Innovating to Net Zero: Can Venture Capital and Startups Play a Meaningful Role?*

Silvia Dalla Fontana[1] and Ramana Nanda[2]

[1]University of Lugano and Swiss Finance Institute
[2]Imperial College London and CEPR

July 2022

ABSTRACT

We show that patents related to clean energy generation & storage, changes to industrial production, and carbon capture & sequestration (CCS) – where breakthroughs are seen as being particularly critical to addressing climate change – are more than twice as likely to cite fundamental science than other Net-Zero patents, highlighting their 'deep tech' focus compared to innovation in areas such as energy efficiency, ICT and transportation. Interestingly, VC-backed firms have patents that are significantly more likely to cite fundamental science compared to other firms, including in these 'deep tech' sectors. Net-Zero related patents granted to VC-backed firms are also three-to-five times more likely to be among the group of highest cited patents, indicating the distinctive nature of innovations commercialized by VC-backed firms. However, VC still accounts for a tiny share of all patents related to Net Zero, and the patenting focus of VC-backed firms has shifted away from 'deep tech' in recent years. We discuss the growing literature on the potential frictions facing the commercialization of science-based deep tech innovations and also touch on potential solutions that might enable venture capital to play a more meaningful role in supporting the transition to Net Zero in the coming decades.

Key words: Venture Capital, Net Zero, Financing Deep tech, Innovation.

JEL classification: Q55, Q56, G24, G30, G32.

*Parts of this chapter draw extensively on work by Nanda et al. (2014),Nanda and Rhodes-Kropf (2016),Nanda (2020) and Janeway et al. (2021). We thank Ben Jones, Josh Lerner and participants at the May 2022 NBER PIPE conference for helpful suggestions.

1 Introduction

As the consequences of rising global temperatures and related climate change are becoming more apparent, a growing number of countries – covering over 70% of global CO_2 emissions – have committed in recent years to work towards achieving Net-Zero emissions by 2050, in an effort to limit long-term increase in global temperatures to 1.5° C. Despite this progress, a seminal report released by the International Energy Agency (IEA, 2022) notes that about half the projected CO_2 reductions that will be required to achieve Net Zero by 2050 will depend on technologies that are currently not commercially viable– highlighting the critical need for breakthrough innovations to mitigate the impacts of climate change.

In this chapter, we discuss the prevalence and focus of U.S. innovation related to achieving Net-Zero targets, with a particular focus on the potential role played by Venture Capital-backed startups. We identify patents related to the mitigation of climate change using tags developed by the the Cooperative Patent Classification (CPC).[1] The classification scheme was put together with the help of experts in the field, including the Intergovernmental Panel on Climate Change (IPCC), and was developed to tag technologies with certain attributes rather than to replace the classification of technologies themselves. As described in Table I, the Y02 subclasses include areas related to specific clean energy technologies, but also technologies related to energy efficiency, transportation, industrial production and carbon capture and sequestration –that have the potential to mitigate climate change through lowering green house gas in the atmosphere. Together, these technologies account for about 6.5% of all utility patents in the USPTO between 2000 and 2020, but have grown at over twice the rate of other patents in the USPTO since 2010.

The IEA report (IEA, 2022) notes that breakthrough innovations are likely to be particularly important in areas such as energy generation & storage, industrial production and in carbon capture & sequestration, given their current contribution to CO_2 emissions relative to what is required by 2050. Using a measure of a patent's reliance on fundamental science developed by Marx and Fuegi (2020), we show that patents in these sectors tend to cite fundamental science much more intensively than other sectors such as energy

[1] The Cooperative Patent Classification is a patent classification system, which has been jointly developed by the European Patent Office and the United States Patent and Trademark Office.

efficiency, ICT and transportation. We refer to these three more science-intensive sectors as the subset of Net-Zero patents that are 'deep tech'.

The fact that these deep tech sectors coincide with the areas that require the biggest breakthrough innovations is important in light of growing evidence that large corporations have pulled back considerably from fundamental innovation in recent years (Arora et al., 2018, 2020). Moreover, a large body of academic research has highlighted how the organizational form associated with the commercialization of innovations can have first order effects on the degree to which radical versus incremental innovations are brought to market (Akcigit and Kerr, 2018). The bureaucratic organizational structure and related incentives in large firms are often not conducive to radical innovations (Kortum and Lerner, 2000). Moreover, large corporations often have weaker incentives to commercialize technologies that compete with core lines of business (Reinganum, 1983, Cunningham et al., 2021). This suggests an important role for 'deep tech' inventions emerging from universities and the related importance of sources of finance such as Venture Capital to help support their commercialization.

Consistent with this view, we find that patents associated with mature firms have the lowest citations to science, while VC-backed startups, which tend to be the most science-intensive on average, have over three-times the number of scientific citations compared to mature firms. In addition, when examining the influence of patents, we find that Net Zero patents granted to VC backed startups are three to six times more likely to be in the top percentile of patents in terms of citations received, when compared to USPTO patents granted to mature firms in a same technology class and granted in the same year. This higher influence of VC-backed patents compared to mature firms within Net Zero patents is even larger than the differential identified by Howell et al. (2020) in their analysis of VC-backed patenting in general.

Despite the greater influence and scientific reliance of VC-backed patents which are likely to be of particular relevance in deep tech sectors, we nevertheless also note that VC-backed patents comprise under 3% of all Net-Zero patents and moreover, have disproportionately grown in non-deep tech areas such as energy efficiency and transportation in recent years. In Sections 3 and 4, we discuss potential frictions and possible solutions related to the commercialization of climate-related deep tech that might enable venture capital-backed startups to play a more meaningful role in supporting the transition to Net-Zero in the coming decades.

2 Innovations related to Net-Zero

2.1 Identifying Net-Zero Patents

We focus on patents granted by the USPTO from 2000 and 2020, restricting the analysis to utility patents.[2] To identify innovations related to Net-Zero, we use a novel classification scheme that is part of the Cooperative Patent Classification (CPC) System. The CPC classification is the result of a partnership between the European Patent Office (EPO) and the USPTO that was implemented in 2013. The aim of this project was to harmonize the different classification systems in place, and to bring the best practices from both Offices together [3]. The Y02 category that identifies environmental technologies was first introduced in January 2013 [4]. More sub-classes of that same category were then added in 2015 and 2018, and the scheme is now considered to be complete, with 8 main categories, that are reported in Table I.[5]

The aim of this categorization is to extend the reach of patents related to 'green' technologies to a wider range of stakeholders, including non experts. As such, the Y02 categorization works as a separate class applied by the patent office, that is considered additional to standard classifications of technology classes. An important feature of this categorization is that it spans many different fields and it is able to capture innovations in both mitigation and adaptation technologies (Haščič and Migotto, 2015). This allows for a compelling way to classify ICT and related energy efficiency technologies that are typically harder to classify in terms of their contribution to climate change mitigation.[6]

[2]We obtain patent data from PatentsView.org, a platform that provides data from the United States Patent and Trademark Office (USPTO). We only keep patents for which we observe information on: the date it was applied for, the date it was granted, the patent title, the organization it was assigned to, the type of organization and its CPC technology classification. With these restrictions, our sample comprises 90.3% of the 5,367,164 patents granted over this period.

[3]https://www.cooperativepatentclassification.org/about

[4]https://www.uspto.gov/about-us/news-updates/uspto-and-epo-announce-launch-cooperative-patent-classification-system

[5]Cohen et al. (2020) use the same classification system to examine patenting differences between mature publicly-traded firms to the link between the ESG-ratings of these firms and their innovation. Our analysis focuses on the universe of firms regardless of whether they are publicly traded.

