Innovation and Entrepreneurship in Renewable Energy

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1. Introduction

The global demand for energy is projected to almost triple over the next several decades. Estimates suggest that a growing world population, combined with rising living standards will lead global energy consumption to reach about 350,000 TWh in 2050 from the 2010 level of 130,000 TWh. To put this increase in perspective, it will require the equivalent of setting up 750 large coal burning power plants *per year* for 40 years in order to meet to the increased demand for energy in the coming decades.

Figure 1 provides a breakdown of the sources that produced the energy consumed in 2010 based on data from the BP Statistical Review of World Energy, 2012. It highlights that 87% of the energy was produced from "conventional energy", namely Coal, Oil and Natural Gas. On the other hand, Solar, Wind, Biomass, Hydro and other renewables accounted for a mere 8% of global energy produced in 2010.[2]

In addition to the challenges of meeting the growing energy needs of the world's population with conventional sources of energy, the implications of continued dependence on fossil fuels are believed to be particularly stark for climate change. The shale gas revolution in the US in recent years has implied a reduced dependence on coal. Nevertheless, the benchmark of trying to achieve "zero emissions" has led the US and several European countries to focus more intensely on promoting innovation in renewable energy technologies in recent years. While there is no clear winning alternative at present, there is also a growing belief that progress will come from radical innovations that will allow us to make the jump from the status quo, whether it is in renewable energy or other more conventional sources of

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[2] The BP study only reports data on commercially traded fuels, including renewable energy that is commercially traded. The International Energy Agency (IEA) estimates a slightly higher share of renewables based on estimates of the use of wood chips, peat and other biomass used in developing countries that is not commercially traded. Even so, their estimate of renewables including hydroelectricity is 13%, compared to the 8% estimated by BP.

energy production. We examine the technological and organizational sources of such innovation in renewable energy, with an eye towards understanding the factors that have promoted progress in the past.

Venture capital has been a key source of finance for commercializing radical innovations in the United States, particularly over the last three decades (Kortum and Lerner, 2000; Gompers and Lerner, 2002; Samila and Sorenson, 2011). The emergence of new industries such as semi-conductors, biotechnology and the internet, as well as the introduction of several innovations across a spectrum of sectors such as healthcare, IT and new materials, have been driven in large part by the availability of venture capital for new startups. A key attribute of venture-backed innovation in the US has been the ability of private capital markets to finance a wide variety of approaches in a specific area, as opposed to choosing a specific winner. Since it is hard to know, *ex ante*, which technological trajectory will be successful *ex post*, it seems vital that in order to make rapid technological progress, we need to proceed by conducting numerous "economic experiments" in the energy sector (Rosenberg, 1994; Stern 2003; Kerr, Nanda and Rhodes-Kropf, 2013). This makes venture capital an ideal candidate to play a role in financing radical innovation in renewable energy technologies.

In fact, venture capital financing for renewable energy startups rose dramatically in the mid-2000s after being consistently low in the previous decades. Figure 2A documents that between 2006 and 2008, several billion dollars were channeled into startups focused on solar, wind and biofuels. In the last few years, however, venture capital investment in renewable energy technologies has plummeted, falling as a share of overall VC investment and even within clean tech, shifting away from renewable energy production to investments in energy efficiency, software, and storage (as seen in Figures 2B and 2C).

In this chapter, we investigate the role of venture capital in renewable energy innovation by comparing the patenting activity of VC-backed startups with other types of organizations engaged in renewable energy innovation. We not only examine patenting rates, but also the characteristics of the patents being filed by the different types of organizations. Understanding these factors will help determine the extent to which falling VC investment in renewable energy should be seen as a cause for concern as opposed to being easily substitutable by innovation by others such as large incumbent firms.

We address these questions by using patent data from the U.S. Patent and Trademark Office (USPTO) over the thirty-year period from 1980 through 2009. We find that large incumbent firms have dominated patenting in renewable energy for several decades. For example, the top 20 firms accounted for 50% of the renewable energy patents and the top 50 firms account for nearly 70% of such patents filed at the USPTO in the early 1990s. Innovation became more widespread in 2000s when patenting by VC backed firms grew, but the top 20 firms still accounted for 40% of the patenting activity in 2009. However, despite accounting for the largest share of patents, we find incumbents are more likely to file patents that are either completely un-cited or are self-cited, suggesting a greater focus on incremental or process innovation. Furthermore, they are less likely to have extremely influential patents, that we define as being in the top 10 percentiles of forward citations in a given technology area and given year. Finally, we create a measure of novelty using textual analysis of the patent documents that does not depend on citations. This independent measure also suggests that on average, incumbents firms have

been engaged in less novel patenting than venture capital backed startups, even more so in the period when VC funding for startups increased dramatically.

Given the important role that VC-backed startups seem to play in renewable energy innovation in the last decade, the dramatic fall in financing available for such firms suggests that it will have implications for the nature of innovation we may see going forward in this sector. We highlight that at least some of the decline in VC financing for renewable energy is related to structural factors that make it very hard for VCs to fund such startups. We therefore elaborate on the aspects of the institutional environment that have made sustained experimentation by VCs extremely difficult in renewable energy, and suggest policies that may be effective in helping to channel more risk capital towards innovation and entrepreneurship in renewable energy technologies.

