.01$) after the PA. These results reject Hypothesis 3.

Table 8: Random intercept model with random predictors (step 3)
The dependent variable for this regression is *ln(Investment)*.

Variable	Mission innovation countries (1)	Non-mission innovation countries (2)	Private VCs (3)	Corporate VCs (4)	Young VCs (5)	Old VCs (6)
Startup characteristics:						
PA (dummy)	0.936***	1.013***	0.992***	0.779***	1.039***	0.888***
Cleantech startup (dummy)	0.178***	0.268	0.225***	0.166**	0.170***	0.232***
PA * Cleantech	-0.458***	-0.445*	-0.518***	-0.433***	-0.468***	-0.485***
Startup age (in years)	0.054***	0.071***	0.044***	0.088***	0.079***	0.031***
VC fund conditions:						
Private VC fund (dummy)	0.127***	0.056***	--	--	0.127***	0.193***
Corporate VC fund (dummy)	0.241***	0.142***	--	--	0.258***	0.299***
VC firm age (in years)	0.000	0.001**	0.002***	0.001***	0.007***	-0.001***
Market conditions:						
GDP growth	0.055***	0.038***	0.055***	0.055***	0.053***	0.054***
(L2) intercept variance (τ_{00})	2.053	2.446	1.686	1.481	1.814	1.775
(L1) residual (σ^2)	0.755	0.498	0.766	0.590	0.698	0.822
(L2) slope variance (τ_{11})	2.029	1.738	1.904	2.016	1.992	1.593
Wald chi2	37,361.05	4,075.54	22,463.91	4,522.98	22,552.85	18,454.43
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
No. obs.	308,613	21,785	195,634	29,179	147,857	182,541
Groups	46,105	4,565	42,057	14,233	40,508	41,785

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

5.4 The impact of the PA on syndicate size

Table 9 presents an analysis of the impact of the PA on syndicate size in cleantech investments. Model 1 indicates that controlling for all other factors, syndicate size for cleantech investments decreased ($\beta = -0.107$, $p < 0.01$) after the PA compared to the average syndicate size for all investments. However, when this paper analyzed the subset of early and seed rounds (Model 2), there was no significant effect of the PA on syndicate size. Excluding early and seed rounds (Model 3), the syndicate size for cleantech investments decreased after the PA ($\beta = -0.133$, $p < 0.01$). In Models 4-5, the impact of het PA on cleantech syndicate size was negative ($\beta = -0.116$, $p < 0.01$) for older VC firms and for younger VC firms ($\beta = -0.094$, $p < 0.05$).

Furthermore, the analysis distinguished between cleantech investments in Mission Innovation and non-Mission Innovation countries. For Mission Innovation countries, the PA lowered cleantech syndicate size ($\beta = -0.099$, $p < 0.05$), while the effect was insignificant for non-Mission Innovation countries.

Overall, these findings indicated that the impact of the PA on syndicate size for cleantech investments was negative. Hypothesis 4 suggested that syndicate size for cleantech investments would increase after the PA, but this hypothesis was rejected. Syndicate size for cleantech investments decreased after the PA.

Table 9: DiD regressions on the impact of the PA on syndicate size

DiD regressions on the determinants of syndicate size. The dependent variable is syndicate size, and the variable of interest is the interaction term between *PA* and *Cleantech*. Standard errors are clustered by investment year. *** p <0.01, ** p<0.05, * p<0.1.

	Full sample	Early/seed-stage rounds only	Early/seed-stage rounds excluded	Younger VC firms	Older VC firms	Mission Innovation country	Non-Mission Innovation country
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Startup characteristics:							
PA (dummy)	0.300***	0.385***	0.244***	0.358***	0.252***	0.296***	0.401***
Cleantech startup (dummy)	0.075**	0.008	0.090**	0.053	0.094***	0.073**	0.064
PA * Cleantech	-0.107***	0.029	-0.133***	-0.094**	-0.116***	-0.099**	-0.145
Startup age (in years)	-0.013***	0.000	-0.016***	-0.012***	-0.014***	-0.013***	-0.012***
VC fund conditions:							
Private VC fund (dummy)	0.088***	0.083***	0.090***	0.015**	0.133***	0.092***	0.034***
Corporate VC fund (dummy)	0.198***	0.179***	0.210***	0.109***	0.250***	0.205***	0.118***
VC firm age (in years)	-0.000***	0.000*	-0.001***	-0.004***	0.001***	-0.001***	0.001***
Market conditions:							
GDP growth	0.016	0.015	0.016	0.015	0.017	0.016	0.017***
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	330,398	143,795	186,603	147,857	182,541	308,613	21,785
Pseudo R-squared	0.043	0.052	0.039	0.054	0.038	0.040	0.086

