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THE ROLE OF VENTURE CAPITAL AND GOVERNMENTS IN CLEAN ENERGY: LESSONS FROM THE FIRST CLEANTECH BUBBLE

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ABSTRACT

After a boom and bust cycle in the early 2010s, venture capital (VC) investments are, once again, flowing towards green businesses. In this paper, we use Crunchbase data on 150,000 US startups founded between 2000 and 2020 to better understand why VC initially did not prove successful in funding new clean energy technologies. Both lackluster demand and a lower potential for outsized returns make clean energy firms less attractive to VC than startups in ICT or biotech. However, we find no clear evidence that characteristics such as high-capital intensity or long development timeframe are behind the lack of success of VC in clean energy. In addition, our results show that while public sector investments can help attract VC investment, the ultimate success rate of firms receiving public funding remains small. Thus, stimulating demand will have a greater impact on clean energy innovation than investing in startups that will then struggle through the "valley of death". Rather than investing themselves in startups bound to struggle through the valleys of death, governments wishing to support clean energy startups can first implement demand-side policies that make investing in clean energy more viable.

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1. Introduction

At the start of the last decade, venture capital (VC) investments in clean energy experienced a boom and bust. From 2005 to 2008, the share of venture capital investments going to clean energy technologies more than tripled before falling in subsequent years. Today, once more, billions of dollars are pouring into green businesses. We argue that this renewed interest in clean technologies warrants further study of the initial failure of VC in this sector. Years have passed since the original assessments of the cleantech bust (Gaddy, Sivaram, Jones, & Wayman, 2017; Nanda, Younge, & Fleming, 2015), and greater data availability today allows us both to draw a more complete picture and to contemplate the possibility of success for this new wave of green venture capital investment.

Moreover, providing support for green startups remains a popular policy tool. For example, in 2016, California created the Energy Innovation Ecosystem to support clean technology ventures, which includes seed funding through California Sustainable Energy Entrepreneur Development Initiative (CalSEED) awards. Similarly, the NY Green Bank, founded in 2014, leverages private sector financing to increase clean energy investments (Popp, 2020). The potential success of these initiatives depends on *why* early venture capital efforts failed. If issues such as high capital intensity or long delays between initial investment and commercialization create additional barriers for clean energy to raise funds, government financing can help bridge that gap. But if these investments are not successful because of a lack of demand for clean energy, government investments in these startups will be no more successful than private-sector VC investments.

To study the causes of VC's failure in cleantech, and in particular in clean energy, we obtained data on 149,358 companies launched in the United States between 2000 and 2020 from Crunchbase. The comprehensive coverage of Crunchbase's data allows us to compare venture capitalists' (VCs) performances in clean energy and electric vehicles (EVs) to their performances in other sectors with dynamic startups ecosystem, namely information and communications technology (ICT) or biotech. Using this data, we explore three factors that could explain the failure of VC in cleantech: financial constraints specific to funding clean energy, relative weak demand for green products and limited potential for outsized returns. Varying levels of capital intensity and observed VC returns allow us to analyze the role of financial constraints. Our results do not suggest that these financing constraints are the main factor behind the lack of success of VC in clean energy. For instance, while Bumpus and Comello (2017) argue that digital and modular cleantech startups should be better able to attract early-stage capital providers than capital-intensive energy hardware, recent data shows that digital energy firms have been no more successful than other energy startups.

Instead, we argue that weak demand for clean energy technology is the main reason for the fall in VC investments. To demonstrate the importance of expected demand, we implement a differences-in-difference estimation (DiD) centered around the passing of Ted Kennedy and the unexpected election of a Republican, Scott Brown, to replace him in 2010. Brown's victory in a special election in January 2010 made passing a comprehensive climate bill very difficult (Goldenberg, 2010), providing us with an exogenous negative shock to demand expectations for clean technologies. We find that expectations of weaker demand have a significant impact on VCs' willingness to fund clean energy startups. Finally, we show that clean energy firms have displayed a lower potential for outsized returns than startups in ICT or biotech, making them less appealing to VCs.

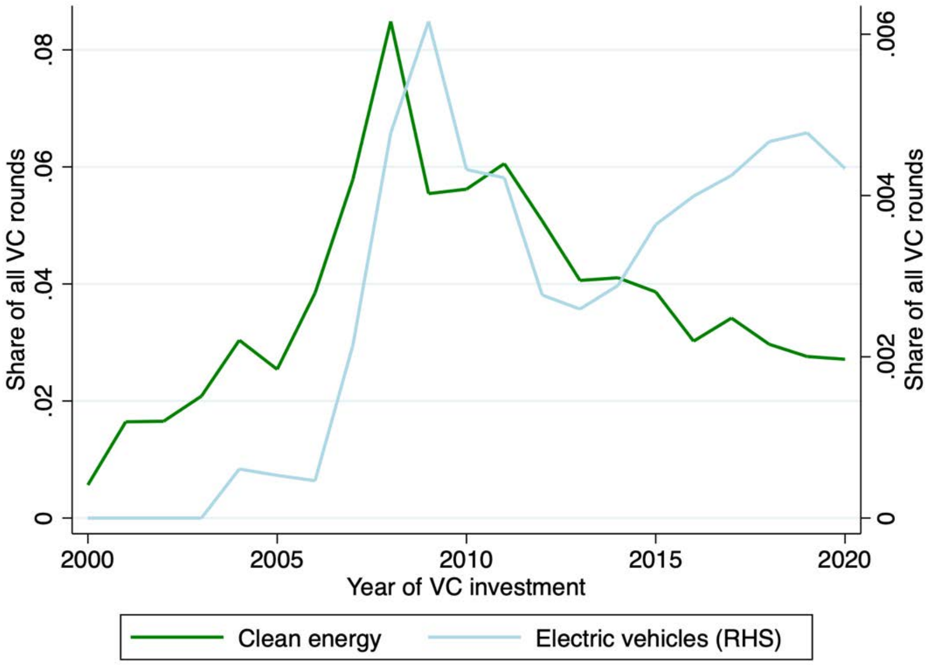
Our findings suggest that if governments want to support early-stage investments in clean energy, implementing policies such as carbon pricing that stimulate widespread private demand for clean energy products is important. However, implementing such policies in the United States is an arduous political task, as demonstrated by the failure of a cap-and-trade bill in 2009-2010 when Democrats controlled the Presidency and both houses of Congress. The recent inclusion of funding for green technologies in the Infrastructure Investment and Jobs Act attests that spending money to support clean energy is more palatable politically. Thus, we also look at the role of the government as an active provider of funding to young companies. We show that in early stages, public investors provide small-sized grants that help startups prove the viability of their project and attract Series A funding. However, the firms that do secure a Series A after their public grant are no likelier to have long-term success than other VC-funded firms. In later stages, governments provide significantly larger sums aimed at helping startups expand and scale their business. When providing later-stage funding, we find that public investors have not fared worse than their private-sector counterparts, and may improve chances for exit if one assumes that public funding goes to startups less likely to attract late round private funding on their own. Here, our comprehensive data including companies in multiple sectors provides additional context compared to earlier studies focusing solely on public investments in the energy sector (e.g., Howell (2017) and Goldstein *et al.* (2020)). Since venture capital investments in clean energy as a whole perform much worse than in other sectors, simply matching private sector performance in the clean energy sector is not enough. Public investments alone cannot plug all the funding gaps in cleantech innovation. We, therefore, argue that a long-term positive demand shock is needed for private investors to be consistently successful when funding clean energy startups. Only then can governments use targeted public sector investments to address any remaining gaps in the valleys of death for cleantech innovation, such as by providing financial support for firms developing products where the potential for outsized returns is limited.

The paper is organized as follows. The next section provides background information on venture capital, its failure during the 2009 cleantech boom and governments' role in addressing funding gaps. Then, Section 3 describes our data. Section 4 presents our analysis of the underlying causes of the failure of VC in cleantech and evaluates the role of governments in addressing funding gaps. Finally, Section 5 discusses our findings and their implication.

2. Background

The years 2005 to 2008 saw rapidly growing interest in clean energy from venture capitalists, policy-makers and the media. However, clean energy startups proved to be an unprofitable experiment. Gaddy *et al.* (2017) estimate that less than half of the over $25 billion provided to cleantech startups from 2006 to 2011 was returned. As a result, the cleantech boom went bust as VC funding dried up. Figure 1 shows that while more than 8% of VC rounds (Series A to J) reported in Crunchbase went to clean energy firms in 2008, this figure dropped to around 3% between 2016 and 2020. While most clean energy VC activity remains low, Figure 1 also shows renewed investor interest in EVs, which experienced a similar boom from 2006-2009, and are now returning to those previous levels of investment.

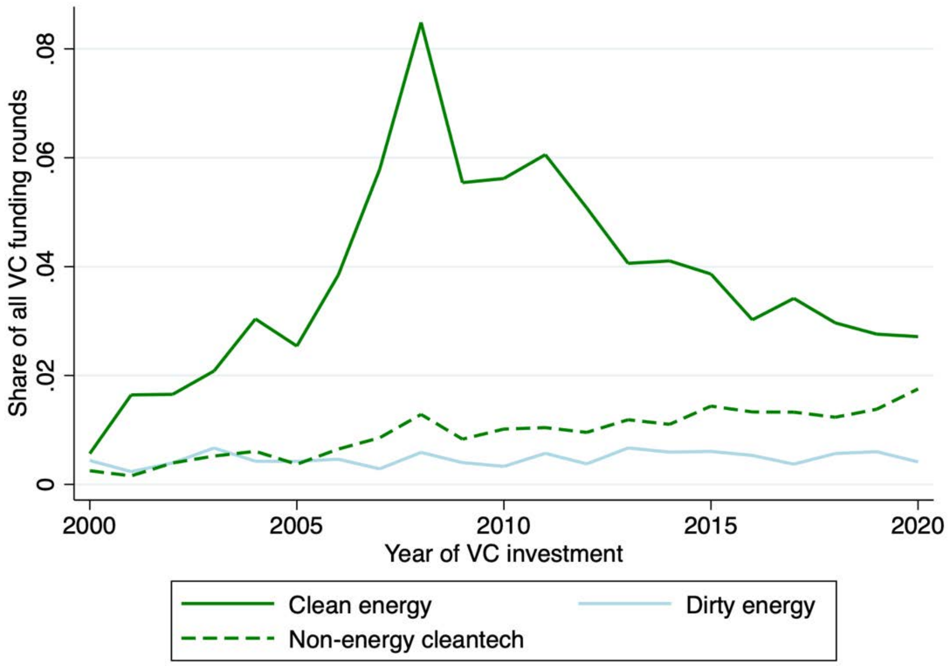
Figure 1: The cleantech boom and bust



Notes: This figure shows the share of all VC rounds (Series A to Series J) going to clean energy (LHS) and electric vehicles (RHS).