[6]In the CPC tagging, a patent can belong to multiple Y02 classes. However, this happens for a minority of patents. 293,278 out of 356,996 (82.2%) belong to one group only. In the case of patents being assigned to more than one Y02 class, we proceed to allocate each patent to a unique group as follows: first, we sum the number of subcategories for each group. We allocate the patent to the group that has the highest number of sub-classes with the rationale that a patent with more tags in one group suggests that this group is the most relevant for the patent. This procedure is applied to 20,191 patents (6% of total). Second, for patents that do not have a prevalent sub-class, we allocate them to one group after considering the different combinations of sub-classes. When carbon captures technologies

As shown in Table I, the classification system of climate change technologies include innovations related both to climate change mitigation and to adaptation. A deeper examination of the adaptation technologies tagged in Y02A shows that they are largely related to technologies helping to address growing threats of vector-borne, fly-borne, or waterborne diseases whose impact is exacerbated by climate change. Y02W is focused on waste management and wastewater. While technologies in these two groups can play a role in climate change, they are less related to addressing the specific goals related to reaching Net Zero targets, so we exclude them from our analysis.

For our analysis we therefore focus on the six main categories related to Net-Zero. Panel A of Figure I reports the number of Net-Zero patents granted by the USPTO from 2000 to 2020 in relation to all other USPTO patents, where Net-Zero patents refer to the six categories of Y02 patents noted above that are related to achieving Net-Zero targets. As can be seen from Panel A, Net-Zero patents constitute a small share of total patents in the USPTO, but have grown from 4% in 2000 to 8% in 2020.

Panel B reports the growth of Net Zero patents and all other patents relative to the baseline year 2000. As can be seen from Panel B, Net-Zero patents have grown over twice as fast as other patents in the USPTO, with a large inflection emerging in 2010. The inflection seen in 2010 could represent changing fundamentals driving an increase in Net-Zero innovation, or could be driven at least in part by the new classification being implemented in those years leading to a greater focus on these technologies.[7]

We turn next to validating the CPC classification using text taken from the titles of all Net Zero patents and identifying distinctive words associated with patents in each category. The distinct words associated with each category are derived using a Term Frequency - Inverse Document Frequency (TF-IDF) procedure, where the frequency of each word in a document (TF) is weighted by the inverse of the frequency across all

are combined with energy efficiency classes, this is usually because GHG obtained with carbon capture can be also used for other purposes. In this case we consider carbon capture as the main technology group. When technologies related to transportation, efficiency in buildings and ICT are combined with classes such as energy generation, this is because they are related to technologies that improve energy efficiency, and make use of energy from renewable sources, in this case we keep the main intended use of the technology (home appliances, car engines and batteries, etc.) as the main technology group. Lastly, when the sub-class of energy generation is combined with waste, it is because these are technologies related to fuels obtained from waste, so we consider them as generation technologies. Overall this second step is applied to 41,694 of patents, which represents 11.7% of total.

[7]Although the classification was applied retrospectively, it is possible that it was more effective for identifying patents applied for from that moment on.

documents in the corpus (IDF).[8] Panels A to F of Figure II report word clouds of the content of patents titles of the six Net-Zero categories. As can be seen from Figure II, the types of keywords emerging from the patent titles in each of these categories appear intuitive, which is reassuring in terms of the quality of the classification. Figure III shows the total trend of patents in each of these categories from 2000 to 2020. In relative terms the highest growth was reported in the category of mitigation technologies related to household appliances and ICT. Column 1 of Table II reports the precise number of Net Zero patents issued in each category over the 2000 to 2020 period, ranging from just over 4,000 patents for GHG capture to nearly 110,000 patents related to generation and storage.

2.2 'Deep Tech' Sectors that rely more on fundamental science

As noted in the introduction, one of our goals is to understand differences in the Net-Zero sectors in terms of their reliance on fundamental science as this is likely to impact the commercialization frictions they face. The word clouds reported in Figure II provide an intuitive sense that the first three categories of renewable energy generation & storage, carbon capture & sequestration and industrial production are likely to be much more reliant on fundamental science relative to the the categories related to energy efficiency and transportation. However, we also validate this intuition using data provided by Marx and Fuegi (2021), that identifies citations that a patent makes to scientific papers.[9]

Column 2 of Table II reports the share of patents in each category that cites at least one scientific paper. As can be seen from the Table, the first three rows correspond to sectors with a much greater reliance on science. Between a third and half of all patents cite science in these sectors, compared to 27% for all utility patents over the 2000-2020 period. Columns 3-8 report the means and quantiles of scientific paper citations of these patents, conditional on citing at least one science paper. They reinforce the stark difference in reliance on science across these categories. Not only do the first three sectors have

[8] In our dataset, each list of patents titles belonging to a certain category is a separate document, and the corpus is composed by all documents. We start by cleaning the text of titles and removing all punctuation and special characters, and use lemmatization to group together the inflected forms of a word in order to be analysed as a single term. We then apply a list of stop-words to be excluded from the frequency count. The list includes standard English stop-words, as well as USPTO stop-word lists that are specific for technical language processing. With TF-IDF we then add a list of stop-words created from terms that are recurrent in all documents of the corpus. The frequency of the remaining words is then adjusted for how rarely a word is used in the corpus.

[9] The authors link data from the USPTO to a broad set of scientific articles not limited by industry or field. Their algorithm can capture up to 93% of patent citations to science with an accuracy rate of 99% or higher.

a much greater propensity to cite science at the extensive margin, but have a significantly greater intensity of reliance on science, as can be seen by the larger number of scientific papers cited at all points above the 25th percentile. As noted before, these deep tech categories coincide with the sectors where we need some of the most important breakthrough innovations to reach Net Zero targets. We return to this fact and the implications for policy in the subsequent sections.

2.3 The Role of Venture Capital

We turn next to understand differences in Net Zero patenting by the type of assignee. To do so, we first distinguish firms from other assignees such as universities, government labs and individuals by supplementing the USPTO classification of assignees (as reported in the disambiguated assignee data) with text analysis to better distinguish institutions, hospitals and universities from the company or corporation group.[10]

Within firms, we further distinguish between mature firms, young firms and those backed by venture capital. We define young firms as those whose first patent was granted less than 10 years before the focal patent. In other words the same firm could have some of its patents categorized as being associated with a young firm indicator and others being associated with mature firm indicator. Finally, we merge the patent data with the Refinitiv VentureXpert database, following a similar procedure to Bernstein et al. (2016) in order to identify venture capital-backed startups.[11]

In light of the fact that corporations have been documented to be pulling back from fundamental research in recent years (Arora et al., 2018, 2020), we turn next to looking specifically at firm-type differences in Net Zero patents, given the particular importance

[10] This is performed taking into account that inventors are international, so the same word that indicates for example a university, has to be considered in different languages.

[11] We start by matching each standardized name of a company in VentureXpert with standardized names from the USPTO dataset: if an exact match is found, this is taken to be the same company and removed from the list. For the remaining companies, we use a fuzzy matching technique that gives a similarity score to matches of stem names weighted by the inverse frequency of use of each word in the names list. If a similarity score higher than 85% is found, we combine this information with other identifying information, such as founding dates and patents grant dates, and standardized city/nation combination. In the overall sample of international startups we identify 18,987 startups that have at least one patent granted by the USPTO, this is approximately 20% of the overall VentureXpert dataset of VC-backed startups and this ratio is in line with other papers matching these two datasets. As we want to identify innovations that are in the portfolios of VC and not all innovations belonging to companies that were funded by VCs many years beforehand, we apply two more restrictions: first, we define a patent to be VC-backed if it was applied for between the first and last round of financing by VC funds. Second, we restrict patent level that indicates if a patent is applied for within 10 years since the first patent was issued by that same firm.

of deep tech innovations in order to achieve Net Zero targets. As seen in Table III, mature companies account for about two-thirds of the Net Zero patents granted between 2000 and 2020. A further fifth is accounted for by 'young' firms. VC-backed firms account for just under 3% of Net Zero patents. Universities, government labs and individuals account for the balance. Columns 3-8 look at variation in the share of these patents by the different Net Zero sectors. Generation and Storage accounts for the largest relative share of patents for all assignees. However, it can be seen that while all the other assignees have 40-50% of their Net Zero patents in this category, mature companies have a relatively smaller 30% share in generation and storage. In comparison, mature companies have a much larger relative share of patents related to mitigation in Transport. Energy Efficiency in buildings and ICT account for between 30% and 35% of patents for all the firms. GHG capture has a very small share of patents across all assignees, with the greatest relative share coming from universities, government labs and individuals.