The rest of the chapter is structured as follows. In Section 2, we outline the data used for our analysis. Section 3 provides a detailed description of our main results on the differences in innovation across incumbent and venture-capital backed firms. In Section 4, we discuss the challenges faced by venture capital investors in sustaining the financing of renewable energy startups. Section 5 offers policies that may make it easier to finance such startups and Section 6 concludes.

2. Data

2.1. Sample selection criteria

Our focus in this chapter is on patenting in sectors related to renewable energy production, namely solar, wind, biofuels, hydro-electric power and geothermal technologies. Before moving to a description of the data, however, we first outline the criteria for selecting our sample.

Our approach was to define a set of technologies that would first, allow us to build a comprehensive and well-delineated dataset of patenting activity within the chosen technology, and second, enable us to compare the characteristics of innovation between venture capital backed startups and other firms engaged in innovation.

This led us to leave out some technologies that are often associated with clean energy production but are not renewable energy. For example, although natural gas has a lower carbon footprint than oil and coal, it is difficult to break out innovations related to energy production in this area, as opposed to other businesses pursued by oil and gas companies.[3] On the other hand, we have also left out other "clean-tech" sectors that receive VC finance but are not energy production. For example, venture capital has been involved in financing a number of innovations in software related to smart grid and energy efficiency. These innovations are extremely difficult to isolate in a systematic manner from other

[3] Similarly, although nuclear energy is not "renewable", we have collected data on it given the ease with which we could classify patents in this technology and the fact that a few nuclear energy startups have recently been backed by venture capital (e.g. see Sahlman, Nanda, Lassiter and McQuade, 2012). However, the level of patenting by VC-backed startups in nuclear is extremely low in our sample, so we have chosen not to report the results of nuclear in our main estimations. However, our results are unaffected by the inclusion or exclusion of nuclear energy.

software patents that startups could be working on (e.g. a GPS software that helps route trucks in a manner that conserves fuel is hard to distinguish from other GPS patents, even when manually classifying patents). Our focus, therefore, is on renewable energy production technologies. Although our scope is narrower than either "energy production" or "clean tech", our hope is that our tradeoff buys us greater confidence in defining a clear and consistent set of technologies within which we can characterize both the trends in patenting over time, and the differences in the nature of patenting across the various organizational forms.

2.2. Data used to create the sample

We created our sample using three steps. First, we worked with a private research firm, IP Checkups, to define a set of renewable energy patents at the U.S. Patent and Trademark Office (USPTO) in each of the energy production sectors, of solar, wind, biofuels, hydro and geothermal. IP Checkups has particular expertise in clean energy, including a database of clean technology patents filed at the US and foreign patent offices (we consider only patents filed with the USPTO). They provided us with a sample of 17,090 renewable energy patents whose application dates were between January 1980 and December 2009 across the 5 sub-sectors listed above. [4]

Second, we developed a procedure to validate and extend the sample from IP checkups in order to ensure that the sample was comprehensive. Specifically, we used the patents from IP Checkups as a training-set, and applied the LIBLINEAR machine classifier algorithm (Fan et al., 2008), to search through every patent title and abstract in the universe of approved utility patents at the USPTO with application dates between January 1980 and December 2009. The machine classifier algorithm aimed to identify other patents (based on their titles and abstract) that looked "similar" to those in the training set provided by IP checkups. The assumption behind this approach is that IP Checkups may have missed patents at random, but would not have a systematic bias in the types of patents they did not provide us. In this case, the algorithm would be able to search efficiently among the over 4.3 million patents in the universe of patents for others with similar titles and abstracts that may have been overlooked by IP Checkups. The classifier returned an additional 31,712 patents for consideration.

Finally, we contracted with IP Checkups to have a Ph.D. expert in clean-technologies manually review each of the candidate patents identified by the machine classifier and select appropriate ones for inclusion into the final sample. An additional 5,779 patents were selected for inclusion, resulting in a final sample size of 22,869 patents.

We believe that this 3-step process outlined above has produced one of the most comprehensive samples of patents looking specifically at renewable energy. Given the systematic, and replicable approach used by the machine learning sample, we believe this method will allow subsequent researchers to easily update the sample, as well as apply similar techniques to identify patents in others

[4] Although the USPTO data goes as far as 2012, we truncate the sample at the end of 2009 to allow for our analysis of forward citations.

sectors that share the property with renewable energy of not easily demarcated by specific technology-classes at the USPTO.

Having thus identified our five primary categories of clean-tech patents by technology type, we further categorized each patent into one of four organizational types: Academia & Government, VC-backed startups, Non-VC-backed firms and Unassigned. Unassigned patents were those with no assignee provided in the patent application. These have typically been assumed to be independent inventors, but may also be corporate patents with just a missing assignee field. As we show in the following section, unassigned patents seem significantly different in terms of their characteristics. While we do report some analyses that include unassigned patents, the majority of our analyses focus on comparisons between VC-backed startups, non-VC-backed firms and inventors in academic institutions or government labs. We classified firms as venture-capital backed, if the assignee name and location corresponded with firms in either the Cleantech i3 or the Bloomberg New Energy Finance database of venture capital backed financings.[5] To classify assignees as university or government, we used a text-matching process followed by manual review to identify academic institutions (assignees with words such as "university," "universitaet," "ecole," "regents," etc.) and governmental organizations (assignees with words such as "Department of Energy," "United States Army," "Lawrence Livermore," "Bundesrepublik," etc.)