5.5 The impact of the PA on exit outcome

The exit outcome variable is a count variable, so to research the impact of the PA on cleantech exits, this paper used multinomial logistic regressions controlled for industry-fixed effects. There were three exit outcomes, namely negative, positive, or active. When the VC did not yet exit its investment, the exit outcome is labeled as active, which was the baseline for the multinomial regressions. To interpret the coefficients from the regression model, the paper made a conversion from log odds to odds ratio. The odds ratio was computed by taking the exponent of the coefficient in Table 10 (see footnote for an example). The odds ratio suggests that a coefficient greater than 1 is considered as having a positive effect on the exit performance. Similarly to this, a coefficient smaller than 1 has a negative effect on exit performance. For the full sample, the odds ratio for a negative exit outcome relative to the baseline is 0.34[11] if the cleantech investment was made after the PA while keeping all other model parameters fixed (Model 1). This means that the probability of a negative exit diminishes with a factor of 0.34. The odds ratio for a positive exit outcome relative to the baseline is 1.51 when the cleantech investment was made after the PA (Model 2). This means the probability of a positive exit outcome increased with a factor of 1.51. These results are not in line with Hypothesis 5 that states that cleantech exits were less successful since the PA. For the Mission Innovation subset, the odds ratio for a negative exit outcome relative to the baseline was 0.36 when the cleantech investment was made after the PA (Model 3). This means the probability of a negative exit outcome is reduced with a factor of 0.36. The odds ratio for a positive exit outcome relative to the baseline was 1.46 when the cleantech investment was made after the PA (Model 4). This means the probability of a positive exit outcome increased with a factor of 1.46. Models 3 and 4 indicate that cleantech exits after the PA are more successful. Models 3 and 4 also reject Hypothesis 5.

[11] The odds ratio is computed by taking the exponent of the coefficient in Table 10. So, this makes exp (-1.065) = 0.34.

Table 10: Multinomial regressions on the impact of the PA on exit outcomes
Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Full sample		Portfolio companies located in countries part of Mission Innovation	
	Negative exit	Positive exit	Negative exit	Positive exit
Variable	(1)	(2)	(3)	(4)
Startup characteristics:				
PA (dummy)	-2.655***	-1.952***	-2.628***	-1.938***
	(0.411)	(0.368)	(0.403)	(0.361)
Cleantech startup (dummy)	-0.367**	-0.244***	-0.395**	-0.234***
	(0.148)	(0.0802)	(0.170)	(0.0823)
PA * Cleantech	-1.065*	0.409***	-1.026*	0.379***
	(0.593)	(0.124)	(0.595)	(0.132)
Industry dummies	Yes	Yes	Yes	Yes
No. obs.	330,398	330,398	308,613	308,613
Pseudo R-squared	0.1355	0.1355	0.1328	0.1328

6 Conclusion and discussion

The purpose of this study was to investigate the impact of the PA on the distribution of capital from VC firms toward cleantech startups. By analyzing over 12,000 investments in 2,021 cleantech startups and comparing them to a control sample of over 300,000 investments in non-cleantech startups, the paper can answer the research question: *"How has the PA influenced the distribution of capital from VC firms toward cleantech startups?"*

The study constructed five hypotheses to answer the main research question. Hypothesis 1 stated that since the PA, Mission Innovation countries have invested more of their funding in cleantech compared to before the PA. However, the results showed that cleantech investments after the PA decreased for countries part of the Mission Innovation initiative. Therefore, Hypothesis 1 was rejected.