Looking at the sum of shares for Deep Tech patents (columns 3-5) vs. Non Deep Tech (columns 6-8) for different assignees in Table III, it can be seen that Deep Tech constitutes a larger share of VC-backed firms' overall patenting (60%), compared to young firms (55%) and mature firms (44%). In Table IV, we document the degree to which patents granted to different assignees rely on fundamental science, broken down by whether or not the patent is in one of the three deep tech categories. The difference between the average number of scientific citations between Deep Tech and non Deep Tech for all assignee groups is consistent with the pattern documented in Table II. However, it is also striking that VC-backed firms are much more likely to cite fundamental science relative to firms in general. This is driven by both the extensive and intensive margin, as well as the fact that (as seen in Table III), VC-backed firms have a larger share of deep tech patents among the set of patents that they have been granted.

Another way of examining differences in nature of patenting by assignees is to look at the impact of these patents through their citations. In Table V, we report the share of patents granted to each type of assignee that are in the top (10 and 1) percentiles in terms of citations received, relative to all other patents granted in the same year across the entire USPTO patent database. The reason for looking at the right tail of citations is that some patenting is 'defensive'. Looking at the most highly cited patents gives a better indication of the degree to which there is a pattern in terms of the firms where the most influential patents are being developed. Given the large share of patents comprised by these assignees, we see that Net-Zero patents filed by other – particularly mature –

firms are about proportional to what might expect at random, albeit a bit less influential. These results are consistent with mature firms focusing more on incremental, sustaining innovations. On the other hand, and consistent with the findings of Howell et al. (2020), we find that VC-backed startups are disproportionately likely to have top cited patents. They are almost three times more likely than random to have Net Zero patents that are in the top 10% of citations and almost 5 times times more likely to have patents in the top 1% of citations. Given the role that Venture Capital can play in stimulating breakthrough innovation (Kortum and Lerner, 2000, Bernstein et al., 2016, Lerner and Nanda, 2020), these results suggest that VC has the potential to play an increasingly important role in helping to drive the breakthrough innovations needed to achieve Net Zero targets.

Despite the outsized impact the VC-backed patents appear to have among Net Zero patenting, one potential limitation of Venture Capital's impact is the small number of firms and Net Zero patents it is associated with. However, this is equally true of VC-backed innovations in general and yet VC-backed firms are associated with some of the most innovative, transformational and valuable firms in the world (Lerner and Nanda, 2020). Of potentially greater concern is that fact that, following a brief increase during a boom in venture financing for renewable energy startups (Nanda et al., 2014, Popp et al., 2020), Venture Capital funding within Net Zero is increasingly associated with non-deep tech patents. Figure IV shows that while venture capital-backed startups continue to dominate mature firms in terms of the share of deep tech patenting in Net Zero, the share has declined from over 70% in 2012 to about 55% in 2020.

3 Potential Frictions in Financing Deep Tech

Venture Capital investment in the US – encompassing all investments, not just those related to Net Zero – has grown substantially since the early 2000s. The number of startups doubled over this period and the amount of capital being invested has risen more than five-fold since the early 2000s. However, as Lerner and Nanda (2020) note, this growth has not been uniform. It has come disproportionately from sectors such as IT software and related services such as consumer internet, enterprise software and media and communication. Hardware, Energy, materials, and resources combined accounted for about 10% of capital invested by VCs in 2020, falling from a high of 40% in earlier part of the sample. To some extent, these ebbs and flows of funding across sectors reflect technology life cycles, the huge wave of application-related innovations made possible by the Internet revolution in the late 1990s, and the subsequent rise of cloud computing in the mid-2000s (Nanda, 2020). Nevertheless, growing academic research has begun to articulate certain aspects of start-ups that tend to make them have lower risk-adjusted returns and hence less attractive to Venture Capital investors. We turn next to reviewing this work.[12]

3.1 Capital Intensity and Time Scale of Experimentation Cycles

Venture Capital (VC) investors do not shy away from investing large sums of money, particularly when financing the *scale-up* of successful ventures. Many business-to-consumer social networks and business-to-business enterprise software firms have raised hundreds of millions, or even billions, of dollars of equity financing from Venture Capital investors in the prior decade.

However, VCs are particularly sensitive to how much time and money it takes to achieve *initial* de-risking milestones. To see why, it is useful to recognize the skewed nature of risk and return in VC: over half of the investments that even the most successful VCs make fail entirely, while the majority of return for VC firms is generated by one or two extremely successful investments that are very hard to predict (Kerr et al., 2014). VCs therefore invest in stages, where each stage or round of financing by the VC can be thought of as an experiment that generates information about whether or not a start-up can achieve its promised potential. Staged financing is tied to milestones and effectively gives VCs real options—they can choose to invest further in the next round of financing when start-ups achieve milestones, or they can choose to abandon follow-on financing if they do not feel the start-up is showing sufficient promise. VCs are therefore naturally drawn to start-ups where early experiments are quicker and cheaper since it means their real option to reinvest or abandon at the next round is more valuable and the returns from their investments can be higher.

Ewens et al. (2018) highlight how the introduction of cloud computing services dramatically lowered the cost of learning about the ultimate potential of risky web-based start-ups. Specifically, it allowed those start-ups to rent hardware in small increments from providers like Amazon Web Services, use this to quickly gauge customer demand, and postpone expensive investments to scale up until after learning about the size and nature of demand from consumers. This, in turn, led to a disproportionate rise in the number of start-ups that could benefit from such lowered cost of experimentation and

[12] This section draws extensively on Nanda et al. (2014), Nanda and Rhodes-Kropf (2016) and Nanda (2020).

faster experimentation cycles. Related to this, VC investors are often drawn to startups with limited technical risk and where the key uncertainty relates to market demand for the product or service. Rapid iteration around early customer validation can either show a lack of demand or help reduce market risk substantially, thereby making the initial de-risking cheap and efficient.

It is true that there is increasing scope for software and related information technologies to play a role in addressing climate and related challenges because products emerging from energy technologies are now more likely to be smaller, modular, and able to rely on innovation in high-tech sectors (Popp et al., 2020). However, our analysis of VC-backed Net Zero patents has also shown that the 'deep tech' patents that rely more on fundamental science are disproportionately related to startups in sectors such as semi-conductors, computer hardware and industrial production. These are areas where early prototypes still embody substantial technical risk, where initial experiments involved in technical de-risking are expensive and do not always benefit from the faster experimentation cycles that VC investors are drawn to. This friction is consistent with the relative decline in such innovations coming from VC firms in recent years.

3.2 Learning Efficiency of Lab Experiments

When considering the role of experiments in early de-risking, it is also helpful to recognize that real options are more valuable in sectors where initial experiments *generate more information* —in other words, where achieving or missing initial milestones helps VCs learn more about the ultimate potential of a venture (Nanda and Rhodes-Kropf, 2016). This is because more informative experiments help VCs learn faster about firms that might ultimately fail, enabling them to "throw less good money after bad". More informative experiments also show firms achieving their promise earlier in their life, enabling start-ups to raise their next round of financing at much higher valuation step-ups. VCs who fund the initial rounds of financing in these ventures are therefore less diluted—that is, they maintain greater equity ownership—and hence generate a larger return for any given exit value.

Some of the challenges associated with deep tech commercialization stem from the fact that it is difficult to project how successful lab experiments might work at scale. For example, forecasting the unit costs – at scale – associated with energy storage using a new battery material or carbon capture and sequestration technology can be extremely difficult, even if the technology has been shown to work in a controlled laboratory environment. Moreover, since demand is tied to the ability of firms to produce at certain price points, this also implies that technology and market risk can often be intricately tied to each other in the energy sector (Arora et al., 2022). In such instances, the costs and timelines associated with the lower learning efficiency and de-risking process can be prohibitively large for commercial investors, as they may need to finance a full-scale demonstration pilots before learning whether the technology is sufficiently good to disrupt a market. The equity needed by a profit-seeking investor in such instances can be prohibitively large, leading projects with potential to not make it past the early de-risking phase.

