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# Climate tech 2.0: social efficiency versus private returns

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# Climate tech 2.0: social efficiency versus private returns*

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**Abstract**

Billions of dollars in private and public capital have poured into climate tech in the United States since 2005. This raises questions around the social efficiency and financial performance of these investments. We find that, since 2015, more private capital is allocated to technologies with a higher emission reduction potential and that investors have prioritised more mature technologies. Moreover, more private capital is directed to innovative companies as the sector matures and grows and financial frictions abate. Higher allocative efficiency of investments, defined as the capacity of financial markets to direct more funds to "high growth" sectors, is in turn associated with better financial performance, both at the company level and at the investor level. US government subsidies have been allocated more to technologies attracting less private capital. Their crowding-in effect is greater when allocated to nascent technologies that are not yet patented.

**JEL Classification**: G11, G14, G24, Q54.

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# 1 Introduction

Curbing the emission of greenhouse gases (GHGs) is key to a sustainable economic growth, robust ecosystems and biodiversity. Yet changes in consumption behaviours and preferences alone will not suffice to reach the long-term goal of keeping the rise in global average temperatures below $2^o$ C relative to pre-industrial levels, as prescribed in the 2015 Paris Agreement. Indeed, Bouckaert et al. (2021) attribute less than 5% of $CO_2$ emission reduction by 2050 to behaviour change, against 55% to technologies already in the market and the remainder to technologies currently under development.[1] Massive investments are needed to support the development and commercialisation of new 'green' or energy-efficient technologies.

During 2005–11, a period sometimes dubbed 'climate tech 1.0', technological solutions to enable this transformation, mostly through solar and wind technologies, attracted investors' interest. The sector then abruptly fell out of favour as key investors started to record huge losses: of the USD 25 bn invested by venture capitalists, only USD 15 bn was recovered by 2014 (Gaddy et al. (2017)). While climate tech 1.0 included some big successes, like Tesla, positive returns were concentrated among a few investors, with the vast majority recording losses.

The collapse in climate tech 1.0 was partly due to the Great Financial Crisis and Great Recession in 2008. Yet when recovery came, it did not immediately include the climate tech sector. The delayed recovery was attributed particularly to poor investments by dominant generalist funds who then withdrew and shunned the sector in the years after. Short-horizon investors lost appetite for a sector viewed as being too capital-intensive and requiring long payback periods, often running into decades. Lacklustre demand due to falling fossil fuel prices and a lower potential for outsized returns meant that investors' attention was diverted toward other sectors (van den Heuvel and Popp (2022)).

[1] Other studies similarly estimate a modest contribution of changes in consumer behaviour. See eg Moran et al. (2020) and Matasci et al. (2021).

This bleak picture of climate tech 1.0 painted by earlier research can be nuanced if one accounts for its positive externalities. Climate tech 1.0 was an important step forward, laying the groundwork for future innovation. Indeed, from climate tech 1.0, the sector learned lessons and gained experience. Society gained technological advancements that have led to important reductions in the cost of solar and wind energies. These initiated the development of a wider range of effective solutions both to reduce $CO_2$ emissions and adapt to the consequences of climate change.

In the last years, climate tech is back in investors' sights. The renewed interest in green technologies, dubbed 'climate tech 2.0', has been characterised by huge investment inflows, with a peak of USD 22 bn in the 3rd quarter of 2021. This far exceeds previous waves. Several firms have successfully raised first-time and follow-on funds, representing 11% of US global annual venture capital (VC) funding in 2021. The growth rate of capital invested between 2015 and 2021 reached over 150%. These massive inflows into the sector raise questions about the social efficiency and economic performance of these new investments. This is particularly relevant in light of the Inflation Reduction Act of 2022, which channels over USD 400 billion in subsidies and tax breaks to clean energy, electric vehicles and other areas over the next decade.

This paper addresses three questions. The first concerns the social efficiency of climate tech investing: does the market channel capital toward (mature) technologies that have a higher potential to reduce $CO_2$ emissions in the short to medium run? Second, at the company level, is capital geared toward companies that develop new technologies? And third, what is the performance of investments geared toward innovative climate tech companies? When answering the first two questions, we also touch upon the problem of the alignment of public and private goals in this context. On the one hand, as capital expands more, it may be allocated to less impactful technologies and the composition of companies may worsen. On the other hand, as investors face less binding capital constraints during boom times, they may be more willing to back new and more innovative companies. This could include technologies with a greater environmental impact, that is, true technological breakthroughs. Further, as the sector grows and matures, and more information becomes available about the quality of new investment opportunities, information asymmetries and misallocation could decline, hence improving the allocative efficiency of capital.

We use detailed deal-level data covering the US market to shed light on these issues. Our data cover all private deals by climate tech companies from the first quarter of 2005 to the last quarter of 2021. Importantly, our dataset covers both funding deals and exit deals. It identifies the sources of the capital raised, distinguishing between venture capital (VC) funds, corporate VC and individual investors (angels), private equity (PE), debt and government subsidies. In addition, we have detailed data on the characteristics of the companies and institutional investors (VC funds in particular).

VC investors dominate the market for climate tech funding. Previous research finds that they pursue a value-maximising investment strategy, allocating capital to companies that innovate, have patented intellectual property (IP) and are hence expected to grow more in an emerging sector (Akcigit et al. (2022)). There is evidence that VCs choose companies that already have good growth opportunities, and whose innovation strategies are already well developed (Sørensen (2007), and Bottazzi and Da Rin (2002)). By contrast, long-horizon investors, including corporate and angel investors, take more risk; their strategy is to target companies at a very early stage with no previous track record and no patented IP. Meanwhile, the objective of governments should be to target companies that are rationed by private investors due to various financial frictions, including information asymmetry, asset intangibility and contract incompleteness. Indeed, there is empirical evidence that the benefits of government subsidies are maximised when targeted to young innovative companies in emerging sectors (Howell (2017)). Hence, ideally, the different sources of capital should complement each other.

Allocative efficiency is the optimal distribution of resources, ensuring climate tech investments are directed towards the most impactful and sustainable environmental solutions. We develop an empirical approach to estimate the efficiency of capital allocation at a quarterly frequency. As in Wurgler (2000), we infer allocative efficiency by directly observing investment flows across companies. Specifically to our study, we take this as a measure of the ability of the financial market to direct more funds to subsegments that use or develop technologies with high emission reduction potential (ERP) and to more innovative companies within those subsegments. We focus on this measure, as previous research established a link between financial development and economic growth through improved allocative efficiency (Beck et al. (2000)). Our main finding is that private investors channel more capital toward mature technologies with a high ERP. These technologies have been served first. By contrast, dollar amounts invested by the US government are channeled towards low-ERP nascent sectors that receive less private capital. While taken individually these sectors have a low ERP score, together their impact is potentially significant. We also show that, as the government supports these sectors and as the market expands, they attract more private capital.

At the company level, private investors target innovative companies with already patented intellectual property. They do this to a greater extent since 2015 than they did during the previous cycle. Moreover, this allocation strategy translates into higher returns. Further, we find that government subsidies are now more targeted towards patented technologies, but their crowding-in effect is stronger for recipient companies with no patents. To interpret our findings, we draw on a detailed account of climate tech investing over time. With this, we uncover important changes in the population of companies that tap the market, and in the investor base. We trace the improvement in the allocative efficiency of private capital in part to an increase in the proportion of mature companies over time. Further factors are a shift toward less capital-intensive software solutions, an increase in the participation of better informed investors, and the presence of a more comprehensive regulatory framework since the Paris Agreement.

The rest of this paper is organised as follows. Section 2 presents the data. Section 3 describes the key historical trends in capital investing in the climate tech sector. Section 4 develops our methodology and interprets the results. Section 5 discusses the financial performance of climate tech investing. Section 6 draws the policy implications of our results.

## 2 Data sources and sample construction

Climate tech can be defined as technology-enabled solutions that mitigate the drivers and impact of GHG emissions. The universe of climate tech companies encompasses a wide range of sectors including renewable energy, food and agriculture, land use, carbon capture, energy storage, energy optimisation, smart grid, waste and wastewater treatment, renewable power manufacturing, climate/earth data, advanced materials and transport. The climate tech 2.0 boom, which spans Q4 2014 to 2021, covers a broader range of technologies than climate tech 1.0 boom, which covered 2005–11. Climate tech 2.0 addresses the full range of sources of GHG emissions (rather than just energy) and has a larger role for software solutions, alongside hardware solutions.

We use US company, deal and fund-level data from PitchBook Data Inc.[2] We group companies into homogenous segments and subsegments according to the technologies they use or develop and the type of activities they perform based on their detailed description (see Table A1 in the online appendix). For each subsegment, we calculate and report in Table A1 the average emission reduction potential (ERP) and the average technology readiness level (TRL) across technologies used or developed by companies. ERP data by technology are from Project Drawdown.[3] TRL data are from the International Energy Agency (IEA) and ENTSOE.[4]

[2]For recent work using PitchBook data on investment deals in fintech, see Cornelli et al. (2024, 2021)

[3]See https://drawdown.org. For digital technologies we also use estimates by the World Economic Forum available at https://www.weforum.org/agenda/2022/05/how-digital-solutions-can-reduce-global-emissions/

[4]See https://www.iea.org/data-and-statistics/data-tools/etp-clean-energy-technology-guide, and https://www.entsoe.eu/news/2021/03/23/ensto-e-technology-factsheets-take-a-tour-of-power-

At the deal level, we observe the dollar amount, the deal stage or purpose (eg for exit deals via initial public offerings (IPOs), mergers and acquisitions (M&As) or bankruptcy), the institutional source of the deal (VC, corporate, individuals (angels), PE, debt and government), the number of investors and pre and post-deal valuations. We observe the deal amount for 12,309 of the 15,800 deals with an industry vertical "cleantech" or "climate tech".[5] Because climate tech 2.0 encompasses a wider range of sectors than climate tech 1.0, only about 15% of climate tech 2.0 investments are follow-on deals. We use real 2021 amounts calculated using the consumer price index (CPI) from the Federal Reserve Bank of St. Louis.[6] Pre and post-deal valuations are observed for only 30% of the deals. The data cover the period Q1 2005 to Q4 2021.

From the company-level database we observe various characteristics: the year the company was founded, the number of employees, the number of active patents at the time of a deal, the number of forward citations and the state of incorporation. We lose 2,200 observations due to missing observations for company age or number of employees. We also observe chief executive officer (CEO) characteristics including CEO gender, education level and experience (as proxied by years since graduation), but the latter two characteristics are sparsely populated. We calculate an indicator of cite-weighted patents which we use to measure company innovation or more broadly the quality of a company.

From the funds database we observe measures of investor fund performance, including the internal rate of return (IRR) and total value to paid-in capital (TVPI) ratio. Moreover, we observe the US state in which a fund is incorporated, the fund type, the amount of assets under management, the vintage, the sequence number of the fund and the proportion of climate tech investments in the fund's portfolio.

We classify as "specialists" any fund that is specialised in a particular stage or sector

transmission-technology-developments/

[5] A "vertical" refers to a group of companies. According to PitchBook, "verticals are designed to slice across industries such that a single vertical may be comprised of companies that span multiple industries. A company is tagged to as many relevant verticals as possible and each vertical is given equal weight."

[6] https://fred.stlouisfed.org/series/CPIAUCSL

or the intersection of the two and create four categories: VC generalist, VC specialist, non-VC generalist and non-VC specialist. VC specialist funds include VC early-stage, VC late-stage and VC debt funds. Non-VC funds include mostly PE funds (including buyout funds) but also real assets funds, funds of funds and co-investment funds. In total our sample covers 2,569 funds, but the IRR is observed for only 700 of these. VC funds represent about 65% of the sample.