Moreover, while dubbed the cleantech bubble, the boom was concentrated in sectors related to clean energy, such as clean energy production, energy efficiency or EVs. Figure 2 shows that non-energy cleantech (e.g., sustainable farming, recycling or carbon capture) has been growing steadily since the start of the millennium without displaying a boom and bust pattern. Additionally, the bubble did not affect all energy firms equally. The share of VC funding to dirty energy (i.e., fossil fuels) has indeed remained relatively constant (and low) over the past two decades.

Figure 2: The bubble was concentrated in clean energy



Notes: This figure shows the share of all VC rounds (Series A to Series J) going to clean energy, dirty energy and non-energy cleantech.

Literature review

Venture capitalists (VCs) are the primary source of early-stage funding targeted at young companies with the potential for rapid growth and high returns (Metrick & Yasuda, 2021). In addition to funding their internal growth, VCs monitor and mentor the startups in their portfolio. VC is structured as a fund whose manager (or general partner – GP) invests the capital of investors (limited partners – LPs) in a portfolio of companies. After an initial investment period of around 5 years, the GP has 5 to 7 years to return capital to the LPs (Kaplan & Schoar, 2005). The goal of VCs is to exit their investments via an acquisition or an initial public offering (IPO) within the lifespan of the VC fund.

VCs invest at different stages of a startup lifecycle, providing capital to entrepreneurs in a stepwise manner (Neher, 1999). This process, called staged financing or VC staging, is a way to mitigate the agency problem. Rather than providing all the necessary capital to exit upfront, the VC investor retains the option to abandon a startup if it fails to meet stage targets (Nanda & Rhodes-Kropf, 2016; Tian, 2011). VCs start to become involved at the seed stage alongside angel investors, where a small amount of funding (i.e., usually less than $1M according to Crunchbase) is provided to prove a concept. Then during Series A, the first of the typical VC rounds, VCs offer more than $7M on average to young companies with a track record that illustrates the potential of the idea or technology and a solid strategy to transform this idea into a profitable business. As the company matures and proves its potential, the rounds become increasingly generous (Series B, C, D, etc.). Most papers that study the investments decisions of VC investors focus on Series A as it corresponds to the stage where the initial investment decision is made and then follow these Series A investments to see their eventual outcome (Ewens, Nanda, & Rhodes-Kropf, 2018; Gaddy et al., 2017; Nanda & Rhodes-Kropf, 2013).

Investing in early-stage companies offers the opportunity for huge gains but also staggering losses. The expectation is that within a portfolio of 10 to 20 companies, a few will succeed, some will break even, and most will fail (Gaddy et al., 2017). The few successes need to be able to offer sufficient returns to compensate for all the failures. Therefore, the ideal investment will be easily and rapidly scalable with the potential to return 10 to 100 times the amount invested within 5 to 7 years.

Several studies done in the wake of the cleantech boom and bust provide explanations for VCs' poor performance, arguing that clean energy does not fit the VC model (Gaddy et al., 2017; Nanda et al., 2015; Saha & Muro, 2017). First, as a seller of a commodity, clean energy startups compete in markets with thin margins. The electricity produced by sun or wind is indistinguishable from coal-produced electricity, making product differentiation difficult. On top of that, in sectors like biotech, incumbent firms are willing to buy promising startups before commercial viability has been proven. Big energy firms and utilities have been less active in acquiring promising clean energy ventures, which makes investing at early stages less appealing. Finally, and most importantly, these papers suggest that high capital intensity, as well as long-lasting technological and commercialization uncertainty, are to blame for VCs' failure in clean energy. Overall, they argue that the VC model seems poorly suited for clean technologies (Lerner & Nanda, 2020).

In this paper, we explore two other reasons for the failure of VC in clean energy. The first is that demand for clean goods was simply too low because environmental externalities are not priced in. The peak in VC investment in clean energy & EVs coincides with the failure of the cap-and-trade bill in the US Congress and the disappointing Copenhagen Climate Conference (COP 15). Investors had to subsequently reassess their expectations of future policy support for clean technologies. Second, we document the inability of clean energy firms to earn oversized profits. As noted earlier, clean energy companies find it difficult to differentiate their products and boost their market power. As a result, compared to startups in sectors like ICT or biotech, they struggle to earn the 10 to 100 times returns that VC investors look for.

Finally, our paper also considers the potential role of public sector investments in clean energy startups. These include programs aimed at very early-stage startups, allowing them to prove their technological viability and attract future Series A funding (e.g., CALSEED), as well as larger interventions after Series A rounds to help commercialize new products, such as the department of Energy's Loan Guarantee Program. Scholars have studied the individual usefulness of some of these public programs. Howell (2017) finds that the US Department of Energy (DOE) Small Business Innovation Research (SBIR) R&D grants are helpful because they fund technology prototyping. Moreover, she shows that this early-stage award increases the probability of securing subsequent venture capital. However, Goldstein *et al.* (2020) find that receiving an early-stage award from the US Advanced Research Projects Agency-Energy (ARPA-E) does not significantly increase the probability of exiting compared to comparable but non-participating cleantech startups.

We argue that reconciling these results depends on the underlying causes of the failure of private investors in cleantech. If clean energy companies' unattractive characteristics (i.e., capital intensity and long development timeframe) are to blame, then patient public capital can bolster the success of cleantech startups. If a lack of demand for the eventual green product is the culprit, publicly-funded startups will, like their privately-funded counterparts, struggle to exit and return money to their investors. In that case, public money, will not solve the funding gaps alone. Understanding the causes of the failure of VC in clean energy is, therefore, key to guiding public policies.

3. Data

To study the performances of early private and public investors in clean energy, we gather firm-level data on startups and funding activity from Crunchbase, a provider of business data for private and public companies. Crunchbase provides detailed information on companies, such as their founding date, headquarters' location at the postal code level, industry classification and founder characteristics (i.e., previous entrepreneurial experience, degrees and gender). Most importantly, they provide detailed information on funding rounds as well as exits (i.e., date, amount, investment/exit type and actors involved). This information includes the type of organization making each investment, such as a government office, venture capital, or an investment bank.

Crunchbase collects its data through companies and investors' self-submissions, the work of their own data analysts and by using AI and machine learning. As a result, there may be selection concerns, for instance, as more innovative companies are more likely to appear in the data. Contemporaneous and past coverage increase over time as new data is made available and as more companies use the platform (Dalle, Den Besten, & Menon, 2017). In the final one or two years, coverage is more partial given the time lags to collect recent data. Furthermore, some firms may misleadingly indicate that they operate in a particular sector for self-promotion purposes to attract more funding, as sector categories are not cross-checked against traditional sectoral classifications. While we do not explicitly model selection into Crunchbase, our regression analysis uses year and sector fixed effects to partially control for such selection issues. For instance, year fixed effects control for changes in the completeness of Crunchbase coverage over time.

To conduct our analysis, we link nine different datasets provided by Crunchbase.[1] Beginning with the whole cross-section of 1,382,795 organizations registered in Crunchbase, we keep organizations located in the United States categorized as companies (as opposed to an investor or a school) and who launched between 2000 and 2020.[2] We then focus only on the 149,358 companies operating in our three sectors of interest: clean energy & EVs, ICT and biotech. Companies in these three broad sectors account for a disproportionate share of funding activity in the United States. They represent 59% of all startups launched between 2000 and

[1] We use the organizations, acquisitions, ipos, funding_rounds, investments, investors, jobs, degree and people datasets.
[2] We downloaded the data using an Academic Research Access on the 25th of May 2021.

2020 and are responsible for 75% of the funding recorded in Crunchbase. Among these 149,358 companies, 51,705 (35%) have at least one recorded funding deal for a total of 123,408 deals.[3]

Our clean energy & EVs categories include companies focused on supply and demand of clean energy. Supply includes companies working on technologies related directly to clean energy production, such as solar and wind energy, or those working indirectly through grid management. Demand-side technologies include energy efficiency and electric vehicles.[4] Such companies played a central role in the VC boom and bust of the early 2010s. Among clean energy companies, we differentiate between the companies that develop energy technologies with some digital or ICT elements and those that do not. Examples of digital energy startups include companies that develop smart sensors or software that optimize battery-related processes. Popp *et al.* (2022) document increasing cross-fertilization between clean energy and digital technologies. As we show in this paper, digital energy startups are less capital-intensive, which could make them more attractive targets for venture capital (Gaddy et al., 2017). As electric vehicles were a small portion of the previous clean energy VC boom but are attracting growing attention from investors (see Figure 1), we treat electric vehicles as a separate category in our analysis. ICT companies provide a relevant benchmark to the success of clean energy firms, as ICT is the sector with the most active startup ecosystem. Biotech firms provide another interesting comparison group that has attracted a lot of VC investments despite its high capital needs (Hudson & Khazragui, 2013).

The top panel of Table A.1 in the Appendix shows the composition of relevant industry categories, and its bottom panel displays the criteria for each company's placement into our five mutually exclusive categories (i.e., non-digital clean energy, digital clean energy, EVs,

[3] While we use all the 28 funding types registered by Crunchbase in our analysis, we focus mainly on venture capital rounds (Series A, B, C, …, and seed). Crunchbase provides an overview of its funding types: https://support.crunchbase.com/hc/en-us/articles/115010458467-Glossary-of-Funding-Types

[4] It is important to note that we categorize as *clean energy* all the energy startups that are not involved in fossil fuel technologies. We also include in our *clean energy* category the startups involved in both *fossil fuel* and one of the *clean* categories in Table A.1.

ICT and biotech). As we are interested in studying the performances of early-stage investors in clean energy, we focus on the success of investors involved during Series A rounds. The success of VC investors can be measured by whether they have been able to exit their early-stage investments through an initial public offering (IPO) or an acquisition by another company or later-stage investor (Metrick & Yasuda, 2021). We, therefore, use startups' exit events to draw conclusions about the performances of VCs across sectors. 10.8% of the companies in clean energy & EVs, ICT and biotech manage to exit; 1.2% doing it via an IPO and 9.6% through an acquisition. Among startups that secure series A funding the exit rate is much higher, reaching 31.6%.

In addition to exit dummies, we also develop more granular measures of VC investment return. These allow us to differentiate between startups that exit while returning 2x invested amount to their Series A investors from those that are home run successes and yield a 100x return to their early-stage investors. As a first measure of return, we use the value of the company at exit. Then, to judge investments of different size on an equal footing, we also build a cash-on-cash (CoC) multiple measure that represents the ratio of the returned over invested capital. Finally, we create four binary variables that indicate whether startup *i* yielded at least a 5x returns, 10x returns, an exit above $1 billion or above $5 billion. All funding and exit amounts are converted to real 2020 dollars using the US CPI from the Bureau of Labor Statistics (BLS). We provide further detail about the construction of these measures of success in Appendix A.2.