Advances in digital chemistry and synthetic biology, as well as huge increases in computational power that enables more accurate simulation of material properties at scale, are helping to improve the ability to forecast from successful lab experiments to success at scale. However Siegmund et al. (2021) also point to the fact that lab experiments are often not conducted with a view to increasing learning efficiency. In the context of new catalysts, they point to specific examples of how success being defined on a different temperature, pressure and time-scale can lead to a large number of false positives – potential solutions that are deemed to be promising in lab experiments but could have been identified as having 'failed' in the lab if the thresholds used were more consistent with the requirements of at-scale commercial applications. Some of this is due to the fact that the early de-risking is increasingly done in university environments, where there can often be a lack of understanding of the specific industrial specifications or bottlenecks that need to be optimized in an industrial setting. Even within large organizations however, the R&D and product teams may not work to jointly set early-stage technical milestones in a manner that increases the information value of the early experiments.

3.3 Human Capital involved in Deep Tech translation

There are numerous challenges to building a new venture that faces large amounts of technical risk in addition to having to sell into highly regulated industries with large entrenched incumbents who are averse to adopting new technologies unless they have a huge economic benefit. This makes the challenge of having the right entrepreneurial talent to build such ventures and sell these products to commercial customers non-trivial (Nanda et al., 2014). Those with technical talent may not have the skill or inclination to get involved in commercialization, while those with entrepreneurial talent can find it hard to evaluate the quality of technical ideas at the nascent stages, making it unappealing to select into entrepreneurship for those with very high opportunity costs (Hall and Woodward, 2010). This is likely to be particularly true when the experimentation cycles and hence time to product is longer as is the case with many science-based deep tech ventures (Ewens et al., 2020).

3.4 Appropriating Value being Created

The discussion above has focused on supply-side frictions that make it harder to reduce the technical, market and execution *risk* associated with building Deep Tech ventures relative to sectors such as information technology, software and services.

It is also the case that software ventures often have the potential to more easily generate *return*. One of the attractive features of information technology is the highly scalable and asset-light businesses it is associated with. This leads to high levels of profitability and more cash flow to investors per unit of revenue, which in turn creates enormous opportunities for outsized returns.

In many of the deep tech sectors such as energy generation, storage, capture and industrial production, new firms are typically selling to large incumbents with substantial market power and low willingness to adopt new technologies, thereby making it hard to command high profit margins when selling to them. Many of these customers could also be competitors, making it harder to appropriate value. Finally, to the extent that these require substantial investment in physical assets to generate cash, the path to becoming a valuable company can be slower. Indeed as van den Heuvel and Popp (2022) note, a combination of 'lackluster demand and a lower potential for outsized returns' makes clean energy firms less attractive to venture capital investors.

4 Policy Implications

Having discussed some of the key frictions making Deep Tech investment less attractive to VC investors, we turn to a discussion of some policy implications. We note that innovation is clearly an important part of environmental policy, and encouraging innovation is often an explicit goal of policymakers. A large literature on the links between between environmental policy and innovation is beyond the scope of this paper (see for example, Popp (2019) and (Fu et al., 2018)). Similarly, the speed required to develop Covid-19 vaccines underlines how much society depends on the pace of scientific research and how effective science funding can be. A bias against funding risky research has also been discussed in the literature (Franzoni et al., 2021, Stephan, 2014) but we do not focus on this. We focus more narrowly on policies that might help address the specific sets of frictions outlined above that have been argued to reduce the risk-adjusted return of Deep Tech opportunities for VC investors.[13]

4.1 Government's role in stimulating demand

Many successful examples of government involvement in the commercialization of tough tech have been related to the government's role as a customer (Mowery, 2010, Mazzucato, 2013). A key reason for this may have to do with such advance market commitements substantially reducing market risk through a willingness to pay for early versions of an emerging technology. A large military contract can also help to establish standards and coordinate the direction of technology trajectories.

Mazzucato (2013) notes the spillovers to ICT from NASA's decade-long mission to put a man on the moon. In a compelling case study of the iPhone, she also shows how several of its key components—GPS, touchscreen glass, accessibility of the Internet, and voice-recognition technology—benefited either directly or indirectly from state funding. Evidence has also been found that federal investment during World War II subsequently led to increased private sector investment. It is also suggested that a very substantial increase in federal investment in the life sciences and the growth of the biotechnology revolution was triggered by President Nixon's declaration of "War on Cancer" in 1971 and the substantial commitments to federal funding of biomedical science in the subsequent years through the National Institutes of Health.

Mowery (2010) discusses the role of the U.S. military R&D and procurement budgets in driving substantial innovation and technological change in the United States in the post–World War II era. The government's role as a customer was very important in the 1960s and 1970s to the semiconductor industry—the one sector downstream from materials science where Venture Capitalists have profited at scale. The U.S. Department of Defense along with NASA played the role of collaborative customer, pulling the new industry down the learning curve to low cost, reliable production, as military customers had done for the preceding microelectronics industry up to and during World War II. Similarly, the U.S. government's role in reimbursement of new drugs and devices through Medicare and Medicaid substantially reduces market risk for drug development, implying that biotechnology ventures have enjoyed very high rates of access to the IPO market,

[13] This section draws extensively on Janeway et al. (2021).

despite the very high degree of technology risk, the very long and expensive path to regulatory approval, and hence substantial cash flow deficits (Pisano, 2006). In the context of clean energy, Germany's role in committing to purchase electricity generated from renewable energy sources is likely to have played a role in driving the growth of the industry and bringing the solar-PV down. Paying part of the contract value in advance can substantially reduce start-ups' dependence on external finance. This important role of the government as customer is often underappreciated when considering the role that policymakers can play in jump-starting innovation.

Government's role as a customer can also be used in outlining property rights, particularly those that help to level the playing field for and enable innovation by start-ups. Program managers of the Defense Advanced Research Projects Agency (DARPA), especially in its early years when it was funding general-purpose IT-related research, conceived of their mission to include protection of the new entrants from the established incumbents (Azoulay et al., 2019). Related to this, strong intellectual property rights and a well functioning Markets for Technology (Arora et al., 2021) helps startups motetize the value of their innovations.

4.2 Supporting Financing and Certification of Technical De-Risking

The record of government involvement in trying to directly subsidise the financing of startups has been mixed at best. Nevertheless, one setting where start-ups engaged in innovation have been shown to benefit substantially is the U.S. Department of Energy's SBIR grant program, which has helped start-ups finance the prototyping of new technologies and thereby substantially increase the odds of receiving venture capital (Lerner, 1999, Howell, 2017). This ties in directly to the friction outlined above—where start-ups in some sectors cannot attract VC due to the difficulty they face in learning about the effectiveness of a new technology in the field as opposed to the lab, and hence have trouble convincing investors they can achieve product-market fit and generate sufficient customer demand.

In the context of Net Zero innovations, organizations such as ARPA-E also play an important certification role in helping to vet promising technologies. This can help provide independent validation that a technology is meeting technical milestones as VC and other commercial investors very often do not have the technical capability to assess and evaluate the efficacy and promise of a new technology.

4.3 Supporting New Organizational and Financing Models

As noted above, Deep Tech solutions to global challenges such as achieving Net Zero targets are increasingly being developed within universities. Many of the frictions noted above relate to the challenge of effective effective hand-off from a university lab environment to a commercial setting.

Given that they already have a lot of the specialized equipment, talent and technical expertise needed to support and validate technical de-risking, academic institutions have the potential to play a central role in helping to support the initial technical de-risking and development prior to start-ups raising risk capital from investors. Beyond cost, another potential key benefit of de-risking in a university environment is the potential to recycle knowledge arising from failure. Since most early stage experiments fail and the insights from the failure of such technical experiments is instructive for future generations of entrepreneurs, the different incentive system of a university related to scaling knowledge can be extremely valuable in this context, particularly in settings where there are strong externalities as is the case with knowledge around early stage de-risking and translation.