Our residual category, therefore, is the category of assignees that are not-VC backed and not from academic institutions or the government. The residual category can therefore be thought of as incumbent firms (keeping in mind the qualifications described above). As far as possible, we manually matched subsidiaries to their parent's name, so that for example, all known subsidiaries of GE were classified as GE. While this categorization is imperfect, cases where we missed matching a subsidiary to a parent will tend to bias us towards finding less concentration in patenting and our findings should be seen as a lower bound to the true level of concentration across organizations involved in renewable energy patenting.

[5] Both databases have more comprehensive coverage of venture capital financings in clean energy than Thompson Venture Economics and Dow Jones Venture Source, that are the two databases typically used for studies on venture capital backed startups.

3. Results

3.1. Patenting Rates in Renewable Energy

We begin by providing an overview of the patenting landscape in renewable energy technologies. Table 1a and Table 1b provide a breakdown of the total number of patents used in our sample, broken down by organizational form and technology area. Table 1a reports the breakdown for the entire sample, while Table 1b reports the results for inventors who are based in the US.[6] As can be seen from Table 1, about 85% of the patents in our sample are accounted for by solar, wind and biofuels. Incumbent firms account for nearly two thirds of the patents in the dataset and about 55% of the patents filed by US-based inventors. While Table 1 provides a sense of the most important technologies and organizational forms, it does not give a sense of shares over time or the quality of the innovations. We turn to these next.

Figures 3A and 3B report the absolute and relative amount of renewable energy patenting at the USPTO. They show that renewable energy patents fell over the 1980s, both in absolute and relative terms. While the patenting rate increased slightly in the 1990s, it rose considerably in the 2000s, increasing at a disproportionate rate relative to overall patenting activity at the USPTO. In fact, both the number of patents filed per year and the share of patents filed in the USPTO approximately doubled over the 10-year period from 2000-2009.

Figure 4 shows that the main driver of the increase was patenting by US-based inventors. In fact, there was a sharp break in the trend of patenting by US-based investors relative to foreign inventors around 2004. Figure 5 documents that VC-backed startups increased their proportional share of patenting by US inventors the most over this period, increasing the share of patenting from under 5% in 2000 to about 20% of the patents filed in 2009.

Despite the sharp increase in patenting by VC-backed startups, however, patenting in renewable energy still remains concentrated in a relatively small number of firms. Figure 6 documents the share of total patents filed by US inventors working at either incumbents or venture capital-backed firms that are attributed to the 10, 20 and 50 most actively patenting firms in each year. As can be seen in Figure 6, the top 20 firms accounted for about half of all the renewable energy patents filed by firms in the early

[6] Since our sample looks only at patents at the USPTO, "foreign inventors" are those who live outside the US and have chosen to patent their inventions in the United States. Of course, there are likely to be significant number of renewable energy inventions by foreign inventors that are not patented at the USPTO. For example, a number of patents related to solar in Germany are not patented in the US. However, given that the US is such an important market, our prior is that important patents would in fact be patented in the US in addition to other countries. Anecdotal evidence suggests that this is indeed the case. Nevertheless, the structure of our sample does not allow us to make substantive conclusions about US vs. Foreign patents, or speak to differing trends in patenting between US and Foreign inventors in renewable energy over time.

late 1980s and early 1990s. Although the concentration has fallen from that peak, it is still over 40% in 2009.

Table 2 provides more detail by listing the most active US-based assignees patenting in renewable energy in recent years and the number of patents associated with these. Specifically, it focuses on the assignees with at least five patents between 2005 and 2009, in each of the technologies. As can be seen from Table 2, large incumbents account for the disproportionate share of the overall patenting. Firms such as GE, DuPont, Chevron, ExxonMobil, Applied Materials are among the most active firms patenting in renewable energy. However, a number of VC-backed firms are also on this list. For example, Solopower, Konarka Technologies, Stion, Nanosolar, Solyndra, Miasole, Twin Creek Technologies and Solaria are all VC-backed firms, so that 8 of the top 20 assignees with US-based inventors patenting in solar between 2005 and 2009 were VC-backed startups. Similarly, Amyris, KiOR and Ceres in Biofuels, Clipper Wind Power and FloDesign Wind Turbines in Wind, Ocean Power Technologies and Verdant in Hydro are all venture-capital backed firms. This list highlights how VC-backed startups have grown to become major contributors to innovation in renewable energy in the last few years.

Appendix 1 provides a more detailed list of the top assignees from VC-backed startups, incumbents and academia/government, including both US and foreign inventors patenting at the USPTO and over the period 2000-2009. Given that the list includes assignees with many foreign inventors, other familiar names such as Vestas, Sanyo, Sharp, Gamesa and Schott AG are now also among the leading assignees involved in renewable energy innovation.