As a last step, we address the fact that it is impossible to know with certainty whether startups still operating will end up as successes (exit) or failures (no exit). To deal with this issue, we exclude firms that are still active (i.e., actively looking for funds or trying to exit) from our analysis. In Appendix A.3, we explain how we determine whether startups in our sample are still active or if they continue to survive with no prospect of exiting (so-called "living-dead" companies). Our data for regressions includes startups launched or funded between 2003 and 2016. We do not include the startups launched before 2003 because they are less affected by the cleantech boom and therefore less informative and we do not include those launched after 2016 because these companies simply have not yet had the time to exit and return money to their investors.

4. Analysis

I. The underlying causes of VC's failure in clean energy

While several papers document the poor performance of early clean energy VC investments, understanding why these investments fail is important for understanding what role, if any, public investors can play in supporting clean energy startups. This depends on the extent to which financial constraints themselves hinder clean energy investments relative to a lack of demand. That is, do clean energy startups face funding gaps because of the particular characteristics of energy innovation making clean energy unattractive to VC investors, or is it simply a result of historically underpriced environmental externalities reducing demand for cleaner technology?

In this section, we present evidence that the lack of demand for clean energy is a crucial reason for VCs' poor performances and low interest in clean energy. Although we cannot definitively rule out that financial constraints for clean energy exist, we find no evidence that increasing financing for clean energy technologies will, on its own, be successful. Additionally, we document the low potential for outsized returns in clean energy for early-stage investors, which is not only a consequence of subdued demand but also, we argue, of the weak market power of energy companies.

A. The role of startups' characteristics and financing constraints

In this section, we test two hypotheses about the role of financial constraints in clean energy VC. First, after a first wave of hard to fund, hardware-focused cleantech startups, investors and scholars have argued that the second wave of digital and modular cleantech startups should be better able to attract early-stage capital providers (Bumpus & Comello, 2017). This reasoning stems from the fact that ICT startups, in general, are an attractive investment for VCs because they have relatively low capital needs and the uncertainty about the viability of their product and the market demand can be resolved quickly (Lerner & Nanda, 2020). Supporting this claim, Gaddy *et al.* (2017) found that digital cleantech startups were the only ones to have posted positive returns for their Series A investors during the cleantech boom and bust. This leads to the following hypothesis:

Hypothesis 1: *If clean energy startups' unappealing characteristics are the main reason behind VCs' failure in energy; the less time- and capital-intensive digital energy startups should have both fared better and attracted more VC money since the bust than the rest of the clean energy sector.*

Advocates of increased public funding for clean energy startups often argue that investors ignore clean energy because it is capital intensive and provides slow returns, so that clean energy firms have less access to VC than other sectors (Weyant, 2011). That is, clean energy firms face more liquidity constraints than other types of firms, so that likely profitable opportunities are unable to raise funds. To check for the presence of such financial constraints in the energy sector, consider the alternative. With equal access to capital in all sectors, investments should flow so that the expected return is equal across sectors. If liquidity constraints limit the flow of VC into clean energy, the limited funds that do flow to clean energy should go to the most promising clean energy firms. As such, the expected returns to investments in clean energy should be *higher* than the expected returns in other sectors. Instead, if the flow of VC into clean energy is limited by lackluster demand, the expected returns should not be higher than in other sectors. While we can only observe actual, not expected, returns, we argue that evidence that investors are "leaving money on the table" would be evidence of significant financial constraints. Investors are "leaving money on the table" if the performances (i.e., realized returns) of the clean energy startups that do get funded by VCs are significantly higher than the performance of clean energy without VC funding, in comparison to other sectors. We call this differential between the performances of VC-funded and non-VC-funded startups the *VC premium*. Therefore:

Hypothesis 2: *If financial constraints affect clean energy more than other sectors, investors will leave money on the table, leading to a higher VC premium for investments made in this sector.*

Methodology & Results

We first use Crunchbase data to verify whether digital energy startups are indeed less capital intensive than other clean energy firms. To do so, we look at the money raised after Series A round by the startups that eventually exited, excluding the funds raised after their exit. While this is not a perfect measure of capital intensity, the amount raised is directly linked to the capital needed to grow a company to the point where it can exit. Table 1 shows that digital clean energy startups raise $49.6M (2020 US dollars) after their Series A on average, nearly 50% less than the $94.2M raised by non-digital clean energy startups.[5] At the same time, ICT companies have similar capital needs than digital energy companies, which is what we would expect. Biotech and non-digital energy companies have similarly high levels of capital intensity. Therefore, we can separate our sample into the capital-intensive companies (i.e., non-

[5] EV companies raised $216.1M on average but It is important to note that this average is only based on 9 observations, including Tesla and ChargePoint who have each raised more than $680M.

digital energy, EVs and biotech) and the less capital-intensive companies (i.e., digital energy and ICT).

Table 1: Average amount raised before exit by startups with Series A (2000-2020)

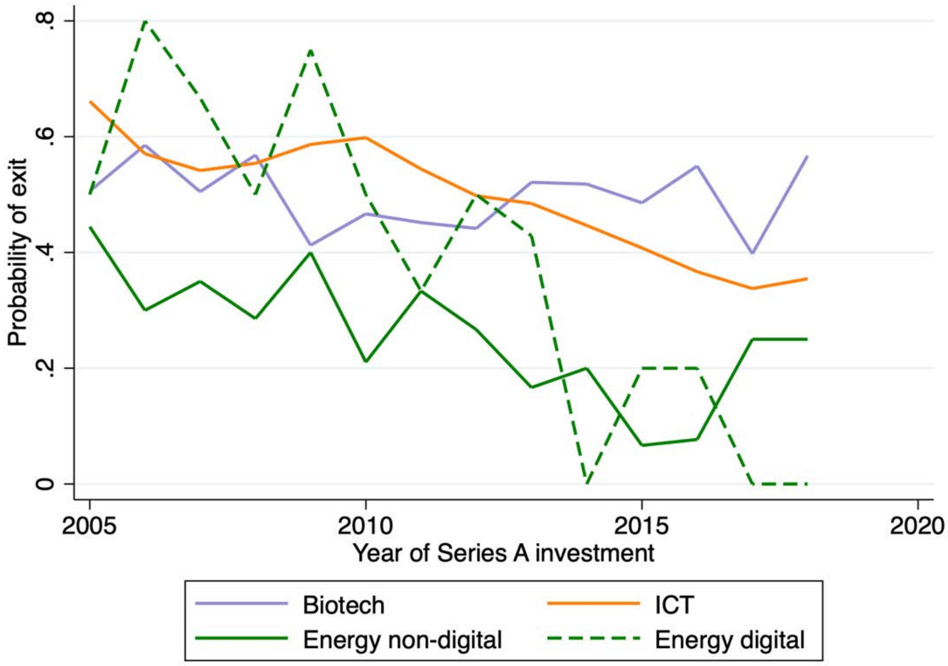
in 2020$ million	Non-digital energy	Digital energy	EVs	ICT	Biotech
Post-Series A Funding	94.2	49.6	216.1	50.1	80.4
Observations	78	46	9	3446	707

Finding #1.1: *While VC investments in digital energy initially outperformed non-digital energy, VCs have performed similarly bad in both sectors in recent years.*

We first test Hypothesis 1 by examining VC performances and funding rates across sectors. As a measure of the performance of VC investments, we look at the exit rate of the startups that received Series A investments. Figure 3 shows that digital energy startups that received Series A up until 2013 had a similar probability of exit than VC-funded biotech and digital startups.[6] This is evidence that during and directly after the cleantech boom and bust, digital energy startups outperformed more traditional energy startups, which is in line with the initial studies of the cleantech failure. However, Figure 3 also shows new evidence that this initial outperformance did not last. Digital energy startups funded after 2014 saw their exit rate fall to the low level prevalent in the rest of the energy sector.

[6] Note that in the figures in this section, we do not display results for EVs as the lower number of observations prevents us from providing stable yearly output. See Table 2 for EV results.

Figure 3 : The performance of VC-funded digital energy startups has gone down

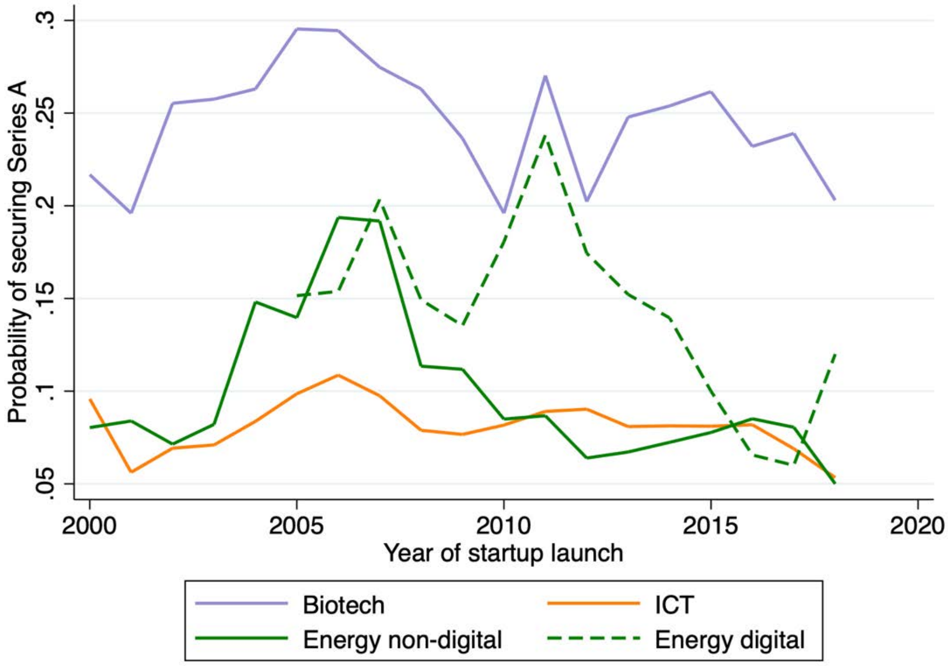


Notes: This figure displays the share of Series A-funded startups that that managed to exit, based on the year they received the Series A round, by industry.

Finding #1.2: *The fall in VCs' performances in digital energy has been accompanied by a reduced interest in funding this industry*.

Our first finding contradicts the idea that digital energy, like ICT, is a good fit for VC. Next, we demonstrate that the worsening performances of digital energy companies has been accompanied by a fall in the willingness of VC to fund them. Figure 4 below shows that while the probability of receiving series A funding fell for non-digital energy startups launched after 2007, digital energy startups launched up until 2011 enjoyed buoyant VC interest. However, while 25% of energy digital startups launched in 2011 received Series A funding, only a little more than 5% of those launched in 2016 and 2017 did. The drop in VC's willingness to fund digital energy startups follows the fall in their exit probabilities to the level of the rest of the clean energy sector (see Figure 3 and Figure 5).[7,8]

Figure 4 : VCs' willingness to fund energy digital startups has also fallen



Notes: This figures displays the share of all startups that manage to secure Series A funding, based on the year they were launched, by industry. Values are not displayed for energy digital startups launched before 2005 because of the low data availability (i.e., only between 3 to 8 startups were funded each year).