Another role that universities can play is in helping founders of deep tech ventures, who often have technical background but less business training, to understand the appropriate customer segments, business models, and financing sources for their new ventures (Cohen et al., 2020, Sauermann and Stephan, 2010). In addition to helping to stimulating the supply of technical talent that is also trained for building ventures, universities can play a role in helping to match strong technical projects with similarly strong entrepreneurial talent.

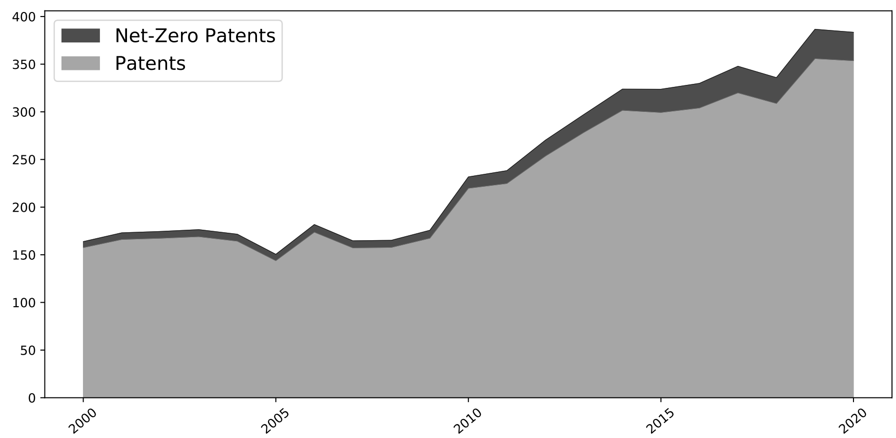
In terms of the transition from universities to Venture Capital, VC firms typically raise closed-end funds, implying that they are required to invest the money they raise and return the proceeds within a fixed period, usually 10 years. Given that investments are made over the first few years, this implies that VCs are naturally drawn to investments where they can realize a return through an exit—either an acquisition or an IPO—within a short time. Not all ventures are amenable to this timeline. For example, start-ups that have a physical component to generating cash flows often take longer to build, particularly if the venture needs to build factories to produce new products—as is the case with energy production, storage and many industrial production methods. Although VCs have some leeway to extend the fund life a few years, the fixed limit to a fund's life can become a binding constraint for investors, although the use of evergreen funds can overcome such constraints Lerner and Nanda (2020).

As noted by Nanda (2020), universities, government labs, corporate R&D, VC firms, corporate venture capital firms, and longer-term "patient capital" associated with family offices each bring different incentives, funding models, ability to experiment, and tolerance for failure. Each has different benefits and constraints. Understanding the degree to which these can be adapted to most effectively help commercialize Deep Tech addressing Net Zero Challenges —perhaps while also harnessing non-dilutive capital from philanthropy for initial experiments—is a promising area of further inquiry.

Figures

Figure I: Level and Growth of USPTO Patents from 2000-2020 This figure shows the number of Net-Zero and all other patents granted by the USPTO from 2000 to 2020 (Panel A). Net-Zero patents include the six groups identified using the CPC classification system and reported in Table 1. Panel B reports the growth of these two groups, relative to the number of patents in each group in 2000.

Panel A: Granted Patents - Levels (in thousands)



Panel B: Granted Patents - Relative Growth

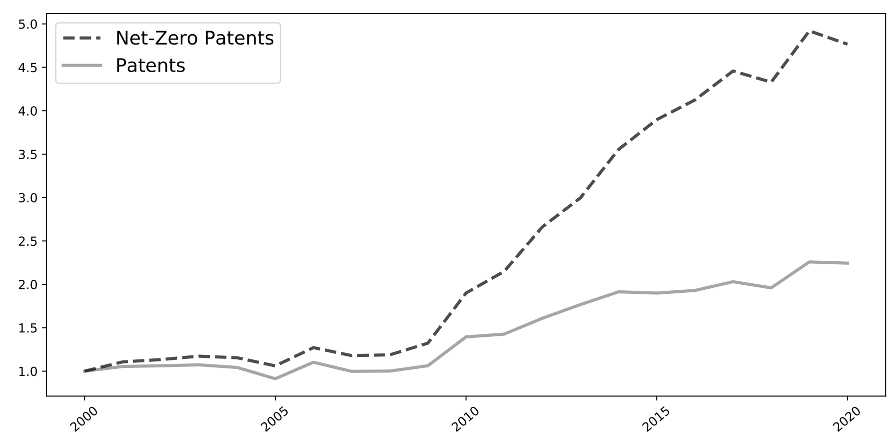
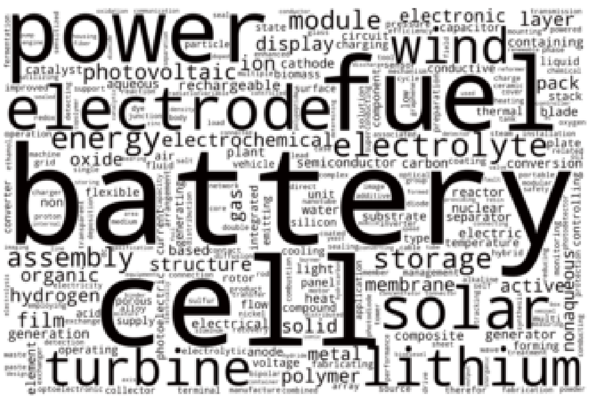
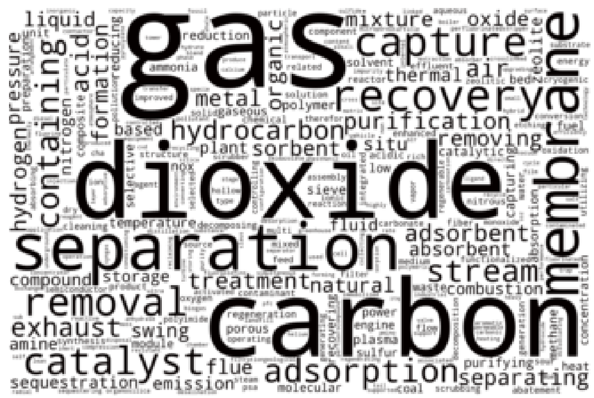


Figure II: Distinctive Words in each Category of Net Zero Patents granted between 2000 and 2020 This figure uses text taken from the titles of all Net Zero patents to identify distinctive words associated with each Net Zero sub-category. The distinct words associated with each category are derived using a TF-IDF procedure, where the frequency of each word in a document (TF) is weighted by the inverse of the frequency of all documents in the corpus (IDF).