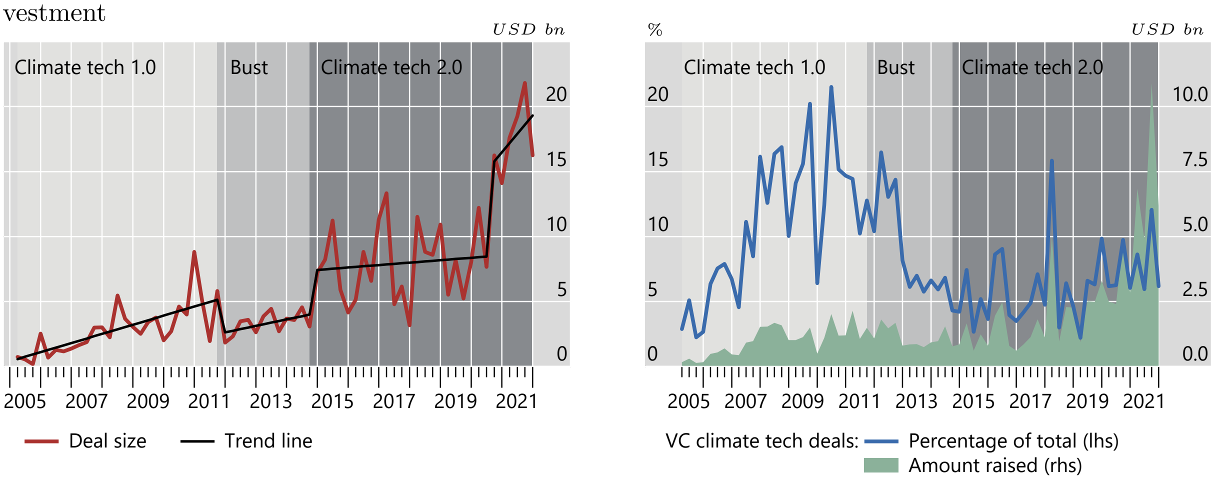
## 3 Background: a tale of two booms

A descriptive analysis of the data reveals several important stylised facts on the evolution of climate tech investing, and the distribution of funding across subsegments and companies. First, since 2005 climate tech has seen three distinct phases (Figure 1, left-hand panel). These are: a boom from Q1 2005 to Q3 2011, which we refer to as climate tech 1.0; a bust that lasted from Q4 2011 to Q3 2014 (also called the "climate tech winter"); and a recent boom, which we refer to as climate tech 2.0, starting in Q4 2014 and with a visible acceleration during the COVID-19 pandemic. VC funding accounts for about 10% of the funding allocated to climate tech companies over the full period of analysis. Interestingly, it corresponds to a lower share of the total VC market since 2015 (right-hand panel).

Figure 1: **Capital raised by climate tech companies**

(a) The three distinct phases of climate tech investment

(b) VCs represent much of the funding




Note: In the left-hand panel, the red line corresponds to the total capital raised by climate tech companies in each quarter in USD billions. The black line corresponds to trend lines corresponding to three phases: climate tech 1.0, the bust, climate tech 2.0, and climate tech 2.0 post-Covid. All stages and sources of capital are included: venture capital, private equity, corporate, individuals (angels), debt, and government. In the right-hand panel, the blue line and the green area do not include corporate VCs because these are long term investors. Sources: PitchBook Data Inc; authors' calculations.

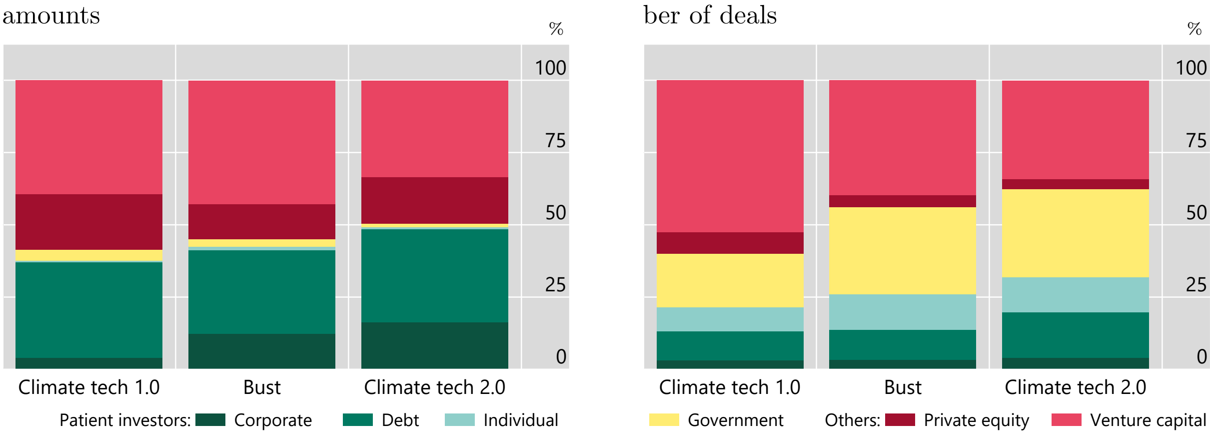
The recent boom in climate tech finance likely reflects a global rise in PE finance driven by low interest rates, high stock valuations and abundant liquidity. It is also driven by sector-specific factors such as rising fossil fuel prices that make clean energies more competitive; more ambitious climate-related public policies (also in connection with the Paris Agreement)[7] and rising awareness of the risks of climate change. This has contributed to higher demand for energy-efficient and eco-friendly products and services.

[7]The Paris Agreement, signed in December 2015, was a milestone: countries representing 97% of global GHG emissions agreed to keep global warming at less than $2^oC$ above pre-industrial levels. Furthermore, the agreement invited nations to publicly communicate their mid and long-term strategies for reducing emissions through Intended Nationally Determined Contributions (INDCs). It also increased peer pressure with regard to meeting global warming targets, as signatories committed to rapidly reducing $CO_2$ emissions to achieve net-zero emissions in the second half of the twenty-first century.

Figure 2: **Distribution of capital to climate tech companies by source**

(a) Distribution of deal types based on deal amounts

(b) Distribution of deal types based on the number of deals




Note: The graphs show the breakdown of the deal amounts (lhp) and deal number (rhp) by deal source across three phases: climate tech 1.0 (Q1 2005 to Q3 2011), bust (Q4 2011 to Q3 2014), and climate tech 2.0 (from Q4 2014 onwards). The sample period is Q1-2005 to Q4-2021. Sources: PitchBook Data Inc; authors' calculations.

A comparison between the two booms reveals several differences in the composition of the investor base and the distribution of investments across companies and industries. The investor base has become more diversified, with a greater involvement of *patient* investors. Particularly corporate investors have increased their share, along with private debt providers (Figure 2).[8] During the bust period corporate investors acted as shock absorbers, while the participation of PE funds shrank. Patient investors gained traction through time, both in dollar terms and in number of deals. This evidence is consistent with the shift in the investor base that we propose as one of the forces driving climate tech 2.0.

We document this trend further in Table 1. This reports regression estimates of differences in the quarterly dollar amounts (value) and deal count (volume) of capital invested by different types of investors during the three periods.

[8]Interestingly, we do not observe a similar increase in the participation of patient investors (corporate VCs and individuals) in other sectors. See figure A1 in the online appendix.

Table 1: **Capital allocation by source over the business cycle**

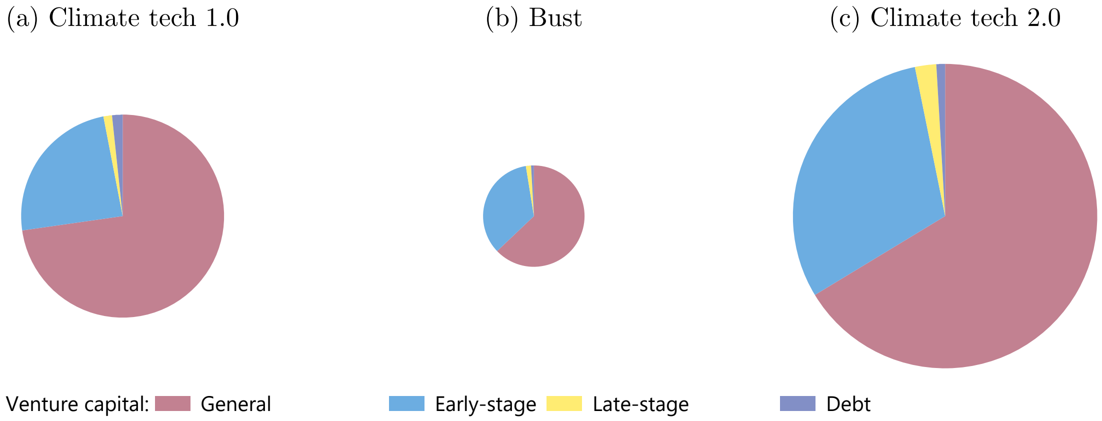
| | Ln(deal value)<br>(I) | Ln(deal volume)<br>(II) |
|---|---|---|
| Corporate | -2.593*** | -1.172*** |
| | (0.295) | (0.098) |
| Individual | -4.349*** | -0.247** |
| | (0.196) | (0.080) |
| Private equity | -0.578* | -0.447*** |
| | (0.247) | (0.065) |
| Venture capital | -2.767*** | 0.274* |
| | (0.185) | (0.114) |
| Government | 0.596*** | 1.860*** |
| | (0.096) | (0.058) |
| Bust*corporate | 0.959* | -0.216 |
| | (0.413) | (0.203) |
| Climate tech 2.0 × corporate | 1.389** | 0.345* |
| | (0.352) | (0.151) |
| Bust × individual | 0.969** | 0.598*** |
| | (0.343) | (0.136) |
| Climate tech 2.0 × individual | 0.608** | 0.898*** |
| | (0.207) | (0.150) |
| Bust × private equity | -0.601 | -0.628*** |
| | (0.454) | (0.108) |
| Climate tech 2.0 × private equity | -0.430 | -0.642*** |
| | (0.292) | (0.158) |
| Bust × government | 0.388 | 0.815*** |
| | (0.232) | (0.111) |
| Climate tech 2.0 × government | -0.602** | 1.044*** |
| | (0.213) | (0.130) |
| Bust × venture capital | -0.076 | -0.246** |
| | (0.145) | (0.066) |
| Climate tech 2.0 × venture capital | -0.636*** | -0.269* |
| | (0.120) | (0.115) |
| Observations | 400 | 400 |
| $R^2$ | 0.803 | 0.878 |

Standard errors clustered by source and year-quarter are reported in parentheses; ***/**/* indicates statistical significance at the 1/5/10% level. The omitted (comparison) source of capital is "debt". The dependent variable is either the dollar amount of capital from a given source or the number of investments (volume). Bust is a dummy for the period Q4 2011–Q3 2014 and Climate tech 2.0 for the period Q4 2014–Q4 2021. The comparison period is Climate Tech 1.0 starting from Q1 2005. Regressions include year-quarter fixed effects. Sources: PitchBook Data Inc; authors' calculations.

The omitted source of capital in this regression analysis is “debt” which has been rather stable throughout our sample period in terms of deal amounts. The coefficients of interest are those of the interactions between the episodes’ dummies (Bust and Climate tech 2.0) and the sources of capital dummies (corporate, individual, private equity, and government). Controlling for common shocks (ie through time fixed effects), we observe that capital from patient sources such as corporate and individual investors has increased by more in the bust phase and, more importantly, during the Climate tech 2.0 phase. This finding holds true whether we consider values or volumes invested.