Finding #2.1: *Venture capital investments are not "leaving money on the table" in the energy sector.*

Turning now to Hypothesis 2, we test (a) whether startups supported by VCs have outperformed the startups that did not receive Series A funding and (b) whether this VC premium is higher than in other sectors. To calculate this VC premium over the years, we implement Equation (1) using OLS:

[7] Note that Figure 3 conditions startups based on the year of investment unlike Figure 4 and Figure 5 that are based on the year of launch. This explains the lag between the two groups of Figures as, in our sample, startups receive their first Series A funding three years after their launch on average.

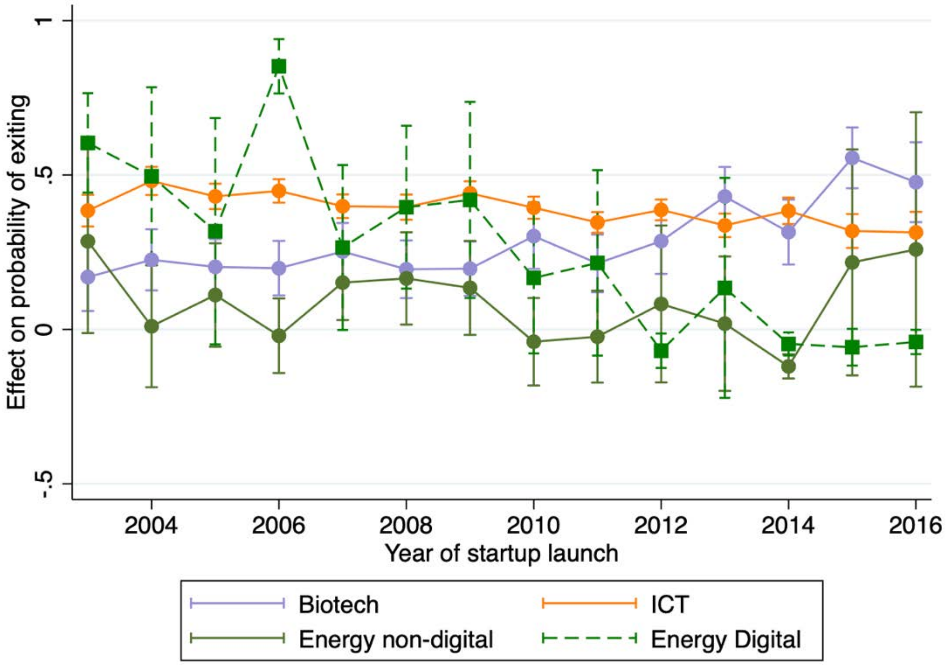
[8] While ICT startups have a relatively low funding rate, this stems from the fact that ICT startups are very common, representing 54% of the US startups on Crunchbase launched between 2000 and 2020, and thus face stiff competition for VC money.

$$Exit_i = \beta_1 VC_i + \sum_{ind=2}^{5} \beta_{2,ind} VC_i * (Industry_{ind} = 1) + \sum_{year=2004}^{2016} \beta_{3,year} VC_i * (Launch\ year_{year} = 1) + \sum_{ind=2}^{5} \sum_{year=2004}^{2016} \beta_{4,ind,year} VC_i * (Industry_{ind} = 1) * (Launch\ year_{year} = 1) + \gamma_{industry} + \gamma_{launch\ year} + \gamma_{industry,launch\ year} + \gamma_{state} + \epsilon_i \tag{1}$$

Here, the unit of observation is startup *i*. The dependent variable *Exit* indicates whether the startup was acquired or had an IPO. *Industry* is a set of dummy variables indicating whether startup *i* is non-digital energy, digital energy, EVs, ICT or biotech. The dummy variable *VC* captures whether a startup received Series A financing. *Launch year* is a set of dummy variables indicating the year in which the startup was founded, which controls for both for common economic conditions and the changes in Crunchbase's coverage. Finally, we include state fixed effects. ICT startups, the year 2003 and the state of California are the reference categories.

Figure 5 below displays the VC premium by industry and year, i.e., Equation (1)'s $\beta_1 + \beta_{2,ind} + \beta_{3,year} + \beta_{4,ind,year}$. Digital energy startups launched between 2005-2008 supported by VCs (i.e. those funded during the cleantech bubble) outperformed non-VC supported digital energy startups and had a similar VC premium than the other (non-energy) ICT investments. However, this has stopped being true for startups launched after 2011. In the past decade, VCs in digital energy, like in non-digital energy, have not been able to pick startups that perform better than average. In contrast, the "VC premium" in biotech and ICT has never disappeared – biotech and ICT firms receiving VC investments are consistently more likely to exit than those that don't.

Figure 5 : The VC premium in digital energy has vanished



This figure displays the marginal effect of receiving VC funding by industry and startup launch date, using Equation (1). Estimates are shown with their 90% confidence intervals.

To compare VCs premiums across sectors and over longer periods of time, Table 2 shows the estimated VC premiums (i.e., $\beta_1 + \beta_{2,ind}$) for each industry from an adjusted version Equation (1) without *Launch year* interactions. We estimate this VC premium by industry for all startups founded during the 2003 to 2016 period as well as during the pre-bust (2003-2009) and post-bust (2010-2016) eras.[9] Both ICT and biotech startups display a very significant VC premium. ICT startups that receive series A have an exit probability around 40 percentage points higher than those that do not, and biotech startups receiving ICT exit at a rate about 28 percentage points higher than those that do not.

[9] As Figure 1 shows, the rapid growth in clean energy VC investments occurred during 2005-2008 and then VC investments decreased slightly but stayed at a high level until 2011. After 2011, they have steadily fallen. Startups founded between 2003 and 2009 have launched and likely received their first funding during the cleantech boom – as they receive their Series A 3 years after launch on average. The startups launched between 2010 and 2016 have operated after the cleantech bust.

Table 2 : The relationship between receiving Series A funding and eventual success

	General (2003 to 2016)			2003 to 2009	2010 to 2016
	(1)	(2)	(3)	(4)	(5)
	Exit	Acquired	IPO	Exit	Exit
VC: ICT	0.3925***	0.3719***	0.0290***	0.4241***	0.3632***
	(0.0067)	(0.0067)	(0.0024)	(0.0096)	(0.0093)
VC: Energy non-digital	0.106***	0.108***	-0.007	0.112***	0.027
	(0.030)	(0.028)	(0.015)	(0.036)	(0.051)
VC: Energy digital	0.320***	0.338***	0.005	0.437***	0.121
	(0.054)	(0.054)	(0.017)	(0.071)	(0.074)
VC: EVs	0.264**	0.209*	0.045	0.246	0.233
	(0.126)	(0.121)	(0.081)	(0.157)	(0.228)
VC: Biotech	0.277***	0.143***	0.170***	0.210***	0.359***
	(0.016)	(0.015)	(0.013)	(0.022)	(0.024)
Industry FE	Yes	Yes	Yes	Yes	Yes
Launch year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	104801	104801	104801	39869	64932
R squared	0.112	0.094	0.073	0.118	0.093

Notes: This table presents results of OLS regressions. The sample includes clean energy & EVs, ICT and biotech startups launched from January 2003 to December 2016. The dependent variable is whether the startup exited in Columns (1), (4), and (5). In Column (2), the dependent variable is whether the startup got acquired and in Column (3) whether it went public. This table only displays the coefficients for the VC premiums by industry, i.e., the sum of the *VC* and *VC x Industry dummy* coefficients and their statistical significance. The level of observation is at the firm-level. Robust standard errors are in parentheses. Asterisks denote * p<0.1, ** p<0.05, *** p<0.01.

By contrast, digital energy startups launched pre-bust display a VC premium similar to ICT startups, but this VC premium has fallen to the point of not being significant anymore during the post-bust period. In non-digital energy, the VC premium has always been low to non-existent. Overall, the VC premium in clean energy has been nearly null in the 2010s and less than half of the VC premium for ICT and biotech in the 2003-2009 era. We, therefore, find no evidence that financial constraints are causing investors to “leave money on the table” in the clean energy sector.[10] Finally, in EVs, VCs seem to have consistently outperformed non-VC investments by around 24 percentage points, but the low number of observations weighs on the statistical significance.

Overall, this section shows that less capital-intensive digital clean energy startups have quickly stopped outperforming the rest of the energy sector after the bust. What is more, EVs, a capital-intensive industry that is trying to normalize the use of a radical new technology, have seen a resurgence in VC funding (see Figure 1) and stable success (see Table 2). We also find that, since the bust, clean energy startups that receive VC funding do not perform any better than those that do not, unlike VC-funded startups in other sectors. The absence of VC premium in clean energy indicates the investors are not "leaving money on the table". These results cast doubt on the preeminence of startups characteristics, and the resulting financing constraints, as an explanation for the lack of success of VC in clean energy.

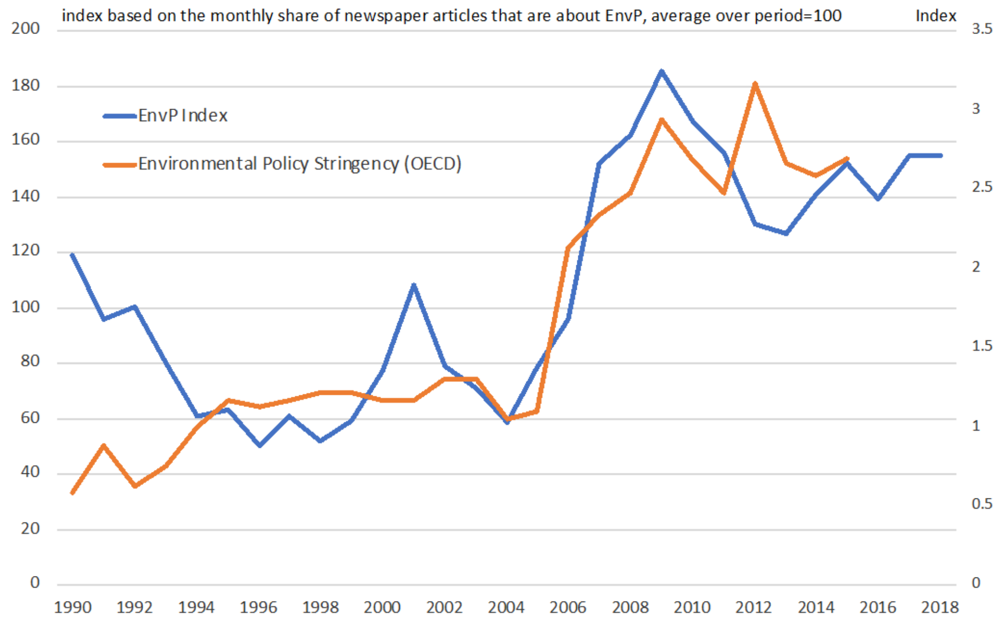
B. The role of expected demand for environmental goods

Having shown that the capital intensity of energy technology cannot, on its own, explain the poor performance of venture capital in the energy sector, we now show that changes in expected demand – caused by changes in policy support – do explain the investment patterns observed during the boom and bust period. Noailly, Nowzohour and van den Heuvel (2021) find that decreases in environmental policy stringency are associated with lower willingness from VC to fund cleantech startups. The first phase of the cleantech boom was accompanied by rising environmental regulations as well as expectations of increasingly stringent future environmental policies. The election of President Obama and a Democratic majority in Congress raised expectations for a national climate policy, which eventually became the

[10] Formally, the null hypothesis for hypothesis 2 (that energy has a higher VC premium than other sectors) is that the coefficient on β_2 is positive and significant for energy technologies. That is never the case. It is aways negative and significant for non-digital energy, and is either insignificant or negative and significant (for exit in 2016-16) for digital energy. Full regression results for these coefficients are shown in Appendix Table A2.