Hypothesis 2 claimed that since the PA, less-experienced VCs invested more in cleantech than VCs that were more experienced. The DiD results indicated that old VCs invested less in cleantech startups after the PA than young VCs. The multilevel analysis in step 3 indicated the same. However, the multilevel analysis in step 2 indicated that young VCs. The model in step 3 was a better fit than the model in step 2 based on the LRTest. Therefore, Hypothesis 2 was not rejected.

Hypothesis 3 suggested that CVCs invested less in cleantech companies after the PA compared to private VCs. The DiD regressions and the third step of the multilevel analyses indicated that private VC invested less in cleantech startups than CVC. However, the second step of the multilevel analyses showed that CVCs invested less in cleantech companies compared to private VCs. Based on the LRTest, the model in step 3 was a better fit than the model in step 2. Therefore, Hypothesis 3 was rejected.

Hypothesis 4 predicted that syndicate size would increase for cleantech investments after the PA. The results indicated that the impact of the PA on syndicate size for cleantech investments was negative. The syndicate size of cleantech investments decreased after the PA, so Hypothesis 4 was rejected.

Hypothesis 5 expected that cleantech exits were less successful after the PA. However, the results showed that exits of cleantech VC investments were more successful after the PA. Based on these findings, Hypothesis 5 was rejected.

Based on the results, the study concludes that the PA had a negative impact on cleantech investments. Additionally, CVC firms and smaller syndicates invested more in cleantech. Furthermore, cleantech exits were more successful for VC firms that invested in cleantech. However, the robustness checks implicated that investments made in the US were responsible for the negative impact of the PA that was found. The alternative explanation for the decrease in cleantech investments is that countries with high CO2 emissions are not benefitted from promoting the allocation of VC funds to cleantech because their economy depends on energy incumbents. The results of the robustness analyses support this alternative hypothesis.

The study acknowledges that not all endogeneity problems may be resolved even with the use of DiD regressions, multilevel analyses, and multinomial regressions. Nevertheless, the findings provide interesting insights into the impact of the PA on VC's allocation of funds to cleantech startups.

This paper is the first to evaluate the impact of the PA on VC's allocation of funds to cleantech startups. Nonetheless, to reach a more definitive conclusion on the impact of the PA, further research has to be done. There are several private datasets with extensive data on cleantech investments, for example, databases from Holon IQ[12], The Cleantech Group[13], and NASDAQ Data Link[14]. However, these databases are not accessible for students and are very costly. Multiple opportunities are available to further analyze cleantech investments and the factors influencing them since the industry is constantly evolving. For instance, the innovativeness of cleantech startups could be studied based on the patents it has and how this influences the allocation of VC funds. Finally, the cleantech investments of energy incumbents are a particularly interesting field for further research because they own excessive amounts of capital since the energy crisis. It would be interesting to see whether this capital can be put to work for more sustainable alternatives such as cleantech.

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[12] Holon IQ is a cloud-based platform that offers artificial intelligence powered employee skills and talent development solutions for organizations.
[13] The Cleantech Group is a research and advisory firm that supports companies and investors in the clean technology industry.
[14] NASDAQ Data Link is a cloud-based platform that provides financial institutions with historical and real-time market data to inform their investment strategies.

7 References

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Appendix A

Table 11: VIF tests
VIF tests for the explanatory variables in the DiD regressions.

	VIF		
Variable	(1)	(2)	(3)
Startup characteristics:			
PA (dummy)	2.55	2.32	1.17
Cleantech startup (dummy)	1.86	1.86	1.86
PA * Cleantech	1.44	1.44	1.43
Startup age (in years)	1.41	1.40	1.39
VC fund conditions:			
Private VC fund (dummy)	1.50	1.50	1.50
Corporate VC fund (dummy)	1.24	1.24	1.24
VC firm age (in years)	1.26	1.26	1.26
Market conditions:			
GDP (in USD)	29.67	--	--
GDP per capita (in USD)	24.93	12.06	--
GDP growth	1.42	1.40	1.35