Figure 3 shows the breakdown of the number of investments by VC fund type. Overall, the number of investments halved in the bust period relative to climate tech 1.0. (The size of the pie in the center panel is roughly half that of the one in the left-hand panel). They then nearly tripled in the climate tech 2.0 boom. The pull-back in the bust phase was driven by VC-generalist funds; the market share of these funds dropped about 10 percentage points in the bust phase relative to climate tech 1.0. The market share of early-stage funds rose by roughly the same amount. On the other side, the rebound in climate tech 2.0 was more equally distributed between generalists and specialists. Compared to the bust phase, the market share of generalist and late-stage funds rose by nearly four percentage points (pp) and one pp, respectively, while the one of early-stage funds fell of about four pp.

Figure 3: **Number of investment by type of venture capital fund**




The graph shows the percentages of each venture capital fund type in the total number of VC investments in each of the three phases, climate tech 1.0 (left-hand panel), bust (center panel), and climate tech 2.0 (right-hand panel). The size of the pies is proportional to the total number of VC investments in each of the three phases. VC funds are classified into four categories: VC generalists, VC early-stage specialists, VC late-stage specialists, and VC debt. Sources: PitchBook Data Inc; authors' calculations.

Results from Table 2 confirm that VC generalists, the excluded fund-category in the regression analysis, retreated from the climate tech sector more aggressively than other funds, and for longer. This finding is supported by the positive and statistically significant coefficients of the interactions terms in column I. This evidence is robust to the inclusion in the specification of fund vintage fixed effects that account for unobservable characteristics for each year in which funds were launched, such as the cyclicality of overall VC fund raising activity. Furthermore, the positive and statistically significant coefficients for Bust $\times$ Non-VC generalist/specialist indicate that non-VC funds, specialists in particular, display less procyclicality than VC funds and continued investing during the bust.

Table 2: **Results on fund exposure**

| | Exposure | |
|---|---|---|
| | (I) | (II) |
| Bust × VC specialist | 0.130 | 0.513 |
| | (1.787) | (2.426) |
| Bust × Non-VC generalist | 5.175** | 5.630* |
| | (1.965) | (2.717) |
| Bust × Non-VC specialist | 11.260*** | 11.663*** |
| | (2.230) | (2.546) |
| Climate tech 2.0 × VC specialist | 5.540*** | 5.041** |
| | (1.381) | (2.096) |
| Climate tech 2.0 × Non-VC generalist | 13.388*** | 14.099*** |
| | (1.452) | (1.797) |
| Climate tech 2.0 × Non-VC specialist | 14.482*** | 14.491*** |
| | (4.151) | (4.271) |
| Fixed effects | Fund type | Fund type and vintage |
| Observations | 2,261 | 2,261 |
| $R^2$ | 0.200 | 0.210 |

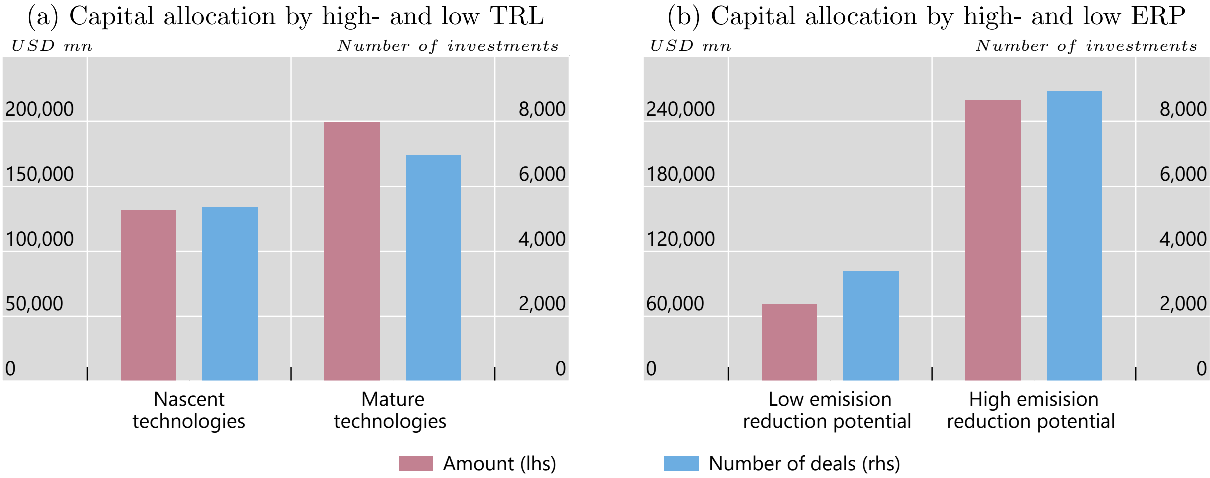
Standard errors clustered by vintage and fund type and are reported in parentheses; ***/**/* indicates statistical significance at the 1/5/10% level. The omitted fund category is VC-generalist. Exposure is the proportion of a Climate tech investments in a fund portfolio. Bust is a dummy for the period Q4 20113 2014 and Climate tech 2.0 for the period Q4 2014–Q4 2021. The comparison period is Climate Tech 1.0 starting from Q1 2005. Additional control variables include log assets under management, log sequence number, vintage year fixed effects. Sources: PitchBook Data Inc; authors' calculations.

Overall, the evidence suggests that since 2009 the market has been shifting toward more stable sources of capital, like non-VC funds, and specialists. This finding suggests that founders prefer to deal with more patient and specialist investors who are experts in their area and can better understand innovative projects. Consistently, Holle (2021) describes specialist funds as more credible, better-informed and more stable than generalist funds. Specialist funds invest more in sector and firm-specific information collection, have a longer investment horizon and display a stronger commitment over time. They also engage in more intensive screening and due diligence, and thus have deep networks and expertise in their area.

A broader investor base, with the continued addition of new investors who are either better informed or more patient, could render financing to the sector more resilient to shocks and hence more stable. Cetorelli et al. (2007) define a resilient market as one that provides a predictable access to capital for funding and investing. They show that changes in investor composition can stabilise markets by dampening the consequence of a large investor failure. The broader investor base in climate tech 2.0 could thus be a source of strength in the face of new shocks. In addition to changes in the investor base there are several noticeable changes in the way capital is allocated across subsegment and across companies between the two booms.

Beyond the composition of the investor base of climate tech firms, there are interesting trends in the way capital is allocated across climate tech subsegments, and across technologies based on their specific stage of development. Specifically, Figure 4 shows the total capital invested and total number of climate tech deals broken down by technology development stage and by climate tech subsegment emission reduction potential. Overall, investors favoured more mature technologies relative to nascent ones (Figure 4, left-hand panel). Consistent with allocative efficiency, more capital went into subsegments with a high emission reduction potential (Figure 4, right-hand panel). These trends are confirmed when looking at indicators based on the number of climate tech deals instead of the ones based on the total amount raised.

Figure 4: **Emission reduction potential and technological stages**




Note: The graph shows the total dollar amounts allocated to each category over our sample period. Nascent technologies correspond to technologies with a low technology readiness level (TRL) (ie TRL $<$ 7). Mature technologies correspond to technologies with a high TRL (ie TRL $\geq$ 7). Low (high) emission reduction potential (ERP) correspond climate tech sub-segments with an average ERP below (above) 20 gigatone carbone dioxide equivalent per year. Sources: PitchBook Data Inc, Project Drawdown, IEA, ENTSOE, and authors' calculations.

Table 3 describes the link between access to capital and company characteristics. A very low but rising share of capital has flowed to female-headed companies (from 2% to 4% by value over the sample period, or from 5% to 11% by deal count). Hardware companies represent the lion's share of investments (over 90%) both in dollar terms and in volume; this has changed only slightly over the sample period, with a small shift toward software since 2015. Meanwhile, less capital has been flowing towards young companies (less than 2 years old) since 2015; there was a fall in dollar amounts from 19% to 9% over the sample period.

Table 3: **Access to capital and companies' characteristics**

| | Climate tech 1.0 (I) | Bust (II) | Climate tech 2.0 (III) |
|---|---|---|---|
| Value | | | |
| Female CEO | 2% | 4% | 4% |
| Young company | 19% | 11% | 9% |
| Hardware | 98% | 98% | 97% |
| Volume (number of deals) | | | |
| Female CEO | 5% | 7% | 11% |
| Young company | 36% | 30% | 30% |
| Hardware | 96% | 94% | 93% |
| Patents | | | |
| Average number of patents | 31 | 13 | 33 |
| Log cite-weighted patents | 1.358 | 1.441 | 1.209 |
| % of companies with at least one patent | 51% | 54% | 63% |
| Venture capital deals only | | | |
| Average number of patents | 22 | 20 | 28 |
| Log cite-weighted patents | 1.522 | 1.831 | 1.749 |
| % of companies with at least one patent | 67% | 71% | 75% |

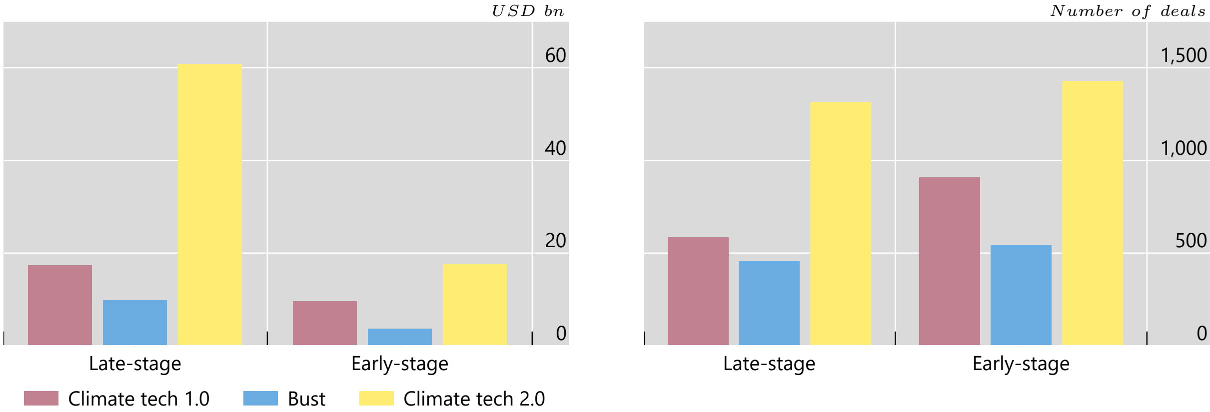
This table shows the distribution of capital by value and volume (number of deals) across different categories of companies. Female CEO headed companies, young companies, and companies in hardware across different periods. Young companies are less than two years old at the time of a deal. Climate Tech 1.0 is the period from Q1 2005 to Q3 2011. Bust is the period Q4 2011–Q3 2014 and Climate tech 2.0 the period Q4 2014–Q4 2021. In the bottom part of the table indicators of patent activity across periods are reported for companies that raise capital. Sources: PitchBook Data Inc; authors' calculations.

The shift toward more mature companies is also visible in Figure 5, which shows the distribution of VC capital by stage. Early-stage financing (series A and B, individual deals and seed capital) fell more during the bust period. This is consistent with previous evidence that early-stage VC is more vulnerable to downturns than late-stage VC (Bernstein et al. (2019) and Howell et al. (2020)). The persistence of the shift toward late-stage financing since 2014 is attributable to the simple fact that as more projects in the sector matured, demand for late-stage financing grew relative to early-stage financing.