Waxman-Markey bill (formally the American Clean Energy and Security Act) that passed the House in 2009. The bill proposed the first national cap-and-trade market for carbon emissions in the US. However, both the Waxman-Markey bill as well as the international Copenhagen Summit (COP15 in December 2009) ended in failure. This reduced VCs' expectations of future policy support and therefore of future returns in clean technologies. To illustrate that, Figure 6 below shows the evolution of environmental policy in the United States using the OECD's environmental policy stringency index and Noailly, Nowzohour and van den Heuvel (2021)'s news-based Environmental Policy (EnvP) Index between 1990 and 2019.[11] We can see that after 2009, the rapid increase in both environmental policy stringency and its salience in the news stalled or even decreased.

Figure 6 : Environmental policy stringency and coverage rose after 2004



Notes: This figure displays the relationship between the Environmental Policy Stringency index of the OECD and the EnvP index constructed by Noailly *et al.* (2021) at annual frequency.

[11] The EnvP index represents the share of articles about environmental policy in ten large US newspapers, and is normalized such that its average value over the 1981-2019 period is equal to 100. More details available at https://www.financingcleantech.com/envp-index.

Methodology

To test whether changing expectations of future demand for clean energy products affect VC decisions, we implement an event study around the death of Senator Ted Kennedy in August 2009, a key vote in Obama's climate policy plans. His passing was followed by the upset victory of the Republican Scott Brown in January 2010 in a special election. Brown gave Republicans a 41st seat in the Senate, thereby robbing Democrats of a filibuster-proof majority. This meant that passing any comprehensive health or climate bill (e.g., the emissions trading Waxman-Markey Bill) became an impossible task (Davenport & Samuelsohn, 2010; Goldenberg, 2010).

Comparing VC investments in clean energy and in a control group just before and after the unexpected victory of Senator Brown allows us to isolate the effect of a change in expected demand for clean goods on VCs' decisions. Before Senator Brown's victory, investors could expect future environmental policies to prop up clean energy startups. However, after Brown's victory, these expectations had to be readjusted. The clean energy startups funded after Brown's election need to be able to survive in a policy environment that is now expected to be less supportive. Therefore, if demand plays a significant role, we expect Series A investors to become more demanding, increase their quality threshold and fund fewer clean energy startups after Brown's election. The higher quality of the firms funded after Brown's election means they should fare better than firms funded directly before, when expectations for strong climate policy allowed more marginal firms to merit funding. This leads to:

Hypothesis 3: *Because of changing expectations, (a) VCs should be less willing to fund clean energy startups after Brown's election and (b) the clean energy startups that received Series A funding in the months directly prior to Senator Brown's election should be less successful than the clean energy funded just after Senator Brown's election.*

To test Hypothesis 3.a, we look at the share of VCs' portfolio going to clean energy startups. To test Hypothesis 3.b, we implement a difference-in-differences estimation using Equation (3):

$$Success_i = \beta_0 + \beta_1 Clean\ Energy_i + \beta_2 PreBrown_i + \delta Clean\ Energy_i * PreBrown_i + \eta_{state} + \epsilon_i \quad (3)$$

Because we only consider firms that receive Series A funding at similar points in time, we are comparing firms at similar levels of development. For these startups, *Success* can be the probability of securing follow-on Series B or C funding, an exit dummy, a cash-on-cash measure or the value at exit. We compare the effect the shift in expectations had on *Clean Energy* startups and ICT startups. The latter industry is a good control group due to its many observations. Moreover, ICT startups should not be affected by changes in climate policy expectations while still controlling for changes in the broader economic outlook. We only include in our *Clean Energy* group explicitly clean energy startups rather than on our broader clean energy & EVs category to focus on the startups most affected by the tentative climate bill. Our sample includes 34 explicitly clean energy startups having secured their first Series A funding in the 9 months before and after Brown's election.[12]

We run regressions using either a 6 or 9-month window around Brown's election. The 6-month window is more targeted but has fewer observations than the 9-month window.[13] We

[12] We argue that the climate policy change would have had more impact on the startups directly involved in producing and storing clean energy and less on EVs and startups in energy efficiency or grid management startups (see Table 8). We include all startups explicitly engaged in clean energy, storage, renewable, solar or wind. We also include all startups with a "cleantech" and "energy" tag. In addition, and because we want to maximize our sample size, we manually verified the activity of 15 startups in either energy efficiency and grid management or non-energy cleantech to include those that might fit into clean energy despite the lack of an explicit tag. This allows us to include one additional firm developing a renewable and CO2 absorbing alternative to petrochemicals, as the value of the emissions-reducing benefits of this technology are minimal without carbon emission regulations.

[13] The period between the 1st and 14th of January is not included in either the *PreBrown* or post-Brown period. Polls conducted at the beginning of January were already hinting at the potential victory of Brown and thus investors' outlook might already have shifted. We choose the 14th of January as the threshold because the seven polls after the 13th of January have Brown winning by a healthy margin (3% to 15% – except the smallest poll that has them tied. The results are robust to using both the 14th or 19th (i.e., the day of the election) as the threshold.

assume that our treatment effect, δ, only captures the effect of the change in expected demand for clean technologies as ICT startups control for potential changes to the overall business outlook and are not directly affected by Brown's election during the timeframe of our experiment. Unlike the previous section, we do not include biotech firms in the regression, as the potential profitability of biotech firms may have been affected by changing expectations for the success of the Affordable Care Act, which had not yet passed the Senate and eventually was passed using reconciliation to avoid a potential filibuster.

Results

Before estimating δ, the *treatment* effect of Brown's election on startups' success, we first look at the prevalence of clean energy startups within VC portfolios in the 9 months before and after Brown's election. We find that 4.9% of the startups that received their first Series A funding during the pre-Brown period were clean energy, compared to only 3.7% in the post-Brown period. This 24.5% drop suggests that VCs did indeed reduce their investments in clean energy in the 9 months after Brown's election.

Turning to the impact of this shift in expected demand on startup quality, Table 3 implements Equation (3) for the 6-month window in Panel A and Panel B shows that the results hold using the 9-month window. In Column (1) we can see that startups that received their first Series A just before Brown's election had a significantly lower probability of securing follow-on Series B and C than those funded directly after. Columns (2) and (3) show that the clean energy startups funded just before the unexpected election of Brown has a slightly lower chance of getting an IPO, but this effect is not statistically significant. Columns (4) to (6) use more refined measures of success that better capture startups' outcome: the logarithm of the CoC and the discounted CoC, as well as whether the startup returned at least 5 times the invested capital. All these success variables show the same thing: startups funded pre-Brown were less successful than those funded post-Brown.

One important caveat with the results in Columns (4) and (5) is that they depend on exit values that are not often disclosed. Indeed, 11 out of the 35 clean energy startups funded during the 18 months of our event study managed to exit. However, we only have the actual exit value for the one startup that did an IPO and 2 out of the 10 companies that got acquired. Companies with missing amounts are not included in Columns (4) and (5). This data limitation is less of an issue for the remaining results, as they are dummy variables available for all startups, with the only assumption being that unreported exit values yield less than 5X returns on investment.

Table 3 : Difference-in-differences estimation, the effect of Brown's election

	(1) Series B/C	(2) Exit	(3) IPO	(4) CoC (ln)	(5) disc. CoC (ln)	(6) 5x returns
Panel A: 6-month window						
Clean energy	0.188	-0.344***	0.00271	-0.441***	-0.351***	-0.0703***
	(0.132)	(0.125)	(0.0530)	(0.153)	(0.126)	(0.0268)
Pre-Brown's election	0.0360	-0.0286	0.0108	0.328*	0.269*	0.0499
	(0.0556)	(0.0554)	(0.0291)	(0.185)	(0.150)	(0.0349)
Clean energy pre-Brown	-0.415**	-0.0530	-0.0762	-0.496**	-0.394**	-0.0895*
	(0.203)	(0.183)	(0.0603)	(0.238)	(0.192)	(0.0498)
Panel B: 9-month window						
Clean energy	0.120	-0.322***	0.0173	-0.312***	-0.240***	-0.00586
	(0.115)	(0.0955)	(0.0471)	(0.0939)	(0.0780)	(0.0313)
Pre-Brown's election	0.0103	0.00861	0.0314	0.281**	0.218**	0.0508*
	(0.0441)	(0.0443)	(0.0215)	(0.132)	(0.108)	(0.0263)
Clean energy pre-Brown	-0.252	0.163	-0.0914*	-0.393**	-0.319**	-0.110**
	(0.171)	(0.160)	(0.0509)	(0.174)	(0.140)	(0.0431)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations Panel A	379	379	379	235	234	353
Observations Panel B	569	569	569	350	349	518