3.2. Characteristics of Patenting by Incumbent vs. VC-backed Firms

We next compare the characteristics of the patents filed by the different types of organizations. Our first step is to examine the citations to the patents that they file. Since citations tend to have a highly skewed distribution, we report the results from count models. Table 3 reports the results from negative binomial regressions, where the dependent variable is the count of citations received for each patent. Although we include technology and year fixed effects to account for fixed differences in patenting propensities across technologies and to account for cohort differences in the number of citations, we nevertheless also account for the fact that patents in 1980 would have received more citations than those in 1995 by looking at the cumulative citations received by patents five years from the year of application. Our measure of citations excludes self-citations, so we examine the influence of the patents on other assignees.

Columns 1-3 of Table 3 report results on both US and foreign inventors, while Columns 4-6 restrict the sample to US-based inventors. We use academic and government patents as our reference group as they are likely to have remained the most stable over the entire period. Table 3 shows some interesting patterns. First, as noted above and consistent with prior findings (Singh and Fleming, 2010), unassigned patents seem to be far less influential than patents with assignees, both in the full sample and for US-based inventors. When interpreted as incidence rate ratios, Column1 in Table 3 implies that unassigned patents are associated with a 75% lower citation rate than academic and government patents. Second, patents filed by incumbent firms are slightly more influential than academic patents, but only marginally

so. The economic magnitude is small and it is imprecisely estimated. Incumbents are associated with a citation rate that is 1.1 times that of university and government patents. On the other hand, patents filed by VC-backed firms are much more likely to receive subsequent citations. The economic magnitudes are large. The coefficients imply that VC-backed startups are associated with a citation rate that is 1.9 times that of university and government patents. In addition, a Chi2 test for the difference in the coefficient between citations to VC-backed firms and incumbents shows that the differences are statistically significant. The P-values lie well below 0.05 and aside from Column 4, are less that 0.01 in each case.

The difference in the overall level of citations could come from two different fronts. First, it is possible that VC-backed firms have fewer marginal, or un-cited patents, so that the difference stems from the left tail of the citation distribution being better. Second, it is possible that VC-backed firms are more likely to have highly-cited patents, so that even if the left tail of the distribution is no better, the intensive margin of citations is higher, including a thicker right tail. To probe these possible explanations, we examine both the share of patents with at least one citation and the share of patents that are highly cited.

Table 4 reports the results from OLS regressions where the dependent variable takes a value of one if the patent received at least one citation. Again, unassigned patents are far less likely to receive a single citation. The coefficients imply a 35-38 percentage point lower chance of being cited relative to academic patents, on a baseline of a 50% citation probability. Both VC-backed startups and incumbents have patents that are more likely to receive citations than patents by inventors in university and government labs. This of course, could be due to the basic nature of academic and government R&D. When comparing VCs and incumbents, however, we find that VCs have an 11-14 percentage point higher likelihood of being cited relative to academic labs, compared to a 5-7 percentage point higher probability for incumbents. These differences are statistically significant, suggesting that on average, VC-backed patents are less likely to be marginal and more likely to influence future R&D.

Table 5 reports the results from OLS regressions where the dependent variable is equal to one if the patent was highly cited. Specifically, we define a patent as being highly cited if the citations for that patent are in the top 10 percent of 5 year forward citations for patents in that technology and year. Table 5 shows that unassigned patents are much less likely to have a highly cited patent. Since the baseline probability is by definition about 10%, the coefficients on unassigned patents in Columns 1 and 4 of Table 5 point out that the chance of an such a patent being highly influential is essentially zero. On the other hand, VC-backed firms are almost twice as likely as academic patents to be highly cited. Incumbent firms have no statistically significant difference in highly cited patents in the overall sample, and a slightly higher chance among US-based inventors. However, importantly, the difference in the chance of being highly cited between VC-backed firms and incumbents is both statistically and economically significant.

Thus far our analysis has suggested that renewable energy innovation by incumbent firms tends to be less influential. Innovation by incumbents is less likely to be cited at all and when it is, it is less likely to be highly cited. These results are consistent with the literature that has documented that incumbent

firms have different goals, search process, competencies and opportunity costs that lead them towards more incremental innovation (Tushman and Anderson, 1986; Henderson and Clark, 1990; Tripsas and Gavetti, 2000; Rosenkopf and Nerkar, 2001; Akcigit and Kerr, 2011), although these papers have not directly compared innovation by incumbents with that by VC-backed startups.

To probe our results further, we turn next to directly examine the extent to which incumbents pursue more incremental innovation, by examining the degree to which they cite their own prior work relative to other types of organizations. Following Sorensen and Stuart (2000), we hypothesize that if firms are citing their own patents at a disproportionate rate, then they may be engaged in more "exploitation" rather than "exploration**" (**March, 1991). We therefore study the extent to which inventors in the different organizational settings tend to cite themselves.

Table 6 reports the results from negative binomial regressions where the dependent variable is the count of the self-citations a focal patent makes, where a self-citation is defined as citing a patent from the same assignee. The regressions control for the total number of citations the patent made, and technology and patent application year fixed effects. As can be seen from Table 6, VC-backed firms are no more likely to cite themselves than academic labs. Although the coefficient is in fact negative, it is imprecisely estimated. On the other hand, the coefficient on incumbent firms implies that they are 50% more likely to cite themselves compared to academic labs. Again, the difference between VC backed firms and incumbents is statistically significant, suggesting that part of the reason that incumbents have less influential innovations is that they are engaged in more incremental R&D than VC-backed startups.