Interestingly, the shift toward late-stage financing is particularly visible in dollar amounts allocated (Figure 5, left-hand panel) and less so in the volume of transactions (right-hand panel): since 2015, early-stage financing continues to represent over 50% of the number of deals. These two facts combined indicate that capital-intensive companies have developed and progressed from infrastructure finance to project finance. This in turn has caused a stronger decline in the proportion of early-stage financing in dollar terms than in deal count. Also contributing to this trend is the fact that a generation of software companies (which are less capital-intensive) has emerged in a sector that remains predominantly hardware-focused (Table 3).

Figure 5: **Distribution of capital by stage and episode**

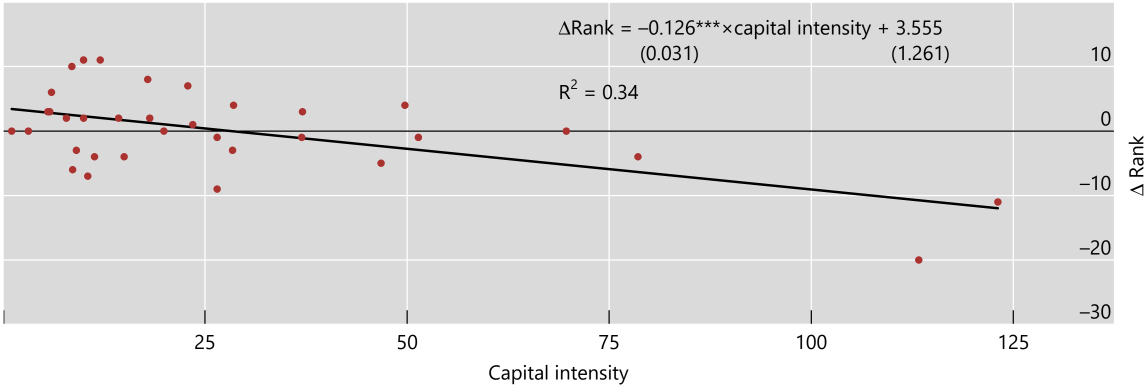
(a) Distribution of deal amounts (b) Distribution of the number of deals




Note: The graph shows the distribution of deal amounts (lhp) and deal number (rhp) by stage of investment across three phases: climate tech 1.0 (Q1-2005 to Q-3 2011), bust (Q4-2011 to Q3-2014), and climate tech 2.0 (from Q4-2014 onwards). Early-stage deals include VC series A and B, individual deals, and seed capital. Late-stage deals include series C and beyond. Sources: PitchBook Data Inc; authors' calculations.

We do observe a shift of investors towards less capital intensive industries. To see this more clearly, we rank industries by the amount received during the two boom periods (climate tech 1.0 vs climate tech 2.0) and then plot the change in ranking against the average industry capital intensity proxied by average deal amount. Interestingly, we find a strong negative correlation between the change in industry ranking and capital intensity (Figure 6).

Figure 6: **Change in capital allocation versus capital intensity by industry**




Each dot corresponds to an industry (34 industries in total). The horizontal axis shows the industry capital intensity measured by average deal size, that is, average USD amounts per deal in million. The vertical axis shows the change in the industry rank in capital allocation (measured by dollar amount) between climate tech 1.0 and climate tech 2.0. Therefore a negative value of Δ Rank indicates that less capital is allocated to an industry after 2015 (ie Climate tech 2.0 period). Standard errors from an OLS regression in parentheses. Sources: PitchBook Data Inc; authors' calculations.

Perhaps the most notable evolution in capital allocation across companies is the shift of capital toward patent-rich companies. This is reflected in an increase in patenting activity of the average company accessing the market (from 31 to 33 patents; see Table 3, columns I and III). More importantly, it is reflected in an increase in the share of companies accessing the market owning at least one active patent (from 51% during climate tech 1.0 to 63% during climate tech 2.0; Table 3, columns I and III). This change is driven by VC investors, with an increase from 67% to 75% of VC-backed companies owning at least one patent, and a 23% increase in average cite-weighted patents.

In what follows we analyse in more depth the allocation of capital across subsegments and across companies over time. We expect the structure of the investor base and the composition of companies that tap the market to have an influence on how capital is distributed.

# 4 Financing of climate tech: allocative efficiency

We infer allocative efficiency by directly observing investment flows across companies. Our approach follows Wurgler (2000). Wurgler measures allocative efficiency as the capacity of the financial market to direct more funds to "high-growth" as opposed to "low-growth" sectors. The spirit of our approach is similar: we measure allocative efficiency as the ability of the financial market to direct more funds to subsegments that use or develop high-ERP technologies, and to more innovative companies within those subsegments. In particular, in the following subsections we would like to answer two questions:

1. Does the market channel capital toward (mature) technologies that have a higher potential to reduce $CO_2$ emissions in the short to medium run?
2. Is capital geared towards companies that develop new technologies?

## 4.1 Across technologies: Do investors prefer high-ERP technologies?

There is a positive correlation between technologies' ERP and capital invested. In Table 4 we further investigate this relationship with a multivariate analysis at the deal level. We regress the natural logarithm of the deal amount, expressed in real dollars, against the natural logarithm of ERP, TRL, company characteristics and various fixed effects to control for differences in capital intensity and maturity across segments, differences in market development across US states and differences in market conditions over time. The results confirm that more capital was channelled into higher-ERP technologies (column I). These technologies were prioritised even more in the climate tech 1.0 period, as indicated by the negative coefficient on the interaction term between ln(ERP) $\times$ Climate Tech 2.0 (column II), though this is only significant at the 10% level. Yet in climate tech 2.0, capital shifted toward high-ERP nascent technologies (column III) and away from high-

ERP mature technologies as their need for capital diminished (column IV).

Table 4: **Elasticity of investments to the technologies' emission reduction potential**

| | Ln(deal value) | | | | | |
|---|---|---|---|---|---|---|
| | | | Nascent | Mature | Nascent | Mature |
| | (I) | (II) | (III) | (IV) | (V) | (VI) |
| Ln(ERP) | 0.062** | 0.125** | -0.202 | 0.210*** | | |
| | (0.024) | (0.041) | (0.225) | (0.056) | | |
| TRL | -0.042 | -0.051 | | | | |
| | (0.025) | (0.062) | | | | |
| Ln(age) | 0.620*** | 0.621*** | 0.749*** | 0.581*** | 0.599*** | 0.445*** |
| | (0.070) | (0.070) | (0.092) | (0.097) | (0.087) | (0.079) |
| Ln(number of employees) | 0.670*** | 0.670*** | 0.666*** | 0.667*** | 0.561*** | 0.547*** |
| | (0.037) | (0.038) | (0.049) | (0.045) | (0.046) | (0.043) |
| Ln(ERP) × Bust | | -0.042 | 0.170 | -0.078 | | |
| | | (0.042) | (0.094) | (0.056) | | |
| Ln(ERP) × Climate Tech 2.0 | | -0.087* | 0.267** | -0.125* | | |
| | | (0.040) | (0.096) | (0.057) | | |
| TRL × Bust | | 0.056 | | | | |
| | | (0.033) | | | | |
| TRL × Climate Tech 2.0 | | -0.002 | | | | |
| | | (0.065) | | | | |
| Ln(ERP) × Corporate | | | | | 0.376** | 0.279*** |
| | | | | | (0.159) | (0.046) |
| Ln(ERP) × Debt | | | | | -0.002 | 0.197* |
| | | | | | (0.159) | (0.096) |
| Ln(ERP) × Individual | | | | | -0.260* | -0.086* |
| | | | | | (0.132) | (0.043) |
| Ln(ERP) × Private Equity | | | | | 0.319** | 0.480*** |
| | | | | | (0.129) | (0.057) |
| Ln(ERP) × Venture Capital | | | | | 0.266* | 0.287*** |
| | | | | | (0.124) | (0.022) |
| Ln(ERP) × Government | | | | | -0.419*** | -0.244*** |
| | | | | | (0.116) | (0.047) |
| Observations | 10,098 | 10,098 | 2,797 | 7,301 | 2,797 | 7,301 |
| $R^2$ | 0.413 | 0.413 | 0.447 | 0.416 | 0.551 | 0.521 |

All regressions include segment fixed effects, headquarter state fixed effects, and year-quarter fixed effects. Standard errors clustered by segment, state and year-quarter are reported in parentheses; ***/**/* indicates statistical significance at the 1/5/10% level. The dependent variable is the log dollar amount of capital raised in a deal. ERP stands for emission reduction potential and TRL for technology readiness level taking values from 1 to 9. Bust is a dummy for the period Q4 2011–Q3 2014 and Climate tech 2.0 for the period Q4 2014–Q4 2021. The comparison period is Climate Tech 1.0 starting from Q1 2005. Column III reports results for nascent technology developers or users (TRL below 7) and column IV results for mature technologies (TRL at 7 and above). Columns V and VI estimate the effect of log ERP for each source of capital. Sources: PitchBook Data Inc; authors' calculations.

In terms of magnitude, the elasticity is economically and statistically significant: a 3 times increase in ERP (corresponding to the difference between the highest value and the mean –see Table A4 in the Appendix) translates, on average, into a 7 percent increase in capital invested per deal over the entire sample period (column I). [9] The same threefold increase in ERP corresponds to a nearly 35 percent increase (column III) and a drop of more than 10 percent (columns IV) in the average deal size of nascent technologies in the Climate tech 2.0 period relative to the Climatech 1.0 episode. [10]

Interestingly there are significant variations across investors (columns V and VI). The tendency to allocate more capital to impactful technologies is verified for corporate VCs, private equity funds and venture capital funds with estimated coefficients about four to eight times higher in magnitude compared to estimates for the full sample. The estimates are insignificant or only marginally significant for debt, and negative for individuals (angels) and government subsidies. These latter investors support companies that struggle to raise VC capital – those that are individually the least relevant in terms of reducing $CO_2$ emissions but, arguably, matter in aggregate. Hence, if we add up the ERP of the ten least impactful subsegments (i.e those with an ERP below the median) we arrive at an aggregate emission reduction potential of 100 giga tonnes by 2050 compared with 36,7 giga tonnes emitted per year based on the latest current value. Such a reduction potential is far from negligible.

## 4.2 Across companies: Is capital geared toward innovative companies?

As the sector matures and grows, more capital flows toward innovative companies. To see this, we calculate quarter-by-quarter estimates of the elasticity between the stock of

[9] $100 \times (\exp(0.062 \times \ln(3)) - 1)$
[10] $100 \times (\exp(0.267 \times \ln(3)) - 1)$ and $100 \times (\exp(-0.125 \times \ln(3)) - 1)$, respectively.

citation-weighted patents and real deal amount. We use the following specification:

$$y_{jt} = \sum_{k=Q1\ 2005}^{Q4\ 2021} \beta_k p_{jt} + \gamma_q + \delta_i + \theta_s + \epsilon_{jt} \quad (1)$$

where the dependent variable $y_{jt}$ is the natural logarithm of the real dollar amount raised by company $j$ at time $t$. Note that since we use irregularly spaced deal-level data rather than aggregate data, the data within fixed length intervals time $t$ corresponds to the time of a deal. $p_{jt}$ is then the natural logarithm of the stock number of citation-weighted patents (plus one) up to the time of the deal.