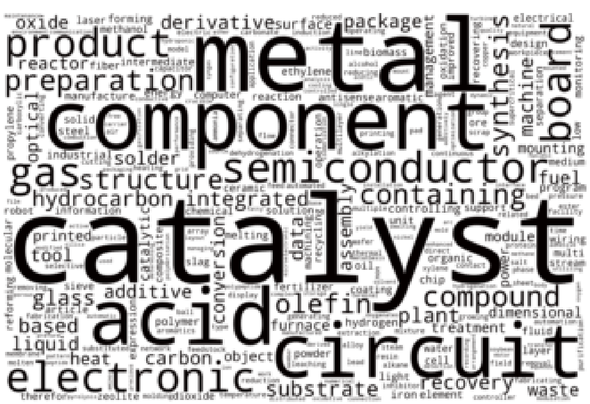
Panel A: Generation and Storage



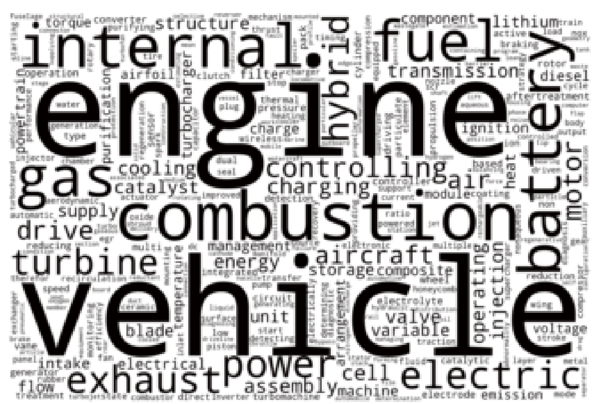
Panel B: GHG Capture



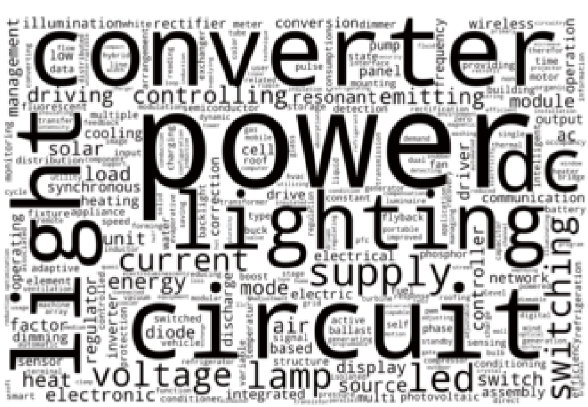
Panel C: Mitigation in Industrial Production



Panel D: Mitigation in Transport



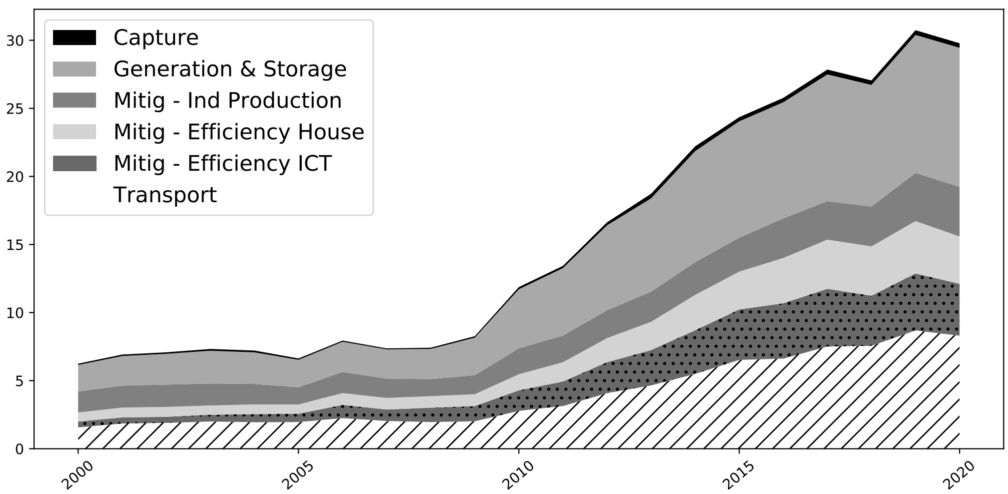
Panel E: Energy Efficiency in Buildings



Panel F: Energy Efficiency in ICT

Figure III: Level and Growth of Net Zero Patents from 2000-2020, by Category This figure reports details on Net Zero patents granted by the USPTO from 2000 to 2020, by the six Net-Zero categories used in this paper. The six Net-Zero groups are identified using the CPC classification tagging system, and they are: energy Generation & Storage (class Y02E in Table I), technologies for GHG Capture (class Y02C in Table I), technologies for mitigation in industrial production (class Y02P in Table I), technologies related to transportation (class Y02T in Table I), technologies related to energy efficiency in buildings (class Y02B in Table I) and in ICT (class Y02D in Table I). Panel A is a stacked chart that reports the overall number of patents in each class, Panel B reports the growth of these groups, relative to the number of patents in each group in 2000.

Panel A: Number of Green Patents by Cleantech Class (in thousands)



Panel B: Relative Growth of Green Patents by Cleantech Class

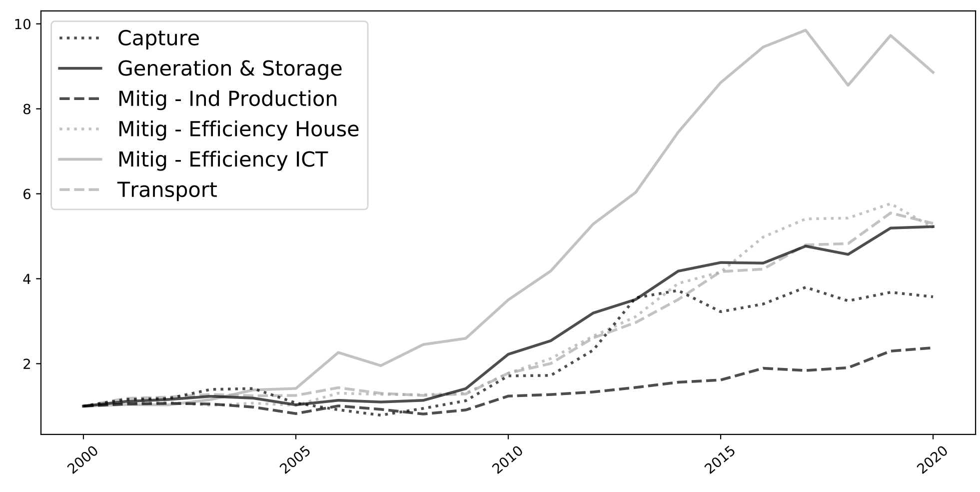
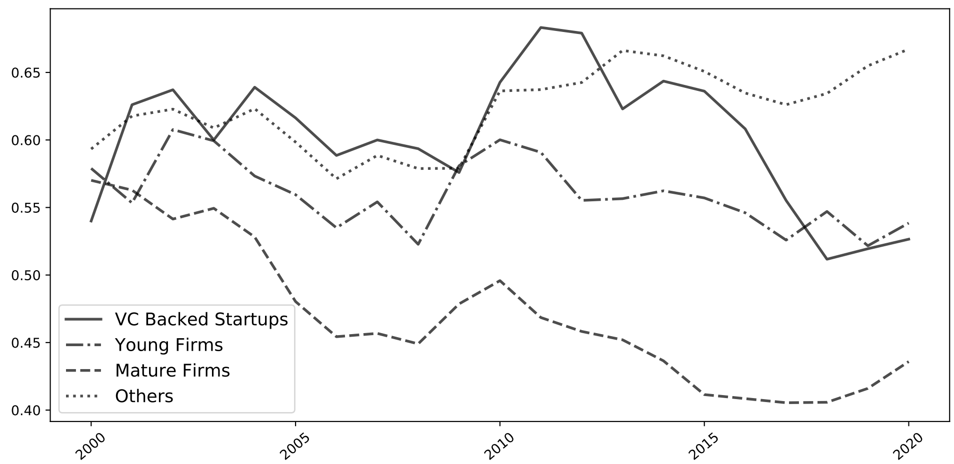


Figure IV: Share of Net-Zero Patents that are Deep Tech, by Assignee Type This figure reports the share of Net-Zero patents that are classified as deep technologies, by assignee type over the 2000-2020 time period. Deep technologies are identified using patents to science citations as described in Table II, and this group includes: energy generation and storage, GHG mitigation in industrial production, and carbon capture technologies.



Tables

Table I: Cooperative Patent Classification of 'Green Innovations' This table reports the description of different CPC classification groups used to tag green innovation. As can be seen from the Table, green patents include the categories Y02A and Y02W, but these have been excluded from our analysis as the focus of this paper is on technologies who can directly contribute to meeting Net-Zero targets.