One possible reason for not being cited at all and for citing one's own work could also be that firms are engaged in extremely novel innovations that have not yet yielded citations. This could be particularly true in nascent technologies such as renewable energy. In addition, since patenting activity is concentrated in a few incumbent firms, it is possible that some of the higher self-citation is purely due to the fact that the prior art to be cited is more likely to be that of incumbents or that VC-backed firms do not have many prior patents to cite.

In order to address these concerns, we use a new measure of novelty that is not based on citation-measure. Instead, we draw on a textual analysis of patent applications to look at the similarity of patent claims and descriptions for patents in a given technology-area. Intuitively, our definition is such that patents with greater textual similarity to neighboring patents are considered to be less novel. Our measure of novelty should be particularly useful in the context of science-based patenting, where technical terms are more unique and therefore more likely to signal differences in the characteristics of innovation, and for more recent time periods, where initial forward citations may be a noisy predictor of ultimate outcomes. The measure also avoids problems with citation-based measures, where citation patterns can suffer from selection biases. A more detailed description of the measure is outlined in Appendix 2 (see also Younge, forthcoming, and Ullman and Rajaraman 2011, pp. 92-93).

As can be seen from Table 7, our novelty measure is quite consistent with the other citation-based measures of patenting. First, it highlights that in addition to unassigned patents not receiving many citations, they are also less novel than patents being developed in academic and government labs. The

regressions highlight that the novelty of the patents for VC-backed startups is no different from that of academic labs. However, incumbent firms have a significantly lower level of novelty. Although the difference between the novelty of patenting by incumbent and VC-backed firms is not significant for the overall sample, it is close to being significant at the 10% level for US-based inventors, particularly in the latter part of our sample. Our results therefore suggest that incumbent firms have been engaged in less novel and exploratory innovation than VCs, in particular in the US.

4. Venture Capital Financing of Renewable Energy Startups

Thus far we have documented that VC-backed startups have increased their share of patenting most substantially over the past decade and that these startups seem to be associated with more radical and novel innovation than that by incumbent firms. The timing of growth in renewable energy patenting by VC-backed firms is closely associated with venture capital dollars flowing into renewable energy startups. In 2002, only 43 clean energy startups received VC funding in the US, raising a combined total of $ 230 M. In 2008, over 200 clean energy startups raised $ 4.1 BN in venture capital in the US.[7] In fact, clean energy investments accounted for about 15% of the total dollars invested by VCs in the US in 2008, of which a majority went to renewable energy technologies.

Although our work cannot distinguish whether VCs lead startups to engage in more radical innovation, or are just able to select more radical innovations than the incumbents tend to fund, it does highlight that venture capital financing seems to have associated with a more novel and high impact innovation in renewable energy, particularly in the late 2000s (Conti, Thursby and Thursby, 2012).[8] This seems important given the need for the widespread experimentation required to make progress in providing low cost, clean energy that will support developing without incurring massive costs in terms of climate change. To the extent that the shift in venture capital finance away from such technologies is due to structural factors, this suggests that it will have a noticeable impact on the type of innovation being undertaken in renewable energy (either through the treatment or the selection effect of venture capital investment).

Needless to say, a number of factors are likely responsible for the rapid decline in VC financing for renewable energy startups. The economic collapse in 2009 had a chilling effect on all venture capital investment, including clean energy. In addition, improvements in hydro-fracking technology that opened up large reserves of natural gas lowered the cost of natural gas considerably and changed the economics of renewable energy technologies in terms of them being close to “grid parity”. Nevertheless, our discussions with venture capital investors suggest that there are in fact structural factors, over and above these historical developments, that have led investors to become unwilling to experiment with

[7] Source: Ernst and Young, National Venture Capital Association Press Releases.

[8] Note that simply looking at the timing of the patents and the investment will not help untangle the causality as VCs will often invest in firms that have promising technologies in the anticipation that they will patent.

renewable energy production technologies. In this section, we outline these structural factors that VCs seem to be facing, making sustained funding of entrepreneurship in renewable energy difficult.

4.1 Financing Risk and Capital intensity of energy production

VC-backed investments are extremely risky, leading to an extremely skewed distribution of returns. Hall and Woodward (2010) and Sahlman (1990; 2010) document that about 60% of VC investments are likely to go bankrupt and the vast majority of returns are typically generated from about 10% of the investments that do extremely well. Furthermore, Kerr, Nanda and Rhodes-Kropf (2013) document how hard it is for VCs to predict which startups are likely to be extremely successful and which will fail. VCs therefore invest in stages, in effect buying a series of real options, where the information gained from an initial investment either justifies further financing or the exercise of the VC's abandonment option to shut down the investment (Gompers, 1995; Bergemann and Hege, 2005; Bergemann, Hege and Peng, 2008; Guler, 2007). Hence properties of startups that maximize the option value of their investments make their portfolio more valuable. For example, investments that are capital efficient (cost of buying the option is less), where step ups in value when positive information is revealed are large relative to the investment (more discriminating "experiments" being run with the money that is invested) and where the information about the viability of a project is revealed in a short period of time are all properties that make investments more attractive for VCs. Sectors such as IT and software, that have relatively low levels of capital investment, and where initial uncertainty about the viability of the technology is revealed quickly, are ideal sectors for VCs. The high returns for several of the most successful VC firms are based on information technology investments. A classic example is that of Google, that had a market capitalization of $23 billion at its IPO 5 years after it received its first round of VC funding, and having raised about $40 M in venture capital along the way.