Using the dollar amount as dependent variable has the inconvenient feature of conflating success in raising investment capital with capital intensity. Yet this is the most consistently available metric. We account for differences in capital intensity by comparing companies within the same subsegment and controlling for company age and company size. $\gamma_q$ is a time fixed effect that accounts for different seasonality and common shocks, $\delta_i$ is a climate tech subsegment fixed effect to control for differences in capital intensity, $\theta_s$ is a state of incorporation fixed effect to account for the fact that VC firms disproportionately invest in local start-ups (Chen et al. (2010)). Table A2 in the appendix reports correlations between the variables used in the regression. Note that the correlation is low between patent activity and company size or between capital intensity and company size, hence there is no *mechanical* relationship among these variables.

$\beta$ is an elasticity: it gives the percentage increase in capital allocated resulting from a 1 percent increase in innovation activity. We refer to this as the "quality premium". Importantly, we are interested in the effect of a company's patenting activity as a proxy for overall company quality, and not in the effect of patents *per se*. Therefore $\beta$ is a more precise measure of allocative efficiency if the correlation between patenting activity and other dimensions of company quality reflected in the error term is strong. Other dimensions of quality include productivity, management quality, sales growth and profitability. These are not directly observed by us but may be available to investors. There is indeed evidence of a strong correlation between patent activity and several measures of company quality. Farre-Mensa et al. (2016) find that start-ups with patents display significantly higher growth in employment and sales. Howell (2017) documents a strong positive correlation between innovation and revenues. Guzman and Stern (2016) show that having a patent predicts being a high-growth VC-backed start-up. We acknowledge, however, that patents are not a perfect measure of company quality. Some companies such as Tesla or software companies choose not to patent because of the accompanying disclosure requirement and instead rely on trade secrets. But patents are the best available measure of a company innovation activity and, more broadly, of its quality.

We estimate a $\beta$ for each quarter $k$ from Q1 2005 to Q4 2021.[11] $\beta$ may vary over time because investors face tighter capital constraints during recessions. Alternatively, as the sector matures, more information becomes available about new investment opportunities, and the composition of companies that tap the market shifts toward more mature companies. Importantly, we later condition $\beta$ on characteristics of companies to shed light on the role of financial frictions in altering the magnitude of $\beta$. We also compare the allocative efficiency of different sources of capital because different types of investors may behave differently and have different objectives. Indeed, non-VC investors do not have the same time and capital constraints as VC investors. This raises the question of whether non-VC investment is a complement or substitute to venture capital.

An important condition for our approach to be valid is the absence of reverse causality. Our identifying assumption is that investment does not yield patents before a long time. This is supported by evidence from Kortum and Lerner (2000) who document a long-lag impact of VC financing on innovation. Further evidence against the possibility of reverse causality is the fact that our data are high-frequency daily transactions and that a significant fraction of deals in our sample are first-time deals. But most importantly, our variable of interest $p$ is the *stock* of citation-weighted patents at the time of a deal,

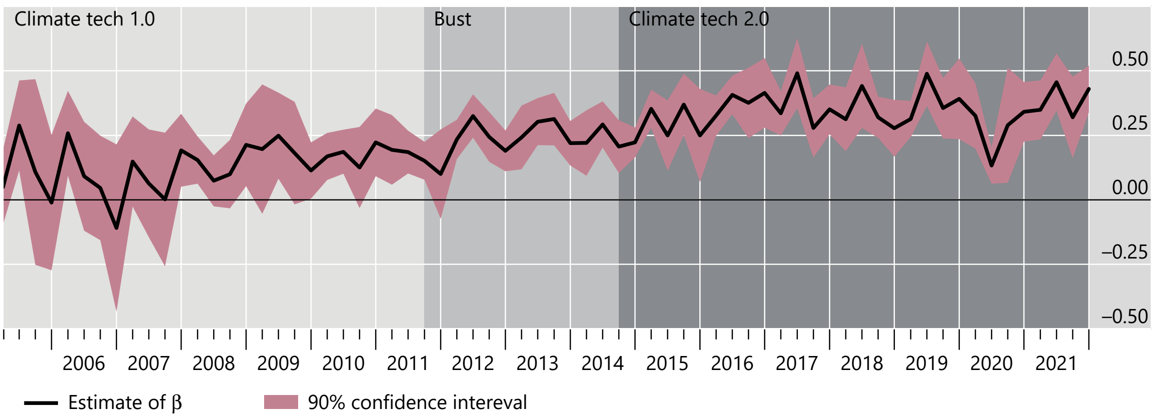
[11] As noted by Wurgler (2000) when time fixed effects are not included this specification allows to assess differences in the time dimension and thus to capture the capacity of the market to marshal a growing value of funds efficiently.

and it is therefore predetermined.

#### 4.2.1 Efficiency of capital allocation over the cycle

The estimated $\beta$s for each quarter are plotted in Figure 7. In this baseline specification we do not control for company age and size to preserve enough observations per quarter. Figure 7 shows that allocative efficiency grows over time and turns positive and statistically significant during the second boom. The average quality premium is 0.35 for climate tech 2.0 investments. This means that, a twofold increase in $p_{jt}$ (corresponding to a one standard deviation increase above the mean) is associated with nearly a 30 percent increase in capital raised per deal.[12]

Figure 7: **Estimates of efficiency of capital allocation to climate tech firms: quality premium**




The graph plots the OLS estimates of $\beta$s from equation 1, one per quarter. $\beta$ represents the elasticity between the amount raised in a deal and the number of patents a company owns at the time of the deal. The range corresponds to the 90 per cent confidence interval. Sources: PitchBook Data Inc; authors' calculations.

In Table 5 we estimate the "quality premium" over the three sub-periods, adding company age and size as control variables. The results are robust overall; allocative efficiency increases in the climate tech 2.0 period (column I). In Table A3 in the online appendix we report additional results showing that our findings are robust to excluding

[12] $100 \times (\exp(0.35 \times \ln(2)) - 1)$

various fixed effects. They are also robust to using an alternative measure of quality, namely a dummy for whether a company has at least one patent at the time of a deal, instead of the stock of citation-weighted patents owned.

Table 5: **Allocative efficiency over the business cycle**

| | Ln(deal value) | |
|---|---|---|
| | (I) | (II) |
| Patents | 0.011 | |
| | (0.020) | |
| Bust × patents | 0.052* | |
| | (0.025) | |
| Climate Tech 2.0 × patents | 0.115*** | |
| | (0.028) | |
| Corporate × patents | | 0.040 |
| | | (0.048) |
| Debt × patents | | 0.028 |
| | | (0.021) |
| Individual × patents | | 0.074* |
| | | (0.039) |
| Private Equity × patents | | -0.011 |
| | | (0.036) |
| Venture Capital × patents | | 0.095*** |
| | | (0.012) |
| Government × patents | | 0.124*** |
| | | (0.024) |
| Ln(age) | 0.544*** | 0.359*** |
| | (0.078) | (0.054) |
| Ln(number of employees) | 0.629*** | 0.492*** |
| | (0.038) | (0.032) |
| Observations | 10,098 | 10,098 |
| $R^2$ | 0.433 | 0.565 |

Standard errors clustered by segment, state, and year-quarter are reported in parentheses; ***/**/* indicates statistical significance at the 1/5/10% level. The dependent variable is the log real dollar amount of capital raised in a deal (2020 USD). The variable Patents is the log cite-weighted patents at the time of a deal. Bust is a dummy for the period Q4 2011–Q3 2014 and Climate tech 2.0 for the period Q4 2014–Q4 2021. The comparison period is Climate Tech 1.0 over the period Q1 2005-Q3 2011. All regressions include industry, state, and year-quarter fixed effects. Sources: PitchBook Data Inc; authors' calculations.

We next compare capital allocation across different types of investors. Corporate investors in long-horizon research and development (R&D) units and high-income angel investors are more patient, willing to invest in companies at a very early stage, including at the founding stage. Meanwhile, government subsidies – paid chiefly in the form of grants – ought to target companies that struggle to access private capital rather than crowd out private capital. There is previous evidence that grants crowd-in VC capital and have a greater impact on performance and innovation when allocated to companies that face acute financial constraints. This includes companies with no patent, young companies, companies in emerging sectors and hardware companies (Howell (2017)).

A test comparing the different sources of capital is reported in column II of Table 5. It includes interaction terms between citation-weighted patents and investor type dummies. Here we find that the quality premium is chiefly driven by VC and government investments. This is consistent with the presumption that corporate and angel investors take on more risk. As already mentioned, these two groups focus on long-term R&D projects often at the founding stage rather than prioritising companies with already patented IP, as VC investors do.

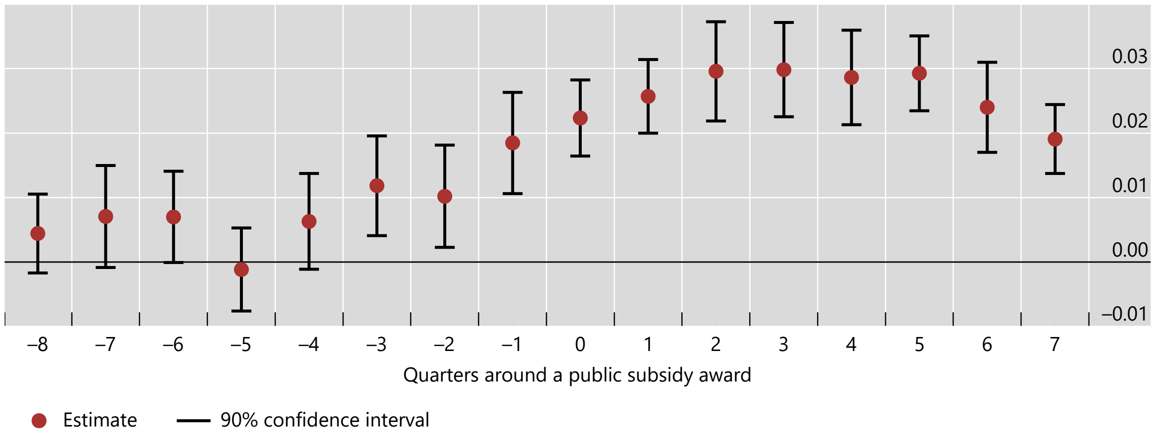
The quality premium is also insignificant for debt and PE. This result is not unexpected. Debt is typically backed by tangible assets while PE is raised by mature, often less innovative companies that have an established relationship with their funders. By contrast, the positive and statistically significant coefficient for government grants is an anomaly for the reasons mentioned earlier. Government subsidies typically target companies that struggle to access private capital.

To better understand the effect of government subsidies on private investments we run an event study. Specifically, we estimate the effect of a company j being awarded a subsidy on the probability of raising VC capital in subsequent quarters:

$$VC_{jt} = \alpha_j + \theta_t + \sum_{k=-A}^{B-1} \gamma_k 1\{S_{jt} = k\} + \gamma_{B^+} 1\{S_{jt} \geq B\} + \epsilon_{jt} \tag{2}$$

where $S_{jt}$ is the relative time, i.e. the number of periods relative to the event "being awarded a subsidy". We include $A = 8$ leads of treatment and $B = 8$ lags. The specific coefficient $\gamma_{B+}$ captures the long-run effects.

Figure 8: **Event study: effect of receiving a subsidy on the probability of raising VC capital**




The horizontal axis shows the number of quarters before and after a public subsidy is awarded. The vertical axis shows the estimates from a panel fixed effect model. The dependent variable is a dummy that takes value one if a company has raised VC capital in each quarter. The explanatory variables are dummies that take value one if the company has obtained a public subsidy within an 8 quarter window around each quarter. The unconditional probability of raising VC capital in each quarter is 2.7%. Sources: PitchBook Data Inc; authors' calculations.