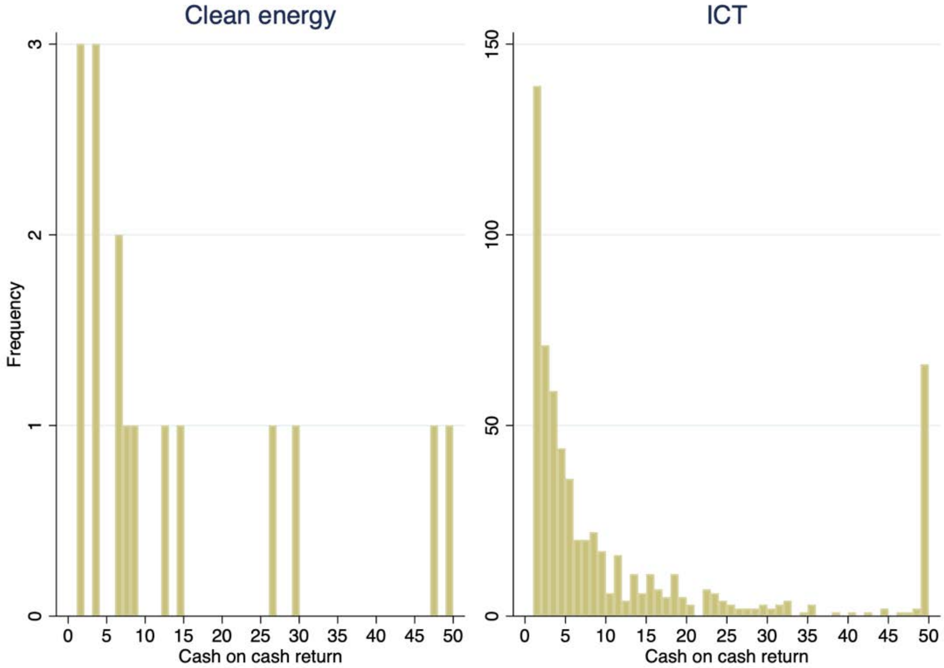
Notes: This table presents results of OLS regressions using difference in differences estimations (DiD), using Equation (2). The sample includes explicitly clean energy and ICT startups that received Series A funding during our 6- or. 9-month windows. In panel A, startups are *pre-Brown* (i.e., *Pre-Brown's election* = 1) if they received their first Series A from the 30th of June 2009 to the 1st of January 2010 and post-Brown if they received Series A from the 14th of January to the 15th of July 2010. In panel B, the pre- and post-Brown time windows are from the 31th of March 2009 to the 1st of January 2010 and from the 14th of January to the 15th of October 2010, respectively. *Clean energy pre-Brown* captures our treatment effect. In Column (1), the dependent variable is whether startup *i* secured Series B or C, in (2) whether it exited, in (3) whether it went public, in (4) the logarithm of its cash-on-cash return, in (5) the discounted value of the logarithm of its cash-on-cash return and in (6) whether it returned at least 5x to its Series A investors. The level of observation is at the firm-level. Robust standard errors are in parentheses. Asterisks denote * p<0.1, ** p<0.05, *** p<0.01.

Overall our results show that demand-side policies matter for clean technologies. We show that after a negative demand shock, VCs allocate a lower share of their portfolio to clean energy companies. In addition, we find that the startups that do get funded tend to outperform those that got funded just before the negative demand shock, when funding requirements were lower. These results are evidence that when VCs foresee lower policy support, they lower their expectations of returns and, as a result, become less willing to fund clean energy startups and increase the quality threshold they must meet. We, therefore, argue that politicians wishing to support clean energy startups must first create a policy environment in which there will be dynamic demand for their products.

C. The role of the low potential for outsized returns

On top of lackluster demand, we document another barrier to VC success in clean energy: the inability to earn high margins because of a lack of product differentiation (Nanda, *et al.*, 2015). VCs like to invest in sectors where they can expect their successful bets to yield phenomenal returns that will compensate for the risk of funding many early-stage ventures, such as ICT or biotech. These great returns stem partly from the fact that ICT and biotech startups can build moats around their product, granting them significant market power. In ICT, network effects and high switching costs mean that once a company has established its dominance, it is very difficult for competitors to challenge it (Gallaugher & Wang, 2002). In biotech, patents protect new drugs and other products. In clean energy, companies have to accept the thin margins of competitive energy markets. Additionally, renewable energy companies cannot differentiate the electricity they produce from the electricity produced using coal or gas. Overall, the lower market power of clean energy firms means that they cannot reach the profitability observed in ICT or biotech. In contrast, EVs' ability to differentiate their product – think Tesla – gives them more market power than energy producers.

Figure 7 : Returns for Series A investors in clean energy and ICT



Notes: This figure shows the cash on cash return of startups with Series A funding that returned at least 1x, by sectors. Startups that return above 50x are grouped in the 50x bin to limit the size of the x-axis

In this section, we look at the returns of Series A investors in our different industries to see whether the data supports the argument that the energy sector does not offer outsized returns. To answer this question, we look at the CoC return and exit value of startups with Series A funding. First, we find that clean energy startups are less likely to provide massive returns to their investors. Indeed, 2.1% of ICT startups and 2.6% of biotech startups that receive Series A return at least 10x to their Series A investors (i.e., have a CoC above 10). This number stands at only 1.6% for clean energy startups.[14] The difference, especially between clean energy and ICT, is even more striking when looking at outsized returns. Figure 7 shows the distribution of returns in clean energy and ICT for the startups that have at least returned the invested capital to Series A investors. We group all companies that have returned more than 50x in the

[14] We do not show the EV share as observations are rather low. According to the available data 1 out of 39 EVs returned more than 10x (2.6%), but exit values were undisclosed for 4 companies.

rightmost bin. In clean energy, the biggest success, Opower[15], returned 56x the invested capital to its Series A investors. At the same time, 36 digital and 3 biotech startups have returned more than 100x the invested capital. Based on past returns, it is fair to say that early-stage investors in clean energy cannot expect to hit the home run successes that Snowflake (704x), Uber (781x), Facebook (832x) or Roblox (4651x) have been.

Table 4 : Probability of outsized returns across sectors

	All Series A startups			
	(1) 5x returns	(2) 10x returns	(3) Exit above 1B	(4) Exit above 5B
Energy	-0.0326***	-0.0211***	-0.0196***	-0.0047***
	(0.0100)	(0.0082)	(0.0041)	(0.0011)
Energy digital	-0.0172	-0.0204*	-0.0203***	-0.0041***
	(0.0176)	(0.0105)	(0.0023)	(0.0009)
Electric vehicles	-0.0091	0.0062	0.0116	-0.0052***
	(0.0401)	(0.0402)	(0.0357)	(0.0014)
Biotech	0.0157**	-0.0046	-0.0058	-0.0032***
	(0.0077)	(0.0054)	(0.0041)	(0.0011)
Constant	0.0385	0.0110	-0.0234***	-0.0010
	(0.0248)	(0.0176)	(0.0083)	(0.0015)
Series A year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	7759	7759	8698	8698
R squared	0.026	0.016	0.017	0.005

Notes: This table presents results of OLS regressions. The sample includes clean energy & EVs, ICT and biotech startups that received Series A from January 2003 to December 2016. In Column (1), the dependent variable is whether the startup returned at least 5x the paid-in capital to its Series A investors and at least 10x in Column (2). In Column (3), the dependent variable is whether the startup exited at a valuation of at least $1B and at least $5B in Column (4). The level of observation is at the firm-level. Robust standard errors are in parentheses. Asterisks denote * p<0.1, ** p<0.05, *** p<0.01.

[15] Opower is a software company that uses AI and behavioral science to optimize its customers' energy consumption. Its ICT features and self-reinforcing use of data, which grants them market power, could explain why it has proven so much more profitable to VC investors that the typical clean energy company.

More formally, we estimate the probability that energy & EV startups will return *at least* 5x or 10x the initial Series A investment (relative to ICT startups) or that it recorded an exit value above $1B or $5B.[16] Table 4 shows that clean energy startups with Series A funding have consistently lower probabilities of being big successes than ICT.[17] The biotech firms have a slightly higher probability of being successful (returning at least 5x) than ICT but a lower probability of being a home-run success (above $5B exit).

Overall, our results suggest that lackluster demand is a key factor behind the failure of VC in clean energy since the boom of 2005-2009. As we do not observe a world in which externalities have been fully addressed, we cannot definitively state that oversized returns would not be possible in clean energy if demand was addressed. However, the inability for many clean energy firms to product differentiate makes it likely that, for at least some clean energy products, addressing demand may not be sufficient to make VC successful for clean energy. On the other hand, we do not find evidence that capital-intensity and long-time horizon are a key factor behind the disappointing performance of VC in clean energy.

II. In this context, what is the role of governments?

Our results suggest that a reliable way through which governments could support early-stage investments and innovation in clean energy technologies would be to stimulate demand to increase startups' profitability. A carbon tax or cap-and-trade system would create higher demand for clean energy & EVs and make startups in these sectors a more attractive acquisition target. Both would increase VCs' willingness to invest in early-stage clean energy & EVs startups. However, while there is a consensus among economists that governments should use

[16] These exit values are relatively rare. Only 28.2% and 6.5% of companies that IPO reach a valuation of $1B and $5B respectively. For acquisitions, which represent two thirds of exit events, these numbers stand at 10.1% and 0.9% respectively. Overall, 35.4% of companies that exit return at least 5x and 21.4% return at least 10x.

[17] We do not discuss the EV results are they are based on only three startups with at least 5x.

market-based instruments to internalize environmental externalities and incentivize investments in clean technologies, actually implementing them is an arduous political task.

In an ideal world, governments would therefore support private investments by stimulating demand. Until this happens, investing in early-stage clean energy will prove challenging. Nevertheless, there is still a great need for more investments in early-stage clean energy startups and providing public funding is easier politically than implementing demand-side policies such as a cap-and-trade system. We, therefore, argue that it is worth looking into the role and performances of public investors.

The role and performance of public investors

Public investors should not be seen as a substitute to VC and its unmatched financial capabilities. According to the National Venture Capital Association, investors poured $156.2B into US startups in 2020. Instead, public investors should be seen as a complement to VC. Tellingly, the success of public programs is often measured by whether recipients of early public awards are able to attract subsequent VC funding (Howell, 2017).

As a complement to VC, public investors can provide funding either before or after Series A rounds. These public investments are designed to help firms cross two main valleys of death, i.e., periods during which they might fail to secure the funding necessary to their survival. The first valley of death is a *technological valley of death* that occurs between the development of the basic concept and the conception of a viable prototype (Hudson & Khazragui, 2013). Later on, startups can enter a second *commercialization* valley of death if, after having proven that their technology is viable at the prototype-phase, they still need to raise capital to show that their product is viable on a commercial scale. The financing required to commercialize is often too high for early-stage VCs and traditional lenders in the private sector are reluctant to fund technologies that have not been proven at scale (Frank, Sink, Mynatt, Rogers, & Rappazzo, 1996).

Table 5 shows that the amount offered varies greatly depending on the timing of the public involvement. Indeed, while public investors give $0.72M on average to clean energy startups pre-Series A, they provide $15.4M post-Series A, a more than twentyfold increase. These numbers highlight that public investors play a very different role in the early and late stages of a startup's lifecycle. Early-stage funding is designed to help clean energy startups prove the potential of their technology and attract VC money, thus bridging the early technological valley of death. The much more generous later-stage funding can help VC-funded energy startups scale up and survive the commercialization valley of death.