On the other hand, the unit economics of energy production technologies need to be demonstrated at scale, because even if they work in a lab, it is hard to predict how they will work at scale. The fact that early stage investors need to finance not just the initial exploration around the technology, but also the scale up of the technology leads to two challenges for renewable energy startups. First, it implies that the resolution of uncertainty takes much longer, as startups often need to build demonstration and first commercial plants before it is clear that the technology is truly viable. Second, since these demonstration plants face technology (rather than engineering) risk, they are too risky to be financed through debt finance. VCs who back such startups therefore need to finance the companies through extremely long and capital intensive investments. The funds required to prove commercial viability for energy production technologies can reach several hundred million dollars over a 5-10 year period, compared to the tens of millions that VCs are typically used to investing in any given startup. [9]

[9] For example, Solyndra, a company that manufacturers photovoltaic systems using thin-film technology, has had to raise $ 970 M in equity finance in addition to a $ 535 M loan guarantee from the Department of Energy, prior to its planned IPO in mid 2010. This amount of capital to prove commercial viability is an order of magnitude greater than the $40-$50 M that VCs are typically used to investing in each company to get them to a successful exit.

This level of investment is not feasible from a typical venture capital fund without severely compromising the diversification of the venture firm's portfolio. For example, investing only $8-15M in a project that is twice as capital intensive halves the dollar return if the startup is successful. On the other hand, investing a sufficient amount to retain a large share in a successful exit requires making far fewer investments across the portfolio and hence makes the portfolio much more risky. Such investments are thus typically too capital intensive for VCs, given the size and structures of most VC funds today.

The inability to raise either debt or venture capital at the demonstration and first commercial stage has led this stage of the startup's life to be known as the "valley of death" (see Figure 6). The fact that investors are now acutely aware of this funding gap before the firm gets to cash flow positive leads to an unraveling of the entire financing chain. That is, since investors forecast that even promising startups may have a hard time getting financing when they reach the stage of needing to build a demonstration plant, the benefits of sinking capital in a startup at the stage before may not be worthwhile. This logic, that VCs refer to as financing risk, works through backward induction to the first investor. Thus, a forecast of limited future funding may lead promising projects to not be funded, even if when fully funded, they would be viable and NPV positive investments (e.g., see Nanda and Rhodes-Kropf, 2013).

This challenge is exacerbated by the fact that potential entrepreneurs who know the energy space often tend to be from large oil companies or from utilities. Hence, they make good CEOs for the stage when the startup is more established, but they tend to be relatively poor entrepreneurs at the early stage of the business where cash is limited and needs to be raised frequently, the business model is not clear, and decisions need to be made quickly with limited information at hand. On the other hand, those with a background of VC backed entrepreneurship may be successful at running small IT-related, biotech or semi-conductor startups, but are ill-positioned to manage and grow energy production companies that have different business models and challenges. Since VCs require entrepreneurs to play a central role in fundraising for the large amounts of money required for commercial testing of the technology, in addition to managing large production facilities, international commodity pricing and anticipating the changing government policies, the combined skill set required of such CEOs is one that is in short supply (Kaplan, Sensoy and Stromberg, 2009). These factors greatly increase the operational risk of companies, and hence this creates important challenges for running and growing stand-alone energy production companies that go beyond their capital intensity.

4.2 Exit opportunities

VCs have invested in some industries such as biotechnology, semiconductors and IT/ networks that also share the attributes of huge infrastructure and management requirements that are outside the scope of a startup. However, in these instances, VCs bank on an established exit mechanism to hand over their early stage investments before they hit the valleys of death in capital and managerial talent. For example, in the biotechnology industry, the VC model has evolved so that pharmaceutical companies step in to buy promising startups at a point even before commercial viability has been proven. This is a key part of the innovation ecosystem as it bridges the potential valley of death and thereby facilitates pre-commercial VC investments in biotechnology. The propensity of pharmaceutical companies to buy

promising startups also facilitates their IPOs at pre-commercial stages, because public investors believe there is sufficient competition among pharmaceutical firms for biotechnology startups with innovative solutions that they will be acquired well before they hit the valley of death. Cisco, Lucent, HP and Juniper networks play an equivalent role in the IT/ networking industry.