Figure 8 shows estimates of $\gamma_k$ obtained using ordinary least squares (OLS). Being awarded a subsidy significantly increases the probability of raising VC capital in the following 8 quarters. At the peak, it increases the unconditional probability of raising VC capital per quarter by around 3%, from 2.7% to 5.7%. The effect is statistically significant even before the award, due to announcements taking place on average around three quarters before a transaction.[13] So, on average, public investors crowd in, rather than crowd out, private investors. This is consistent with the notion that they do not target the same sector. But is it also the case when government subsidies are targeted to innovative companies?

To address this question, we estimate the following specification separately for early

[13]We observe the announcement date for 20% of the deals in our sample. On average, the announcement occurs around three quarters before the transaction for these deals.

and late-stage VC deals:

$$
\begin{aligned}
VC_{jt} = &\alpha_j + \theta_t + \beta^1 1\{S_{jt} \in T\} + \beta^2 1\{S_{jt} \in T\} * c_j + \\
&\gamma^1 1\{S_{jt} \geq 8\} + \gamma^2 1\{S_{jt} \geq 8\} * c_j + \epsilon_{jt}
\end{aligned}
\tag{3}
$$

where $T = \{-8, 8\}$ is the treatment period, $S_{jt} \leq 8$ is the post treatment period, and $c_j$ is a dummy variable indicating that a company has no patent.

We find indeed that, at an early investment stage of development, the crowding-in effect of public capital is twice higher when public investors target companies that have no patent (Table 6, column I). At later investment stages, the opposite is true (Table 6, column II). This is consistent with the fact that mature companies and companies with patented ideas have easier access to private capital so that for these categories of companies access to public capital is more likely to crowd out private capital.

Table 6: **Effect of government subsidies on VC activity**

| | Early-stage VC (I) | Later-stage VC (II) | Early-stage VC (III) | Later-stage VC (IV) |
|---|---|---|---|---|
| Treatment | 0.010*** | 0.024*** | 0.003 | 0.034*** |
| | (0.003) | (0.003) | (0.005) | (0.006) |
| Post treatment | -0.011*** | 0.026*** | -0.015*** | 0.057*** |
| | (0.003) | (0.002) | (0.006) | (0.007) |
| No patent × treatment | 0.009** | -0.018*** | 0.015** | -0.028*** |
| | (0.004) | (0.003) | (0.007) | (0.006) |
| No patent × post treatment | 0.016*** | -0.020*** | 0.032*** | -0.050*** |
| | (0.003) | (0.002) | (0.006) | (0.007) |
| Observations | 225,560 | 225,560 | 225,560 | 225,560 |

Standard errors clustered by year-quarter are reported in parentheses; ***/**/* indicates statistical significance at the 1/5/10% level The sample covers all companies that raised capital during the period Q1 2005–Q1 2021. The dependent variable in columns I–II is a dummy that takes value one when a company raises VC capital in each quarter. In columns III–IV it is the log amount of VC capital raised. Treatment is a dummy that takes value one during the 8 quarters following award of a public subsidy. Post treatment is a dummy that takes the value of one after the eighth quarter. No patent is a dummy that takes value one if a company has no patent. The estimates are obtained from a panel fixed effects model. Sources: PitchBook Data Inc; authors' calculations.

Next, we study sources of inefficiency of capital allocation to understand the changes in allocation efficiency over time. To this end, we examine heterogeneities across companies.

### 4.2.2 Sources of misallocation

The literature on the quality of VC investments over the business cycle has reached mixed results. There is evidence that VC investors rely on their experience and expertise to invest in the most promising companies at an early stage (Akcigit et al. (2022)). At the same time, patent activity of VC-backed companies declines, and it is of lower quality during recessions, even after controlling for aggregate VC investments in each period. This is driven by VCs financing less innovative companies during recessions due to fundraising uncertainty and pressure to support the existing portfolio of companies (Nanda and Rhodes-Kropf (2017); Howell et al. (2020)).

By contrast, Nanda and Rhodes-Kropf (2013) find that companies receiving their first VC financing during boom markets are more likely to go bankrupt. The abundance of capital can be a source of capital misallocation for two main reasons. One argument is that competitive pressure to seal deals during boom times leads investors to allocate more capital to lower-quality firms (Kaplan and Stein (1993)). A related argument is that due to the limited absorption capacity of top-performing funds, more capital flows to weak performers in times of abundant capital, causing capital to be misallocated (Bernstein et al. (2019)).

These earlier findings are not comparable to our study because they evaluate mature markets. The reason that the efficiency of capital allocation is trending upwards in our data, displaying no cyclicality, is likely that we are focusing on a new sector that has been maturing over the past 20 years. As the market matures, financial frictions weaken, leading to improved allocative efficiency. Further, climate tech 2.0 investors may have learned lessons and gained experience from climate tech 1.0. Lastly, as we have documented in section 2 the investor base has shifted toward more informed investors, such as specialist funds. These investors may be more attentive to innovation activity and able to better assess patents' quality.

Markets may fail to efficiently allocate resources across companies due to several frictions. Our dataset allows us to investigate specific sources of misallocation.

A first cause of misallocation is asymmetric information between investors and entrepreneurs (Howell (2020)). The age of a company is a proxy for opacity: the quality of a company is more difficult to assess the younger it is, due to patchy track records. In addition, a patent is a noisier proxy of quality for younger companies because patent quality matters and is assessable only once a company performance is observed, subsequently to obtaining a patent. Finally, an often-used measure of patent quality, namely the number of patent citations, is clearly time-dependent.

Another reason why young innovative companies face tighter financial constraints is that the value of a patent is lower for young companies. This is due to costly enforcement (Boldrin and Levine (2013)) or greater vulnerability to abuse by competitors (Heller and Eisenberg (1998); Galasso and Schankerman (2015)).

Young companies also lack adequate levels of tangible assets to serve as collateral. This also applies for capital-intensive companies, companies in hardware technologies, or larger companies that require high investments upfront.

Gender discrimination is another potential source of misallocation. There is abundant evidence of discrimination against female entrepreneurs in private equity and venture capital (Hassan et al. (2019, 2020)). But while it has been documented that female founders raise significantly less capital than male founders it has also been found that they request lower amounts from investors (Hellmann et al. (2019)).

To estimate the role of each of these frictions in driving down the quality premium we run the following regression:

$$y_{jit} = \beta_1 X_{ij} + \beta_2 p_{jt} + \beta_3 p_{jt} * X_{ij} + \gamma_q + \delta_i + \theta_s + \epsilon_{jt} \tag{4}$$

where the dummy variable $X_{ij}$ indicates the specific source of misallocation being tested and $p_{jt}$ is the natural logarithm of the stock number of citation-weighted patents. In the specification, the coefficient $\beta_2$ captures the quality premium while the coefficient $\beta_3$ is the difference in quality premium between financially constrained and unconstrained companies.

Focussing on the coefficient $\beta_2$, our results confirm that capital misallocation is prevalent among younger companies, hardware companies, capital-intensive companies and larger companies, but not among female-headed companies (Table 7 columns I–IV, respectively). The quality premium is smaller than average for young companies, hardware companies, capital-intensive companies and larger companies and bigger for female-headed companies. Young and female-headed companies also receive smaller amounts per deal. If this difference is supply-driven and investors value patents, then the difference should be reduced if those companies are innovative. We observe that dampening effect in the case of female-headed companies but not in the case of young companies.

These frictions should diminish over time for several reasons. As we documented earlier, the participation of corporate VCs, angel investors, and debt investors has risen over time and may continue to increase as these investors become increasingly concerned about climate risk. These types of investors seek to invest in younger companies with no patented ideas, that is at a very early-stage. This is either because they have a higher risk appetite and a longer investment horizon, or because they can impose an adequate compensation for the additional risk they take. Another perhaps more plausible explanation is that they cannot compete with VC investors for better deals.

Second, the abundance of capital since 2015 has driven a shift toward greater specialisation of institutional investors. This means that more information is being collected and more expertise is available to process, analyse and produce new information.

Third, as the sector matures, the proportion of young companies diminishes, and more companies progress toward follow-on growth and expansion financing. This means that as the sector matures companies interact with better-informed investors with whom they have established a relationship through repeated interactions.

Fourth, less capital is needed at later stages for companies in hardware or capital-intensive industries. This is because once a company has proven its technology and business model it can begin to access lower-growth and project capital. As a result, financial constraints ease for companies in hardware and capital-intensive technologies as they mature.

Fifth, over time the average size of companies tapping the market declines as the sector shifts toward less labour-intensive software solutions (from 836 employees on average for climate tech 1.0 companies to 310 employees for climate tech 2.0 companies).

Last, as the sector develops it attracts new talent and successful repeat founders and engineers. It also benefits from a second wave of management teams who have learned from the previous experiences and are better able to communicate about their innovation with investors and draw the benefits of patents.

Table 7: **Allocative efficiency: cross-sectional heterogeneity**

| | Ln(deal value) | | | | |
|---|---|---|---|---|---|
| | X=Young | X=Hardware | X=K intensive | X=Large | X=Female CEO |
| | (I) | (II) | (III) | (IV) | (V) |
| X | -0.583*** | 0.263 | 0.314** | 0.614** | -0.495*** |
| | (0.132) | (0.181) | (0.116) | (0.191) | (0.139) |
| Patents | 0.082*** | 0.148*** | 0.163*** | 0.143*** | 0.080*** |
| | (0.017) | (0.032) | (0.033) | (0.022) | (0.019) |
| X × Patents | -0.004 | -0.067* | -0.087*** | -0.078*** | 0.129** |
| | (0.057) | (0.034) | (0.026) | (0.018) | (0.049) |
| Ln(age) | 0.374*** | 0.554*** | 0.546*** | 0.541*** | 0.559*** |
| | (0.075) | (0.095) | (0.084) | (0.078) | (0.087) |
| Ln(number of employees) | 0.642*** | 0.632*** | 0.632*** | 0.515*** | 0.632*** |
| | (0.036) | (0.041) | (0.037) | (0.063) | (0.037) |
| Observations | 10,098 | 10,098 | 10,098 | 10,098 | 9,732 |
| $R^2$ | 0.434 | 0.430 | 0.431 | 0.436 | 0.436 |

Standard errors clustered by segment, state, and year-quarter are reported in parentheses; ***/**/* indicates statistical significance at the 1/5/10% level. The dependent variable is the log real dollar amount of capital raised in a deal. Patents is log cite-weighted active patents at the time of a deal. In column I, X is a dummy variable for companies launched less than 2 years before the deal; in column II, X is a dummy for hardware companies; in column III, X is a dummy for companies using capital intensive technologies (subsegment average deal amount¿ 50 million USD); in column IV, X is a dummy for large companies with more than 25 employees; in column V, X is a dummy for female headed companies. Bust is a dummy for the period Q4 2011–Q3 2014 and Climate Tech 2.0 for the period Q4 2014–Q4 2021. The comparison period is Climate Tech 1.0 starting from Q1 2005. All regressions include subsegment, state, and year-quarter fixed effects.

# 5 The performance of climate tech investment

This section is devoted to ex-post performance. In particular, we would like to answer the question: what is the performance of investments geared toward innovative climate tech companies? Specifically, we aim to document that a more efficient allocation of capital is associated with better performance at the company and fund level.