Table 5 : Average size of public investments pre- and post-Series A[18]

Clean energy	in 2020 million USD	Pre-Series A Public Amount	Series A Amount	Post-Series A Public Amount
n = 23	Public before Series A	0.72	6.1	N/A
n = 32	Series A before Public	N/A	10.4	15.4
Digital clean energy	**in 2020 million USD**	**Pre-Series A Public Amount**	**Series A Amount**	**Post-Series A Public Amount**
n = 11	Public before Series A	0.7	4.6	N/A
n = 11	Series A before Public	N/A	5.2	12

Notes: This table displays the average size of public and Series A investments for startups that received public money before their first Series A round and vice versa, by clean energy category. Two outliers that had an outsized impact on the average were removed. A green infrastructure investment firm that received $1B from a public pension fund after its Series A and a firm that received $100M in a pre-Series A public investment.

In this section, we test the effectiveness of both early and late-stage public investments in helping their recipient bridge their relevant valley of death. To do so, we compare the performances of clean energy startups that receive public funding to those that receive similar, but private, funding.

[18] We removed two outliers that had an outsized impact on the average: A green infrastructure investment firm that received $1B from a public pension fund after its Series A and a firm that received $100M in a pre-Series A public investment.

Early-stage public involvement as a way to bridge the first, technological valley of death

While early-public money is limited in size, as shown in Table 5, it can nonetheless prove helpful. Cheap, early-stage public investments can indeed signal value to private investors and provide the resources necessary to prove the viability of their technology to Series A investors. To test that, we estimate whether receiving early-stage public money in the first two years following the startup's launch is associated with better outcomes both in the short (i.e., securing Series A) and the long run (i.e., exit outcomes). However, we need to control for the fact that receiving early money is already a sign of startup quality. We therefore include receiving private seed funding, the first official equity funding stage, in our regression. We argue that seed funding is a good benchmark for early public money. First, the amounts provided are very similar. The average size of an early public funding (within two years of launch) for a clean energy company is \$1.3M versus \$1.41M for early seed money.[19] Second, like early-stage public support, seed funding typically represents the first official outside capital that a startup raises and also helps startups attract Series A investors.

Table 6 looks at clean energy & EVs as a whole. *Early public money* and *Early seed* money are equal to 1 if a startup received either source of funding during its first two years of existence. In Column (1), we see that both early public money and early seed are associated with a higher chance of securing VC funding. The effect of public money is slightly bigger; early public money is associated with an increase of 21.4 percentage point in the probability of securing Series A versus 11.4 percentage points for early seed. However, Columns (2), (3) and (4) show that, compared to other firms that received Series A, having also received early public or seed money is not correlated with additional late-stage success. Our results suggest that early public money is helpful to bridge the first technological valley of death and secure Series A,

[19] Note that this number slightly differs from the numbers in Table 5 because the sample is not identical ("within two years of launch" versus "before series A"). Additionally, one clean energy firm received \$60M in public money within its first two years and is removed from the average as the 77 other clean energy firms only received a bit more than \$100M collectively.

maybe even more so than seed funding. However, we see that once they secure Series A, the early public involvement has no bearing on late-stage success. In other words, it does not help clean energy startups bridge the second, commercialization, valley of death. However, this is not the aim of early-public money, unlike later-stage public support.

Table 6 : Relationship between early public money and subsequent success

	Funding	Success conditional on Series A		
	(1) Series A	(2) Exit	(3) IPO	(4) Acquired
Early public money	0.2125*** (0.0503)	-0.0201 (0.0699)	0.0109 (0.0348)	-0.0369 (0.0609)
Early seed money	0.1063*** (0.0239)	0.0119 (0.0433)	-0.0202* (0.0107)	0.0296 (0.0429)
Constant	0.2904 (0.2755)	0.2801* (0.1443)	0.1355 (0.1101)	0.1959 (0.1244)
Launch year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	4160	510	510	510
R squared	0.071	0.189	0.086	0.185

Notes: This table presents results of OLS regressions. In Column (1), the sample includes clean energy & EVs that launched from January 2003 to December 2016 and the dependent variable is whether the startup received Series A. In Columns (2), (3) and (4) the sample only includes startups that received Series A funding and the dependent variables are whether the startups exited, got acquired or went public. *Early public money* and *Early seed money* are equal to 1 if startup *i* received either source of funding in the first two years after its launch. The level of observation is at the firm-level. Robust standard errors are in parentheses. Asterisks denote * p<0.1, ** p<0.05, *** p<0.01.

Late-stage public involvement as a way to bridge the second, commercialization valley of death

Therefore, we now turn to look at the performance of public actors when supporting post-Series A clean energy startups trying to scale up their business. In particular, we are interested in estimating how public investors compare to private investors. This is important since, as shown in Table 5, public investors provide sizeable amounts to clean energy startups after they secure a Series A round.

As always, estimating the effect of public funding is difficult given the lack of a counterfactual. At its most effective, the public funding goes to clean energy startups that would not have secured late-stage private funding otherwise. In Table 7, Columns (1), (2) and (3) show that companies that receive series A and then public money have a significantly higher probability of exit than those that receive Series A and then nothing. The results suggest that, at best, if private funding is unavailable, public money can help. At its least effective, public funding goes to startups would have been funded by VCs anyway. Columns (4), (5) and (6) show that companies that receive public money after Series A have similar exit probabilities than those that receive VC funding after Series A. At worst, public funding does no better but also no worse than receiving late-stage venture capital money. Overall, companies that receive private and public support fare at least as well as those that only rely on private investors.

Table 7 : The impact of late-stage funding on exit probabilities

	Upper bound effect			Lower bound effect		
	(1)	(2)	(3)	(4)	(5)	(6)
	Exit	IPO	Acquired	Exit	IPO	Acquired
Post-Series A: Public vs Nothing	0.1863*	0.0880*	0.1228			
	(0.1079)	(0.0507)	(0.1022)			
Post-Series A: Public vs VC				-0.0334	0.0731	-0.0861
				(0.0924)	(0.0557)	(0.0921)
Constant	0.1466	0.2281	-0.0937	1.3282***	0.0829	1.1803***
	(0.3446)	(0.2380)	(0.2818)	(0.2893)	(0.1683)	(0.2900)
Launch year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	149	149	149	202	202	202
R squared	0.277	0.277	0.238	0.142	0.208	0.145

Notes: This table presents results of OLS regressions. In Columns (1), (2) and (3), we compare the exit performances of clean energy & EVs startups that received Series A and then no more funding to the exit performances of clean energy & EVs startups that received Series A and then public funding. In Columns (4), (5) and (6), we compare the exit performances of clean energy & EVs startups that received Series A and then VC funding to the exit performances of clean energy & EVs startups that received Series A and then public funding. The sample includes startups that received Series A from January 2003 to December 2016. The level of observation is at the firm-level. Robust standard errors are in parentheses. Asterisks denote * p<0.1, ** p<0.05, *** p<0.01.

However, these results must be viewed in context with the results from the previous section, which showed that venture capital investments in clean energy did much worse than in other sectors. Public funding cannot address alone the overall poor performance of investors in clean energy. As such, public investments are unlikely to bridge the commercialization valley of death for clean energy startups by themselves. However, if policies are put in place to address demand-side problems for clean energy, it seems likely that public sector money will have some role to play. The lower bound estimates above assume that none of the late public sector investments are additional – all of these companies would eventually have received private late round VC funding. But even if demand-side issues are solved, many clean energy firms will still have difficulty differentiating their products in a way that makes the outsized returns demanded by VC investors possible. Thus, it is likely the case that a role for public investment will remain.

5. Conclusion

Using data from 150,000 companies launched in the US between 2000 and 2020, we evaluate the performance of venture capital investments in clean energy. Most importantly, our results show that demand matters. VC investors adjust their behavior in response to changes in expected future demand. The downward path of policy support can therefore explain, at least in part, the post-2009 trajectory of VC in cleantech. The lowered expectation of future policy support, because it reduced VC's willingness to fund clean energy ventures, contributed to the end of the cleantech boom.

We also highlight a second reason for the failure of cleantech VC. Clean energy startups are significantly less likely to become home run successes than ICT ventures. The lack of network effects, the lesser reliance on patents and lower product differentiation make it harder to keep competitors at bay and earn high margins in clean energy. This prevents the formation of winner takes all markets, which makes betting on ICT startups so attractive. While stimulating demand will increase average returns, it will not alter clean energy's market structure. Thus, venture capital is not a one-sized-fits-all solution. Even after demand-side issues are solved, clean energy products are more likely to be attractive to VC investors in cases where product differentiation is possible. A good example is Nest, a smart thermostat that optimizes energy consumption. Nest Labs managed to differentiate its product and attain high levels of brand recognition, and, as a result, got acquired by Google for $3.2B in 2014.

Finally, while the capital intensity and the long development timeframe of energy startups are often cited as barriers to raising funds for energy firms, we argue that they are not the main factor behind the failure of VCs in clean energy. Indeed, after having fared better in the early stages of the cleantech bust, non-capital-intensive digital energy startups eventually also experienced a fall in their profitability and in their ability to secure VC funding. At the same time, biotech and EVs, another cleantech sector, have been able to attract investors in recent years despite being capital-intensive. Moreover, if these startups characteristics were indeed to blame for the limited funding going to clean energy, the few, high-quality, startups that do get funded should yield high returns. However, this is not what we find: there is no evidence that VC investors in clean energy are "leaving money on the table".

In this context, direct financial support to clean energy startups is unlikely to have a major impact since liquidity constraints do not seem to be the main reason behind the lack of success of clean energy investments. While implementing demand-side policies to support clean energy investments and innovation would have a greater impact, political support for such policies is harder to come by. However, Democrats failed to pass a comprehensive climate bill in 2009-2010 when they controlled both Congress and the Presidency. This failure highlights the political difficulties in implementing climate policies. On the other hand, providing financial support to startups remains a popular policy tool. We show that public money can complement VC money in two ways. In the early stage, public investors provide small grants that help startups bridge the technological valley of death and secure Series A funding. In later stages, public investors provide much larger amounts that help energy startups expand and scale their business but does not fully address the commercialization valley of death. More importantly, we show that, as a complement to VC, public investors have not fared worse than their private-sector counterparts. Our results are in line with previous findings that public support is either helpful (Howell, 2017) or, to the very least, not worse than other sources (Goldstein et al., 2020). However, this is setting a low bar given the poor performance of VCs in clean energy. Without a positive demand shock, neither public nor private investors are likely to be consistently successful when funding clean energy startups. Only by creating the conditions for robust demand for green products will governments be able to address the valley of death. After addressing demand issues, public sector funding for startups will be most successful if it targets firms developing products where product differentiation, and thus outsized returns, is most difficult.