Y02E	**REDUCTION OF GREENHOUSE GAS [GHG] EMISSIONS, RELATED TO ENERGY GENERATION, TRANSMISSION OR DISTRIBUTION**
10/00	Energy generation through renewable energy sources
30/00	Energy generation of nuclear origin
20/00	Combustion technologies with mitigation potential
40/00	Technologies for an efficient electrical power generation, transmission or distribution
50/00	Technologies for the production of fuel of non-fossil origin
60/00	Enabling technologies;Technologies with a potential or indirect contribution to GHG emissions mitigation
70/00	Other energy conversion or management systems reducing GHG emissions

Y02C	**CAPTURE, STORAGE, SEQUESTRATION OR DISPOSAL OF GREENHOUSE GASES [GHG]**
20/00	Capture or disposal of greenhouse gases
20/10	of nitrous oxide (N20)
20/20	of methane
20/30	of perfluorocarbons [PFC], hydrofluorocarbons [HFC] or sulfur hexafluoride [SF6]
20/40	of CO2

Y02P	**CLIMATE CHANGE MITIGATION TECHNOLOGIES IN THE PRODUCTION OR PROCESSING OF GOODS**
10/00	Technologies related to metal processing
20/00	Technologies relating to chemical industry
30/00	Technologies relating to oil refining and petrochemical industry
40/00	Technologies relating to the processing of minerals
60/00	Technologies relating to agriculture, livestock or agroalimentary industries
70/00	Climate change mitigation technologies in the production process for final industrial or consumer products
80/00	Climate change mitigation technologies for sector-wide applications
90/00	Enabling technologies with a potential contribution to greenhouse gas [GHG] emissions mitigation

Y02T	**CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO TRANSPORTATION**
10/00	Road transport of goods or passengers
30/00	Transportation of goods or passengers via railways, e.g. energy recovery or reducing air resistance
50/00	Aeronautics or air transport
70/00	Maritime or waterways transport
90/00	Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation

Y02B	**CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO BUILDINGS, e.g. HOUSING, HOUSE APPLIANCES OR RELATED END-USER APPLICATIONS**
10/00	Integration of renewable energy sources in buildings
20/00	Energy efficient lighting technologies, e.g. halogen lamps or gas discharge lamps
30/00	Energy efficient heating, ventilation or air conditioning [HVAC]
40/00	Technologies aiming at improving the efficiency of home appliances, e.g. induction cooking or efficient technologies for refrigerators, freezers or dish washers
50/00	Energy efficient technologies in elevators, escalators and moving walkways, e.g. energy saving or recuperation technologies
70/00	Technologies for an efficient end-user side electric power management and consumption
80/00	Architectural or constructional elements improving the thermal performance of buildings
90/00	Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation

Y02D	**CLIMATE CHANGE MITIGATION TECHNOLOGIES IN INFORMATION AND COMMUNICATION TECHNOLOGIES [ICT], I.E. INFORMATION AND COMMUNICATION TECHNOLOGIES AIMING AT THE REDUCTION OF THEIR OWN ENERGY USE**
10/00	Energy efficient computing, e.g. low power processors, power management or thermal management
30/00	Reducing energy consumption in communication networks

Y02A	**TECHNOLOGIES FOR ADAPTATION TO CLIMATE CHANGE**
10/00	at coastal zones; at river basins
20/00	Water conservation; Efficient water supply; Efficient water use
30/00	Adapting or protecting infrastructure or their operation
40/00	Adaptation technologies in agriculture, forestry, livestock or agroalimentary production
50/00	in human health protection, e.g. against extreme weather
90/00	Technologies having an indirect contribution to adaptation to climate change

Y02W	**CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO WASTEWATER TREATMENT OR WASTE MANAGEMENT**
10/00	Technologies for wastewater treatment
30/00	Technologies for solid waste management
90/00	Enabling technologies or technologies with a potential or indirect contribution to greenhouse gas [GHG] emissions mitigation

Table II: Citation to fundamental science by Net Zero patents, by Category This table reports the propensity to cite science for Net Zero patents and heterogeneity across sub-categories. Column 2 reports the share of Net-Zero patents that cite at least 1 scientific article for each category. Columns 3-8 report the intensity of scientific citations by category, conditional on citing at least one scientific paper. Data on scientific citations are obtained through the open-source dataset provided by Marx and Fuegi (2020). Citations include front-page citations to scientific papers as described in section 2. Energy generation and storage, GHG capture and technologies for Mitigation in Industrial Production cite science more intensively and hence are labeled as 'Deep Tech'.

		# Patents	% with 1 or more scientific citations	Mean	p10	p25	p50	p75	p90
Deep Tech	GHG Capture	4,248	48%	13	1	2	4	10	37
	Mitigation in Industrial Prod.	43,641	39%	12	1	1	4	10	28
	Generation and Storage	108,691	33%	11	1	1	3	9	24
Non Deep Tech	Energy Efficiency in ICT	42,053	29%	7	1	1	2	5	14
	Energy Efficiency in Buildings	37,358	18%	6	1	1	2	5	13
	Mitigation in Transport	84,843	12%	7	1	1	2	5	13

Table III: Net Zero Patenting by Sector and Assignee Type The first two columns of this table document the number and share of Net Zero patents that are associated with different assignee types. Columns 3 to 8 report the share of each assignee-type's patents that correspond to each sector. For example, 45.5% of VC-backed startup patents are related to Generation & Storage, while 1.3% of mature firm patents are related to GHG Capture.

			Share of Total Patents of each Assignee in each Class					
	# of tot patents	% of tot patents	Generation & Storage	GHG Capture	Mitigation in Industrial Prod.	Mitigation in Transport	Energy Eff. in Buildings	Energy Eff. in ICT
VC Backed Startups	8,806	2.6%	45.5%	0.6%	13.9%	11.6%	13.9%	14.5%
Young Firms	70,001	20.8%	38.7%	1.2%	15.6%	21.6%	14.3%	8.4%
Mature Firms	218,417	64.8%	30.4%	1.3%	12.6%	29.9%	10.2%	15.5%
Others	39,935	11.8%	45.9%	2.0%	15.6%	19.9%	12.0%	4.5%

Table IV: Citation to Science associated with different Assignee types This table reports differences in propensity to cite science by patents granted to different assignee types. Columns report results for all patents in the USPTO database from 2000-2020 and separately for Net Zero, Deep Tech and Non-Deep Tech patents and defined in Table II. Data on scientific citations are obtained through the open-source dataset provided by Marx and Fuegi (2020).

Panel A: Unconditional mean of citations to science

	All Patents	Net-Zero Patents	Net-Zero Deep Tech	Net-Zero Non DT
VC Backed Startups	11.6	12.4	17.3	5
Young Firms	3.6	2.9	4.2	1.3
Mature Firms	3.1	2.2	3.7	1
Others	3.9	2.5	3.4	1.1

Panel B: Conditional on having at least one citation to science

	All Patents	Net-Zero Patents	Net-Zero Deep Tech	Net-Zero Non DT
VC Backed Startups	23.3	24.4	29.7	12.7
Young Firms	13.6	10.6	12.1	7
Mature Firms	11.3	9	10.9	6
Others	13.8	4	8.3	6

Table V: Patent Impact by Assignee Type This table reports the share of each assignee's patents that are in the top 10% (Panel A) and top 1% (Panel B) of influential patents, normalized within a given grant year and USPTO technology class. The sample includes patents granted from 2000-2017 as patents granted extremely recently have not accumulated sufficient number of citations to accurately identify outliers.

Panel A: Share of Patents being in the top 10% of Citations Received

	All Patents	Net-Zero Patents	Net-Zero Deep Tech	Net-Zero Non DT
VC Backed Startups	21.4%	27.3%	23.6%	33.4%
Young Firms	10.6%	13.3%	11%	16.3%
Mature Firms	9%	10.2%	8.8%	11.5%
Others	6.9%	9.7%	8.1%	12.5%

Panel B: Share of Patents being in the top 1% of Citations Received

	All Patents	Net-Zero Patents	Net-Zero Deep Tech	Net-Zero Non DT
VC Backed Startups	2.9%	4.6%	3.7%	6%
Young Firms	1.1%	1.6%	1.2%	2%
Mature Firms	0.9%	1.0%	1.1%	1%
Others	0.6%	0.9%	0.6%	1.2%

References

Net zero by 2050 - a roadmap for the global energy sector. *International Energy Agency*, 2022. URL `https://www.iea.org/reports/net-zero-by-2050`.