## 5.1 Analysis at the company level

We consider two indicators of company performance as outcome variables. These are: (i) the probability of a successful exit through an IPO or an M&A deal, and (ii) conditional on the occurrence a successful exit, the probability of achieving an outsized return. We calculate the cash-on-cash return multiple as the post-exit valuation divided by the average post deal valuations across all deals of a company weighted by amount raised per deal. Our key explanatory variable, *Eff*, is the average estimate of the efficiency of capital allocation to climate tech firm obtained from equation 1 over a company funding period and weighted by the capital raised per deal. The model is specified as follows:

$$Exit_{jt} = \lambda Eff_j + \tau t_j + \theta_s + \mu_t + \delta_i + \epsilon_{jt} \tag{5}$$

Control variables include average value-weighted funding time ($t_j$), and fixed effects for state of incorporation $\theta_s$, launch year $\mu_t$ and industry $\delta_i$.

Table 8: **Allocative efficiency and company success**

| | Exit | IPO | M&A | One bn | 5x return | 10x return |
|---|---|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) | (V) | (VI) |
| Eff (at mean value) | 0.266*** | 0.114** | 0.179** | 0.223*** | 0.155*** | 0.133*** |
| | (0.086) | (0.045) | (0.083) | (0.045) | (0.030) | (0.026) |
| Eff = 0 | 0.208*** | 0.051*** | 0.149*** | 0.044*** | 0.094*** | 0.085*** |
| | (0.050) | (0.003) | (0.056) | (0.007) | (0.008) | (0.009) |
| Eff = 0.35 | 0.280*** | 0.159** | 0.188** | 0.309*** | 0.184*** | 0.156*** |
| | (0.095) | (0.081) | (0.091) | (0.083) | (0.040) | (0.035) |
| Observations | 5,003 | 3,250 | 5,000 | 2,239 | 4,042 | 3,964 |
| Adjusted $R^2$ | 0.14 | 0.17 | 0.13 | 0.27 | 0.20 | 0.21 |

Standard errors clustered by climate tech segment are reported in parentheses; ***/**/* indicates statistical significance at the 1/5/10% level. The table shows the marginal effects. The dependent variables are dummies for successful exits. Eff is an average measure of market allocative efficiency of capital over a company funding period weighted by amounts of capital raised by the company at each funding stage. Controls include state, subsegment, launch year fixed effects, and average funding time. Sources: PitchBook Data Inc; authors' calculations.

Table 8 shows the results of our estimation using a logit model. Specifically, it shows marginal effects and standard errors clustered by segment, with the latter reported in parentheses. Companies that were funded in a more efficient market are more likely to succeed. Importantly since the regression model is non-linear this cannot be deduced simply from the reported marginal effects; it is obtained by evaluating the effect at *Eff* =0 and at *Eff* =0.35 and taking the difference. An increase in *Eff* from 0 (as for climate tech 1.0 investments) to 0.35 (as for climate tech 2.0 investments; see Figure 7) is associated with a seven-percentage point increase in the probability of experiencing a successful exit (column I), an 11-percentage point increase in the probability of an IPO (column II) and a four-percentage point increase in the probability of M&A (column III). These effects correspond to an almost one standard deviation increase in the probability of an IPO and a 10 percent of a standard deviation increase in the probability of an M&A deal (see Table A4 in the Appendix). The effect on the probability of experiencing an M&A deal does not get much bigger if we exclude buyouts – our results indicate an increase of one percentage point only.

Finally, successful exits are more likely to yield outsized returns. An increase in *Eff* from 0 to 0.35 causes a 26-percentage point increase in the probability of an exit over $1 bn (column IV), a nine-percentage point increase in the probability of returning 5x more than the invested amount (column V) and a seven-percentage point increase in the probability of returning 10x more than the invested amounts (column VI).

### 5.2 Analysis at the fund level

At the fund level we measure performance by the internal rate of return (IRR). This is the discount rate of all future cash flows that produces a net present value of zero. Alternatively, we use the total value to paid-in capital (TVPI) ratio. This is simply the total estimated value of an investment portfolio divided by the total capital invested.

We only observe the performance of the overall portfolio of VC funds invested in climate tech and not the performance of their individual climate tech investments in isolation. However, we observe the weight of climate tech investments in their portfolio. Therefore, to identify the effect of changes in the allocative efficiency of climate tech investments on the performance of climate tech investments specifically, we interact efficiency (*Eff_VC*) with the weight of climate tech investments in a fund portfolio (*Exposure*). The effect of an efficient allocation of climate tech investments on overall fund performance should then be higher for funds that are more exposed to climate tech. Our main explanatory variable *Eff_VC* is the average estimated $\beta$ obtained from equation 1 over a fund investment period and restricted to the sample of VC deals. Our specification reads:

$$\begin{aligned} IRR_{ivs} = {} & \alpha_1 Eff\_VC_i + \alpha_2 Exposure_i + \alpha_3 Eff\_VC_i * Exposure_i + \\ & \alpha_4 X_i + \gamma_v + \pi_s + \epsilon_{ivs} \end{aligned} \tag{6}$$

where the subscript $i$ indicates the fund, $v$ a specific vintage and $s$ the state of incorporation. The coefficient of interest is $\alpha_3$. Following Kaplan and Schoar (2005) we control for a number of factors ($X_i$): fund size measured by the log of total assets under management, vintage year fixed effect ($\gamma_v$), state of incorporation fixed effects ($\pi_s$) and the fund log sequence number as a proxy for the fund's experience in the market. Standard errors are clustered by vintage year and state of incorporation.

Note that of the 1,656 VC funds in our sample only about 18% report performance data, but these funds represent 40% of committed capital. There is therefore a bias toward larger funds. Large funds tend to perform better than small funds (Kaplan and Schoar (2005)) potentially inducing an upward bias on the performance of funds with returns. For our purpose however the selection bias should be small for two reasons. First, company size is not correlated with our fund-specific measure of market efficiency or the exposure of a fund to climate tech. Second, equation 6 controls for fund size.

The results of equation 6 are reported in Table 9. The coefficient $\alpha_2$ on exposure is negative. This means that, on average, climate tech investments underperform other investments. This can be attributable in part to renewable energy prices exceeding fossil fuel prices over our sample period. At the same time the coefficient $\alpha_3$ on the interaction term $Eff\_VC \times Exposure$ is positive and significant; this means that returns are higher when climate tech investments are geared toward innovative companies. For example, if *Eff_VC* goes from 0 to 0.35, as observed from climate tech 1.0 to climate tech 2.0, then the contribution of climate tech investing to a VC funds' performance increases by almost 5% of one standard deviation for IRR and TVPI (see Table A4 in the appendix), respectively, assuming the fund has an average exposure to climate tech. The results are not much different if we use a measure of performance relative to a benchmark.

Table 9: **Allocative efficiency and fund performance**

| | Internal rate of return | Total value to paid in |
|---|---|---|
| | (I) | (II) |
| Eff_VC | -24.469 | -1.535 |
| | (35.382) | (1.337) |
| Exposure | -0.392** | -0.022** |
| | (0.087) | (0.004) |
| Eff_VC × Exposure | 1.896** | 0.090* |
| | (0.537) | (0.030) |
| Ln(AUM) | -0.127 | 0.023 |
| | (0.281) | (0.033) |
| Ln(sequence) | -1.468* | -0.096** |
| | (0.613) | (0.024) |
| Observations | 284 | 301 |
| $R^2$ | 0.484 | 0.344 |

Standard errors clustered by vintage, fund type, and state are reported in parentheses; ***/**/* indicates statistical significance at the 1/5/10% level. Eff-VC is the average allocative efficiency of VC capital over a fund's investment period. Exposure is the proportion of a Climate tech investments in a fund portfolio. Additional control variables include vintage year- and state of incorporation fixed effects. Sources: PitchBook Data Inc; authors' calculations.

# 6 Conclusions

Climate technologies are at a double disadvantage relative to more polluting incumbent technologies: they attract less private capital because they are less mature, and their positive externalities on climate change are un- or under-priced. Both factors induce greater information asymmetry between entrepreneurs and investors. Furthermore, polluting incumbent technologies, such as advanced oil and gas, cement, livestock and transportation technology benefit from not having to internalise their negative externalities (Aghion et al. (2016)). Clearly, introducing carbon taxes and other policies to curb GHG emissions is the most direct means to internalise these externalities, in line with the "polluter pays" principle. Beyond this, research subsidies and taxes could be used to influence the direction of research toward clean technologies until clean technologies become competitive (Acemoglu et al. (2012, 2016)). Howell (2017) provides empirical evidence that R&D

subsidies are more effective at increasing innovation in clean energy technologies than in dirty conventional energy technologies. They also crowd-in private capital by transforming green projects from negative to positive net present value. This turns them into privately profitable investments. However, one condition for public grants to be effective is to target companies that are promising but underserved by private investors.

In this paper, we have studied how private and public capital is allocated to climate tech companies. Our analysis reveals that the market allocates more capital to technologies that have a higher potential to curb $CO_2$ emissions. Further, following the massive losses recorded on climate tech investments in the 2000s and early 2010s, the leading investors in the market – venture capitalists – have significantly reallocated capital toward established companies with already patented ideas. This trend is accelerating as the sector matures and offers investment opportunities that better match the risk, return and time profile of traditional VC capital. We further show that the rebalancing of VC capital toward companies with more mature technologies is associated with a higher rate of successful exits and higher private returns.

The drawback of such rebalancing is that innovative companies at an early stage face more severe financial constraints unless alternative investors (willing to take the additional risk) step in. Our analysis shows that more patient capital from private investors has progressed significantly since 2011. These types of investors have distinct investment strategies, as they do not have the time constraints of VCs and look to realise returns in the long run. Hence, they target young companies at a very early stage, including at the founding stage. However, they are typically capital-constrained, and still represent a modest fraction of the total capital allocated to the sector. Helping to steer more capital towards young and innovative entrepreneurs requires more and better targeted government subsidies. Indeed, our analysis shows that there is room to re-address allocation of government grants towards companies under more stringent restrictions on access to capital. Boosting innovation in clean technologies requires redirecting government subsidies towards promising companies that are rationed by private investors. In this way, public policy can contribute towards the technological breakthroughs that are needed to mitigate climate change.

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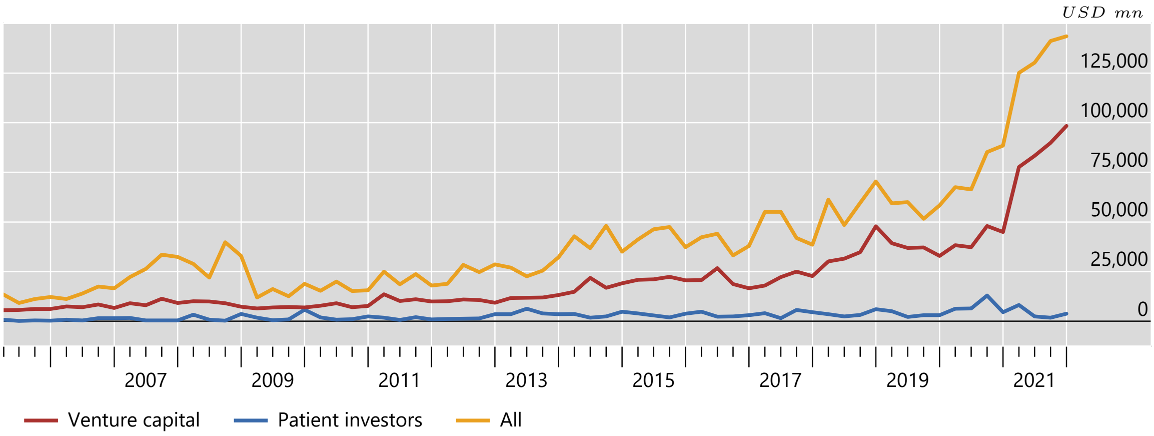
# Online appendix

Figure A1: **Distribution of capital by source**




This graph represents the composition of capital invested in climate tech companies over time by source and all sources included. Patient investors include corporate VCs and angels. Sources: PitchBook Data Inc; authors' calculations.