The role of demand in the second cleantech boom

The importance of strong demand can help us understand the second boom in cleantech VC and provide insights as to which investments are more likely to succeed. First, government policies are becoming more supportive than they were in 2009. In November 2021, President Biden signed the Infrastructure Investment and Jobs Act that contains more than $70M in support of clean energy and better electrification of the United States. This first bill might be followed by a second, larger, spending plan to fight climate change. Regardless of the outcome of this second bill, government support is strengthening. For instance, Biden signed an executive order declaring that half of the new cars sold in 2030 should be EVs. Finally, the COP26 in Glasgow saw the United States and many other countries committing to a netzero emissions economy by no later than 2050. This more supportive policy environment is boosting demand for all clean technologies.

However, VC investments in clean energy are likely to continue lagging behind other cleantech sectors like EVs (see Figure 1). Indeed, VCs have learned to focus on cleantech sectors with already high demand, notably these sectors in which using the "clean" technology requires little sacrifice (The Economist, 2021). Some sectors like EVs or sustainable food (e.g., plant-based meat) have few barriers to mass adoption, helping fueling demand. By contrast, regardless of its low cost, renewable energy is dependent on other energy sources because of its intermittency. As long as electricity cannot be stored on a massive scale or easily traded across regions, demand for clean energy will suffer. Finally, sectors like EVs and sustainable food can differentiate their products, which improves their profitability. The ability of firms like Tesla to manage their brand and bolster demand for their particular EVs allows them to generate markups unattainable in the more competitive renewable energy industry. These attractive features have translated into several recent home run successes in cleantech. Tesla returned 20x the invested capital during its IPO in 2010, but its valuation has since increased by 647x to a market value of around $1.1T.[20] This has whetted the appetite for investment in the area. Nikola Motor Company, a producer of electric trucks, returned 125x the paid-in capital to its Series A investors when it went public in 2020. A similar pattern has been visible in sustainable food. Impossible Foods, a maker of plant-based meats is now valued at $7B and should go public in 2022, returning 82x to its early-stage investors. These companies have proven that some cleantech sectors are able to produce outsized returns, fueling this new cleantech boom.

Examples like these show that investors are increasingly able to identify cleantech firms for which venture capital can succeed. Thanks to a policy environment expected to become

[20] All amounts are in 2020 US dollars and were obtained in November 2021.

increasingly supportive in the future and a focus on sectors with both relatively higher demand and brand loyalty, the second boom in VC may result in better outcomes than its predecessor. However, the smaller overall size of the second boom is indicative that clean energy startups are likely to continue suffering from a funding gap. Their lack of product differentiation and the absence of carbon pricing will continue to make them relatively unattractive to profit-driven investors. As many technological challenges remain to meet increasingly ambitious emission reduction targets, governments could do more to spur innovation in clean energy to help meet these goals. Rather than investing themselves in startups bound to struggle through the valleys of death, governments wishing to support clean energy startups can first implement demand-side policies that make investing in clean energy more viable. Only then will financing new firms be likely to succeed. The largest impact is likely to come from financing firms in cleantech markets where product differentiation is difficult, as such firms are least likely to attract private sector support.

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Appendix

Appendix A: Additional information on data collection and results

A.1: Sector classification

Table A.1: Firm classifications and descriptions

Firm classification	Crunchbase industry categories	Observations
All energy		6395
Renewables	Clean Energy, Renewable Energy, Storage, Solar, Wind	3112
Fossil fuel	Fossil Fuels, Fuel Cell, Oil and Gas, Fuel	1577
Grid Management	Electricity Distribution, Energy Management, Power Grid	795
Energy Efficiency	Energy Efficiency	569
Other Energy	All other energy types, including biomass and biofuel	1155
Electric Vehicles	Electric Vehicle	270
ICT	Apps, AI, Data, IT, Internet, Telecom, Mobile, Platforms, Software, E-Commerce, Online Auctions	138544
Biotech	Bioinformatics, Biometrics, Biopharma, Biotechnology, Genetics, Life Science, Neuroscience, Quantified Self	9582
Category	Description	Observations
Clean energy & EVs	Clean energy + Electric vehicles	5222
Clean energy	All energy excluding fossil fuel companies	4952
Non-digital clean energy	Clean energy that is not also ICT	*3829*
Digital clean energy	Clean energy also ICT	*1123*
Electric vehicles	All EV	*270*
ICT	ICT but not cleantech or biotech	134810
Biotech	Biotech but not cleantech	9326
Total		149358

Notes: This table's top panel display all the industries of interest to our study, with the constituting sub-categories. The bottom panel defines the exact, mutually exclusive, industry categories that we use in our analysis.

A.2: Building granular measures of success

According to Gompers *et al.* (2020), most VCs use the ratio of return over invested capital to analyze their investments, rather than more complex measures that discount future returns (e.g., IRR or NPV). We, therefore, develop the following cash-on-cash (CoC) multiple metric to analyze and compare the performances of VC across sectors:

$$CoC_i = \frac{Value\ at\ exit_i * VC\ stake}{Series\ A\ amount_i}$$

Value at exit is either the valuation at IPO or the acquisition price.[21] If startup *i* does not exit, its value at exit is set to 0. The *Series A amount* corresponds to the total value of the Series A rounds raised by startup *i*. Finally, the *stake* corresponds to the ownership stake that Series A investors have in the startup *i.* Unfortunately, ownership stakes can vary substantially and are typically not disclosed. Therefore, in line with Gaddy *et al.* (2017), we assume that VCs stake in Series A is 12%.[22]

Finally, both our CoC and exit value variables suffer from the fact that exit amounts are only disclosed for 26% of the acquisitions and 68% of the IPOs of startups with Series A. To circumvent this data availability problem while keeping some of the granularity in returns, we create four binary variables that indicate whether startup *i* yielded at least a 5x returns, 10x returns, an exit above $1 billion or above $5 billion. We then assume that if the exit amount is not disclosed, the startup did not yield at least a 5x return or an exit above $1 billion. We can make this assumption because undisclosed exits are often a sign that an investment did not return capital to its investors (Gaddy et al., 2017).

A.3: Still active firms

While identifying the successful investments is relatively straightforward, we also need to identify the failed investments, which are harder to determine with complete certainty. Indeed, 11% of clean energy, EVs, digital and biotech companies have either been acquired or gone public but not all of the remaining companies are failures. Only a minority (5%) have been officially "closed" and the rest (84%) are still categorized as operating. It can be challenging

[21] If both events happen, we use the IPO value as it is the event that occurs first in 88% of cases, and is therefore when investors will cash in their returns.
[22] While the CoC is a valuable metric that allows us to compare investments on an equal footing (i.e., a startup that require more capital in Series A will need a higher value at exit to compensate), it also has some drawbacks. The first is that we need to make an assumption about the ownership stake. The second is that we do not have the amount for 14% of the Series A rounds. To address these, we also look at the exit value (i.e., IPO valuation or acquisition price) by themselves, a simpler but more widely available metric.

to determine whether operating companies will end up as successes or failures. Some of them may be growing, raising new funding and will eventually exit. Others will continue operating without any prospect of exit, becoming so-called “living dead” companies (Ruhnka, Feldman, & Dean, 1992). These living-dead companies can be considered failures, as VCs’ objective is for their startups to produce a large exit within 5-7 years of the initial investment (Metrick & Yasuda, 2021). To separate these “living dead” from the active companies that are still growing, we use the fact that, in our dataset, around 75% of acquisitions and 85% of IPOs occur within three years of their previous funding round. We therefore assume that a period of inactivity of at least three years is a sign of being “living dead”. Based on that, we classify operating startups into two groups. Firms that were launched or funded in the three years before the 1st of May 2021 (i.e., the first day of the month when data was collected) but have not yet exited are categorized as “still active”. They are excluded from any analysis looking at exit and the associated returns (i.e., when the dependent variable is an exit dummy, our CoC metric or the exit value) as we do not know what their eventual outcome will be (i.e., exit or failure). The companies launched prior to May 1, 2018 and that have not been funded in the three years before the 1st of May 2021 are categorized as failures (i.e., they have not exited) because even though they might technically still operate, they will most likely not return any capital to their investors. In the end, in our sample of 149,358 companies, 10.8% have exited, 14.6% are still active and 74.6% are failures.

Table A2: The relationship between Series A funding and eventual success

	General (2003 to 2016)			2003-2009	2010-2016
	(1) Exit	(2) Acquired	(3) IPO	(4) Exit	(5) Exit
Received Series A (β_1)	0.3925***	0.3719***	0.0290***	0.4241***	0.3632***
	(0.0067)	(0.0067)	(0.0024)	(0.0096)	(0.0093)
Series A X industry (β_2)					
Series A x Energy	-0.2864***	-0.2636***	-0.0359**	-0.3125***	-0.3363***
	(0.0305)	(0.0289)	(0.0151)	(0.0368)	(0.0522)
Series A x Energy digital	-0.0727	-0.0339	-0.0242	0.0130	-0.2425***
	(0.0548)	(0.0548)	(0.0176)	(0.0712)	(0.0741)
Series A x EVs	-0.1288	-0.1633	0.0165	-0.1786	-0.1302
	(0.1258)	(0.1210)	(0.0813)	(0.1574)	(0.2281)
Series A x Biotech	-0.1156***	-0.2291***	0.1408***	-0.2138***	-0.0047
	(0.0173)	(0.0159)	(0.0136)	(0.0235)	(0.0259)
Industry fixed effects (γ)					
Energy	0.0549***	0.0164***	0.0498***	0.0799***	0.0312***
	(0.0071)	(0.0062)	(0.0045)	(0.0112)	(0.0087)
Energy digital	0.0206*	0.0078	0.0120**	0.0354*	0.0098
	(0.0121)	(0.0112)	(0.0048)	(0.0213)	(0.0140)
Electric vehicles	0.0902**	0.0318	0.0668***	0.1375**	0.0639
	(0.0354)	(0.0297)	(0.0239)	(0.0671)	(0.0401)
Biotech	0.1073***	0.0481***	0.0679***	0.1336***	0.0862***
	(0.0061)	(0.0053)	(0.0039)	(0.0098)	(0.0076)
Constant	0.0367***	0.0310***	0.0081***	0.0378***	0.0783
	(0.0068)	(0.0066)	(0.0026)	(0.0068)	(0.0497)
Launch year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	104801	104801	104801	39869	64932
R squared	0.112	0.094	0.073	0.118	0.093

Notes: This table presents results of OLS regressions. The sample includes clean energy & EVs, ICT and biotech startups launched from January 2003 to December 2016. The dependent variable is whether the startup exited in Columns (1), (4), and (5). In Column (2), the dependent variable is whether the startup got acquired and in Column (3) whether it went public. The level of observation is at the firm-level. Robust standard errors are in parentheses. Asterisks denote * p<0.1, ** p<0.05, *** p<0.01.