Ufuk Akcigit and William R. Kerr. Growth through Heterogeneous Innovations. *Journal of Political Economy*, 126(4):1374–1443, 2018. doi: 10.1086/697901. URL `https://ideas.repec.org/a/ucp/jpolec/doi10.1086-697901.html`.

Ashish Arora, Sharon Belenzon, and Andrea Patacconi. The decline of science in corporate R&D. *Strategic Management Journal*, 39(1):3–32, 2018.

Ashish Arora, Sharon Belenzon, Andrea Patacconi, and Jungkyu Suh. The changing structure of american innovation: Some cautionary remarks for economic growth. *Innovation Policy and the Economy*, 20(1):39–93, 2020.

Ashish Arora, Sharon Belenzon, and Jungkyu Suh. Science and the market for technology. Working Paper 28534, National Bureau of Economic Research, March 2021.

Ashish Arora, Andrea Fosfuri, and Thomas Roende. Caught in the middle: The bias against startup innovation with technical and commercial challenges. Working Paper 29654, National Bureau of Economic Research, January 2022.

Pierre Azoulay, Erica Fuchs, Anna P. Goldstein, and Michael Kearney. Funding breakthrough research: Promises and challenges of the arpa model. *Innovation Policy and the Economy*, 19:69–96, 2019.

Shai Bernstein, Xavier Giroud, and Richard R. Townsend. The impact of venture capital monitoring. *The Journal of Finance*, 71(4):1591–1622, 2016.

Wesley M. Cohen, Henry Sauermann, and Paula Stephan. Not in the job description: The commercial activities of academic scientists and engineers. *Management Science*, 66(9):4108–4117, 2020.

Colleen Cunningham, Florian Ederer, and Song Ma. Killer Acquisitions. *Journal of Political Economy*, 129(3):649–702, 2021. doi: 10.1086/712506. URL `https://ideas.repec.org/a/ucp/jpolec/doi10.1086-712506.html`.

Michael Ewens, Ramana Nanda, and Matthew Rhodes-Kropf. Cost of experimentation and the evolution of venture capital. *Journal of Financial Economics*, 128(3):422–442,

2018. doi: 10.1016/j.jfineco.2018.03. URL https://ideas.repec.org/a/eee/jfinec/v128y2018i3p422-442.html.

Michael Ewens, Ramana Nanda, and Christopher T. Stanton. The Evolution of CEO Compensation in Venture Capital Backed Startups. NBER Working Papers 27296, National Bureau of Economic Research, Inc, June 2020. URL https://ideas.repec.org/p/nbr/nberwo/27296.html.

Chiara Franzoni, Paula Stephan, and Reinhilde Veugelers. Funding risky research. Working Paper 28905, National Bureau of Economic Research, June 2021.

Wancong Fu, Chong Li, Jan Ondrich, and David Popp. Technological spillover effects of state renewable energy policy: Evidence from patent counts. Working Paper 25390, National Bureau of Economic Research, December 2018.

Robert E. Hall and Susan E. Woodward. The burden of the nondiversifiable risk of entrepreneurship. *American Economic Review*, 100(3):1163–94, June 2010.

Ivan Haščič and Mauro Migotto. Measuring environmental innovation using patent data. *OECD Environment Working Papers*, 89, 2015.

Sabrina T. Howell. Financing innovation: Evidence from r&d grants. *American Economic Review*, 107(4):1136–64, April 2017.

Sabrina T Howell, Josh Lerner, Ramana Nanda, and Richard R Townsend. How resilient is venture-backed innovation? evidence from four decades of u.s. patenting. Working Paper 27150, National Bureau of Economic Research, May 2020.

William H. Janeway, Ramana Nanda, and Matthew Rhodes-Kropf. Venture Capital Booms and Start-Up Financing. *Annual Review of Financial Economics*, 13(1):111–127, 2021.

William R. Kerr, Ramana Nanda, and Matthew Rhodes-Kropf. Entrepreneurship as Experimentation. *Journal of Economic Perspectives*, 28(3):25–48, Summer 2014. URL https://ideas.repec.org/a/aea/jecper/v28y2014i3p25-48.html.

Samuel Kortum and Josh Lerner. Assessing the contribution of venture capital to innovation. *The RAND Journal of Economics*, 31(4):674–692, 2000.

Josh Lerner. The government as venture capitalist: The long-run impact of the sbir program. *The Journal of Business*, 72(3):285–318, 1999.

Josh Lerner and Ramana Nanda. Venture capital's role in financing innovation: What we know and how much we still need to learn. *Journal of Economic Perspectives*, 34(3): 237–61, August 2020.

Matt Marx and Aaton Fuegi. Reliance on science: Worldwide front-page patent citations to scientific articles. *Strategic Management Journal*, 41:1572–1594, 2020.

Matt Marx and Aaton Fuegi. Reliance on science: Worldwide front-page patent citations to scientific articles. *Journal of Economic and Management Strategy*, 31:369–392, 2021.

Mariana Mazzucato. *The entrepreneurial state : debunking public vs. private sector myths.* Anthem frontiers of global political economy. Anthem Press, 2013.

David C. Mowery. Military r&d and innovation. In Bronwyn H. Hall and Nathan Rosenberg, editors, *Handbook of the Economics of Innovation, Volume 2*, volume 2 of *Handbook of the Economics of Innovation*, pages 1219–1256. North-Holland, 2010.

Ramana Nanda. Financing Tough Tech innovation. In *Global Innovation Index 2020: Who Will Finance Innovation?*, chapter 5, pages 113–119. Cornell University Press, 2020.

Ramana Nanda and Matthew Rhodes-Kropf. Financing Entrepreneurial Experimentation. *Innovation Policy and the Economy*, 16(1):1–23, 2016. doi: 10.1086/684983. URL `https://ideas.repec.org/a/ucp/ipolec/doi10.1086-684983.html`.

Ramana Nanda, Ken Younge, and Lee Fleming. Innovation and entrepreneurship in renewable energy. In *The Changing Frontier: Rethinking Science and Innovation Policy*, NBER Chapters, pages 199–232. National Bureau of Economic Research, Inc, April 2014.

Gary P. Pisano. *Science Business: The Promise, the Reality, and the Future of Biotech.* Boston: Harvard Business School Press, 2006.

David Popp. Environmental policy and innovation: A decade of research. Working Paper 25631, National Bureau of Economic Research, March 2019.

David Popp, Jacquelyn Pless, Ivan Haščič, and Nick Johnstone. Innovation and entrepreneurship in the energy sector. Working Paper 27145, National Bureau of Economic Research, May 2020.

Jennifer F Reinganum. Uncertain Innovation and the Persistence of Monopoly. *American Economic Review*, 73(4):741–748, September 1983. URL https://ideas.repec.org/a/aea/aecrev/v73y1983i4p741-48.html.

Henry Sauermann and Paula E Stephan. Twins or strangers? differences and similarities between industrial and academic science. Working Paper 16113, National Bureau of Economic Research, June 2010.

Daniel Siegmund, Sebastian Metz, Volker Peinecke, Terence E. Warner, Carsten Cremers, Anna Grevé, Tom Smolinka, Doris Segets, and Ulf-Peter Apfel. Crossing the valley of death: From fundamental to applied research in electrolysis. *JACS Au*, 1(5):527–535, 2021. doi: 10.1021/jacsau.1c00092. URL https://doi.org/10.1021/jacsau.1c00092. PMID: 34467315.

Paula Stephan. *The Endless Frontier: Reaping What Bush Sowed?*, pages 321–366. University of Chicago Press, July 2014.

Matthias van den Heuvel and David Popp. The role of venture capital and governments in clean energy: Lessons from the first cleantech bubble. Working Paper 29919, National Bureau of Economic Research, April 2022.