Thus far, however, energy producing firms and utilities that supply electricity to customers have been far from active in acquiring promising clean energy startups. This bottleneck in the scaling-up process has a knock-on effect on the ability for VCs to fund pre-commercial technologies in this space as well. If early stage venture investors face the risk that they may be unable to raise follow-on funding or to achieve an exit, even for startups with otherwise good (but as yet unproven) technologies, they run the danger of sinking increasing amounts of dollars for longer periods of time to keep the startup alive. With incumbent firms unwilling to buy these startups at pre-commercial stages, the time to exit for the typical startup is much longer than the three to five year horizon that VCs typically target (the time to build power plants and factories is inherently longer than a software sales cycle and can even take longer than the life of a VC fund). As shown in Figure 6, this leads venture capitalists to withdraw from sectors where they could have helped with the pre-commercial funding, but where they are not certain that they will be able to either fund the project through the first commercial plant, or they are not sure if they can exit their investment at that stage (Nanda and Rhodes-Kropf 2013).

In the case of biotechnology industry, a clear exit mechanism was facilitated by the fact that the FDA developed well-understood and transparent metrics for success at each stage. Because the set of buyers is uniform and the criteria for a successful exit at each stage have been developed and well-understood, VCs can work backwards and set their own investment milestones. In this way, the downstream exit process has important consequences for the direction of upstream innovation. The fact that there is a well-developed eco-system where large pharmaceutical firms buy promising startups implies that there is greater early stage venture capital funding of such firms. Moreover, stock market investors also have an appetite for such firms, in the knowledge that pharmaceutical firms will be willing to acquire a promising target before it hits the bottleneck of marketing and distribution. This in turn creates another exit avenue for venture investors, fuelling further early stage activity. In fact, the history of capital intensive industries such as biotechnology, communications networking and semiconductors suggests that until the incumbents start buying startups, the innovation pipeline does not truly take off.

The extent to which large energy companies will play an equivalent role in the innovation pipeline for clean energy is not yet clear. While energy companies have not chosen to be active buyers of clean technology startups, it is still early in the life of the clean energy ecosystem, comparable to the biotechnology ecosystem in the late 1980s. There are some signs that this may be changing, with the most promising developments being in the rise of a number of corporate venture capital funds among the large energy companies (Nanda and Rothenberg, 2011).

4.3 Global Commodities and Policy Risk

A final important difference between the renewable energy production and the typical VC-backed startup is that energy is a commodity. Success in energy comes from being a low cost provider rather than having an innovation that can be priced high due to the willingness of end users to pay (as is the case for biotechnology). While incumbents in other industries compete with each other to acquire startups in order to meet end-user demand, the end-user in the energy market cannot distinguish electrons produced from coal, the sun or the wind (unless the government prices the cost of carbon appropriately). In the absence of appropriate price signals or incentives to invest in renewables, incumbents are therefore not pressed to acquire startups in this space. In the case of biofuels, the inputs to their production process are also commodities. Energy producers therefore face commodity risk for both raw materials and end products. Since these markets can exhibit substantial price volatility, it makes running and managing these companies more difficult. For example, second- and third-generation biofuel startups producing ethanol or bio-crude at $80-$90 per barrel were competitive in 2007 prior to the global recession when conventional oil prices topped $100 a barrel, but most went bust when oil prices plummeted in the subsequent recession.

The challenges of backing a global commodity producer are compounded by the fact that energy and clean energy are sectors with large involvement by governments across the world. Given that clean energy technologies have not yet achieved grid parity, government policy is also critical in determining the prices of inputs and finished products. Some governments choose to either tax carbon content in conventional fuels or to buy clean energy at a premium. Others choose to subsidize clean energy companies through direct grants and subsidies or through tax-breaks. Regardless of the policy, it implies that the extent to which a given startup's product is likely to be profitable depends greatly on whether it is included in the subsidy or credit, the extent to which carbon is taxed or the price premium at which the government buys the commodity.

Policy changes and uncertainty are thus major factors hindering the potential investment by private sector players across the clean energy investment landscape (Bloom, 2009). This is particularly true when the periodicity of the regulatory cycle is smaller than the investment cycle required for demonstrating commercial viability. In such an event, no one is willing to invest in the first commercial plant if they do not know what the regulatory environment is going to be by the time success has been demonstrated (based on the rules of the prior regulatory regime).

5. Possible solutions

The section above has tried to demonstrate that VCs enter markets where they believe they can create and then exercise growth options. VC's were initially attracted to renewable energy technologies in the belief that there would be a shift in demand from society for renewable energy, and that shift would create large growth options for them due to a constrained supply of socially-desired renewable energy alternatives. This belief has not yet panned out, and moreover, the cost of creating the growth options have turned out to be much greater, as the innovation pipeline is nascent and the absence of incumbents buying promising technologies means VC investors need to finance the scale up before they

can exercise their options. In this section, we discuss possible solutions that may help drive a more robust financing ecosystem for renewable energy technologies.

5.1 Private capital market solutions

With the appropriate price signals and incentives, incumbents may be incentivized to buy promising technologies, thereby reducing financing risk considerably, as took place as the biotechnology industry matured. We discuss these incentives in the next subsection.

In the absence of energy companies and utilities playing an important role in this innovation pipeline, the alternative for wide-spread innovation by startups in renewable energy production will require the structure of the VC industry to change in key ways.