Table A1: **Composition of the dataset**

| Segment | Subsegment | Technologies | ERP 1.5°$C$ | ERP 2°$C$ | TRL |
|---|---|---|---|---|---|
| Built Environment | Construction Tech | Dynamic glass/green & cool roofs/insulation | 16.24 | 20.07 | 6 |
| | Energy Efficiency | LED/building automation/district heating/high-performance glass | 24.55 | 35.03 | 5 |
| | Heating/Cooling | High-efficiency heat pumps/alternative refrigerants | 46.77 | 57.8 | 6 |
| | Water | Water distribution efficiency/low flow fixtures/water reuse/purification | 1.54 | 2.38 | 9 |
| Carbon Tech | Carbon Accounting | ESG reporting-monitoring//carbon neutral footprint/carbon tracking | 11.816 | 28.696 | 7 |
| | Carbon Capture & Storage | Direct air capture/landfill methane capture/methane leak management | 29.72 | 29.81 | 6 |
| | Carbon Fintech & Consumer | InsurTech/IoT/AI/machine learning/blockchain/impact investing | 85.78 | 85.78 | 8 |
| | Carbon Sequestration | Land & ocean sinks | 70.71 | 123.22 | 7 |
| | Carbon Utilization | Biochar production/methane digesters/converters | 7.38 | 10.05 | 3 |
| Clean Energy Generation | Nuclear | Nuclear fusion | 3.17 | 3.64 | 5 |
| | Ocean & Hydro | Ocean wave & tidal | 2.92 | 4.01 | 5 |
| | Solar | solar photovoltaics/concentrated solar power | 85.48 | 197.96 | 7 |
| | Thermal | geo-thermal power | 6.15 | 9.17 | 6 |
| | Waste | biomass/ethanol/cleantech power/plasma/bioenergy | 10.36 | 11.69 | 8 |
| | Wind | offshore-onshore turbines/micro turbines/drones | 57.26 | 153.56 | 7 |
| Grid Tech | Analytics | AI/machine learning/big data/5G/blockchain | 80.7 | 117.105 | 7 |
| | Battery Technology | Redox flow batteries/Li-ion batteries | 9.27 | 14.47 | 8 |
| | Energy Storage | CAES/LAES/volcanic rock/flywheel/pumped hydro storage | 142.74 | 351.49 | 7 |
| | Grid Management | Digital technologies/refrigerant management/blockchain | 170.24 | 302.99 | 7 |
| | Hydrogen | Fuel cells/ | 60 | 60 | 5 |
| | Smart Grid | small hydropower/micro wind turbine/smart thermostat/smart inverter | 20.045 | 41.45 | 9 |
| Electric Transportation | Aviation | Efficient aviation/zero-emission planes | 5.29 | 5.82 | 4 |
| | EV Battery Tech | Battery technologies | 9.27 | 14.47 | 5 |
| | EV Infrastructure | Vehicle charger/station | 13.41 | 23.67 | 6 |
| | Maritime | Efficient ocean shipping | 6.72 | 9.83 | 7 |
| | Road Consumer | Electric/autonomous/hybrid cars/high speed rail | 3.67 | 5.35 | 8 |
| | Road Industry | Electric trucks/rails/bus/fleet | 9.15 | 10.97 | 8 |
| Food Systems | Ag BioTech | Biotechnologies/drought resistant crops | 19.43 | 18.71 | 7 |
| | Alternative Farming Methods | Improved aquaculture/improved cattle feed/improved rice production | 88.15 | 147.41 | 9 |
| | Alternative Protein | Glut-free/meat substitute/plant-rich diet | 78.33 | 103.11 | 9 |
| | Cultured Meat | Cultivated meat | 29.95 | 75.48 | 6 |
| | Indoor Farming | vertical farming/green houses | 88.5 | 102.2 | 7 |
| | Robotics | autonomous tractors/robot picking/robotic harvesting/robotic milking | 9 | 9 | 7 |
| Industry | Chemicals | plastic recycling/efficient nutrient use/reduced single-use plastic | 5.62 | 9.57 | 7 |
| | Fuel Alternatives | biogas/biofuel | 36.03 | 86.04 | 6 |
| | Lithium Battery Recycling | Lithium recycling | 10.63 | 11.29 | 3 |
| | Manufacturing | Recycled paper/plastics/garment/cotton | 27.31 | 35.34 | 7 |
| | Materials | Alternative cement/bioplastic | 15.07 | 26.34 | 6 |
| | Mining Tech | Robotic/autonomous drilling /digital tech/automation/remote centres | 23 | 23 | 6 |
| Land Use | Climate/Earth Data | Satellite mapping-imagery/big data/digital tech/flood prediction | 47.99 | 72.62 | 8 |
| | Fertilizer Alternatives | Irrigation/Rice intensification/nitrogen/composting/microbiome | 7.93 | 19.39 | 9 |
| | Forest Carbon Tech | Tree intercropping/tree plantation/tropical forest restauration | 91.52 | 144.63 | 9 |
| | Land Use Management | Seafloor protection/coastal wetland protection/peatland protection | 40.1 | 61.08 | 8 |
| Mobility Solutions | Autonomous | Sensing tech/HD maps/sensor fusion/path planning/drive by wire | 10.55 | 57 | 6 |
| | Green Hydrogen | electrolysis renewables/fuels with CCUS | 87 | 87 | 5 |
| | Micro Mobility | Electric bicycle/walkable cities/motorcycle | 1.39 | 1.55 | 7 |
| | Shared Mobility | Carpooling/carsharing | 9.06 | 11.07 | 9 |
| | Smart Infrastructure | Public transit/telepresence/e-mobility/scooter rental-sharing | 5.47 | 7.94 | 5 |

This table reports the segments and subsegments covered by our data and a non-exhaustive list of technologies by subsegment. Then it reports averages of the emission reduction potential (ERP) of technologies belonging to each subsegment by 2050 for a 1.5° C and a 2°C scenario reduction, respectively. The last column gives that average technology readiness level (TRL). Sources: PitchBook Data Inc; Project Drawdown, WEF, ENSTOE, and IEA, authors' calculations.

Table A2: **Pairwise correlations**

| | (I) | II) | (III) | (IV) | (V) | (VI) | (VII) | (VIII) | (IX) |
|---|---|---|---|---|---|---|---|---|---|
| (I) Log real deal amount | 1 | | | | | | | | |
| (II) Log(cite-weighted patents) | 0.321 | 1 | | | | | | | |
| (III) Patent dummy | 0.223 | 0.588 | 1 | | | | | | |
| (IV) Log(age) | 0.326 | 0.267 | 0.136 | 1 | | | | | |
| (V) Log(number of employees) | 0.558 | 0.336 | 0.199 | 0.356 | 1 | | | | |
| (VI) Capital intensity | 0.154 | 0.031 | -0.010 | 0.000 | 0.101 | 1 | | | |
| (VII) Young company dummy | -0.258 | -0.207 | -0.148 | -0.677 | -0.175 | -0.009 | 1 | | |
| (VIII) Hardware industry dummy | 0.019 | 0.033 | 0.039 | 0.075 | -0.026 | 0.208 | -0.045 | 1 | |
| (IX) Female CEO dummy | -0.142 | -0.072 | -0.081 | -0.085 | -0.117 | -0.066 | 0.061 | -0.021 | 1.000 |

This table reports correlations between the variables used in the regression analysis. Patent dummy takes value one when a company owns are least one patent at the time of a deal. Company age is calculated as the number of years elapsed since inception. Capital intensity of an industry to which a company belongs is measured by the average deal amount in that industry. A young company is at most 2 years old. Sources: PitchBook Data Inc; authors' calculations.

Table A3: **Robustness checks**

| | Ln(deal value) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) | (V) | (VI) | (VII) |
| Patents | 0.019 | 0.011 | 0.020 | | | | |
| | (0.020) | (0.019) | (0.021) | | | | |
| Bust × patents | 0.049* | 0.057** | 0.054** | | | | |
| | (0.025) | (0.024) | (0.023) | | | | |
| Climate Tech 2.0 × patents | 0.112*** | 0.109*** | 0.104*** | | | | |
| | (0.032) | (0.022) | (0.024) | | | | |
| Ln(age) | 0.509*** | 0.514*** | 0.479*** | 0.579*** | 0.550*** | 0.544*** | 0.514*** |
| | (0.073) | (0.086) | (0.086) | (0.073) | (0.087) | (0.070) | (0.094) |
| Ln(number of employees) | 0.650*** | 0.620*** | 0.642*** | 0.656*** | 0.647*** | 0.678*** | 0.669*** |
| | (0.036) | (0.035) | (0.032) | (0.039) | (0.036) | (0.038) | (0.034) |
| Patent dummy | | | | -0.110 | -0.131 | -0.062 | -0.082 |
| | | | | (0.170) | (0.178) | (0.120) | (0.122) |
| Bust × patent dummy | | | | 0.244 | 0.267 | 0.220* | 0.250** |
| | | | | (0.156) | (0.167) | (0.116) | (0.100) |
| Climate Tech 2.0 × patent dummy | | | | 0.631*** | 0.618*** | 0.631*** | 0.616*** |
| | | | | (0.130) | (0.111) | (0.147) | (0.099) |
| Observations | 10,098 | 10,098 | 10,098 | 10,098 | 10,098 | 10,098 | 10,098 |
| $R^2$ | 0.417 | 0.400 | 0.383 | 0.428 | 0.396 | 0.412 | 0.378 |

Standard errors clustered by segment, state, and year-quarter are reported in parentheses; ***/**/* indicates statistical significance at the 1/5/10% level. The dependent variable is the log real dollar amount of capital raised in a deal. The variable Patents is log cite-weighted patents at the time of a deal. Patent dummy takes value one if a company owns at least one patent at the time of the deal. Bust is a dummy for the period Q4 2011–Q3 2014 and Climate tech 2.0 for the period Q4 2014–Q4 2021. The comparison period is Climate Tech 1.0 starting from 2005-Q1. All regressions include subsegment, state, and year-quarter fixed effects. Sources: PitchBook Data Inc; authors' calculations.

Table A4: **Descriptive statistics**

| | No obs | Mean | St dev | Min | Max |
|---|---|---|---|---|---|
| Panel A: Emission reduction potential analysis | | | | | |
| ERP | 10,098 | 52.593 | 55.096 | 1.390 | 170.240 |
| TRL | 10,098 | 6.922 | 1.220 | 3 | 9 |
| Age | 10,098 | 7.332 | 12.471 | 0 | 164 |
| Panel B: Allocative efficiency and company success analysis | | | | | |
| Exit | 5,003 | .208 | .406 | 0 | 1 |
| IPO | 5,003 | .021 | .143 | 0 | 1 |
| M&A | 5,003 | .187 | .390 | 0 | 1 |
| One bn | 4,327 | .020 | .139 | 0 | 1 |
| 5x return | 4,327 | .065 | .246 | 0 | 1 |
| 10x return | 4,327 | .060 | .238 | 0 | 1 |
| Panel C: Allocative efficiency and fund performance analysis | | | | | |
| IRR | 284 | 19.315 | 15.358 | -2.780 | 41.100 |
| TVPI | 301 | 1.827 | 0.730 | 0.890 | 2.860 |

The sample includes climate tech deals for the period 2005–2021. Sources: PitchBook Data Inc; authors' calculations.

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