First, it will require significantly larger funds than is typical for venture capital investors, in order to address the challenges associated with financing risk and the "valley of death". Indeed Kleiner Perkins' $500 M Green Growth Fund, and Khosla Ventures' $ 750 M fund are examples of such a trend[10], but the sector will probably require even larger funds to support the scale-up required by energy production companies. The majority of venture capital investors in clean technology do not have dedicated funds for this sector, and continue to raise $250-300 M funds and may need to have far greater levels of syndication, or pre-set partnerships across VCs in order to sustain the level of investment required by this sector. Moreover, if venture capital investment in the energy sector is to be sustained in the absence of early exit opportunities, it will require a radical reworking of the VC fund structures and terms.

Overcoming these challenges will be compounded by another factor associated with the emergence of a new industry: learning through experimentation. Investors in new technologies get feedback on their process of due diligence, the types of entrepreneurs who are most successful, and an understanding of the challenges faced by certain types of business models over the investment cycle (Goldfarb et al 2007). This is also a period when a generation of new entrepreneurs arises, driven in part by the many firms that fail due to a technology that did not work, but where the entrepreneurs developed a good working relationship with the venture capital investors. All of these processes develop faster when the cycle times for "experimentation" by the VCs are smaller. In the context of clean energy, the feedback is much slower, driven by the dual stages of risk and the longer cycle times of clean energy. Many players therefore see a critical role for government in supporting the growth of the clean energy innovation pipeline.

5.2 Government Support

The US government has played an important role in supporting clean technology innovation in the US. However, the vast majority of this has been on the "supply side", through the direct support of specific

[10] Khosla Ventures also created a dual fund structure, where a smaller fund would focus on early stage experiments while a second, larger fund would guarantee funding for commercialization, helping to reduce financing risk.

government and university programs, grants to support pre-commercial funding of new startups through the ARPA-E program and attempts to bridge the valley of death for individual projects through the Department of Energy's loan guarantee program (Roberts, Lassiter and Nanda 2010).

While clearly very helpful in attempting to address the funding gaps inherent in the energy innovation pipeline, a key aspect of ensuring that the pipeline of new projects continue to get funding from the private sector will be to ensure that there is a vibrant set of exit opportunities for these startups before they hit the valley of death. While government guaranteed debt will help reduce some of this risk, widespread experimentation and deployment of new technologies can only take place once startups have a clear path to being acquired or going public on the capital markets. The government can therefore do more in terms of making exits easier. We note three interesting ideas that have emerged through our discussions with VCs and that are also echoed in the broader community of investors looking for solutions to the "valley of death" (Bloomberg New Energy Finance, 2010).

The first area where the government can make a significant contribution is through stable, predictable and long-term policy measures aimed at stimulating demand for clean energy. Removing uncertainty around policies reduces policy risk dramatically and makes it easier for the private capital markets to plan their investments accordingly. Furthermore, in the absence of end-user pressure to drive M&A activity, the government can create this pressure through policies such as Feed-in-Tariffs (FITs). While FITs have their most direct effect on incremental improvements of commercially proven technologies, solutions such as emerging technology auctions may be able to successfully create the appropriate demand for new technologies.

Second, the government can directly stimulate M&A activity either through the regulatory system or through corporate incentives. For example, without decoupling, utilities will have no incentive to adopt new technologies beyond anything that they are mandated to do. Renewable portfolio standards as they stand today tend to bias utilities towards adopting more mature, currently-cheaper technologies. The government can also create incentives for incumbent firms to act as first adopters for new technologies. These can effectively help to bridge the "valley of death", create more early stage funding and drive the growth of a sufficient number of startup firms to ultimately create large firms that will compete with each other to acquire for the next generation of startups.

Finally, the government can create public-private partnership funds that can help either with first commercial testing or as mechanisms that effectively compete with the incumbents. Creating this competition can help stimulate M&A activity in the sector and hence drive the innovation pipeline (Bloomberg New Energy Finance, 2010). This could be designed along the lines of Fernandez, Stein and Lo (2012) who have begun to identify similar challenges in biotechnology and are suggesting innovative financial engineering approaches to funding innovation in cancer therapy, that could also be applied to renewable energy technologies.

6. Conclusion

Innovation in renewable energy has grown in recent years, in part due to the sharp rise in venture capital finance for renewable energy startups in the early 2000s. However, the availability of venture capital finance for renewable energy has fallen dramatically in recent years. In this chapter, we ask whether we should worry that the decline and shift in VC will slow the rate and alter the direction of innovation in renewable energy.

Our results suggest that startups backed by venture capital file patents that are more likely to have at least one citation, are more likely to be highly cited, have fewer self-citations and are more likely to be novel than patents filed by incumbent firms. Although the lag in the patent grants do not allow us to directly observe how the falling levels of VC finance relate to the innovations by VC-backed startups, our results suggest VC financing is associated with a greater degree of economic experimentation and therefore, we should worry that VCs have moved away from funding such startups.

Our chapter has also aimed to shed light on some of the structural factors that have made sustained experimentation by VCs hard, with a particular emphasis on the difficulty of exiting their investments to incumbent firms that have the expertise and capital to finance the scale up of such technologies. Larger/longer Funds may be one alternative, since such funds could get past the uncertainty and to a stable place for exit), but measures designed to incentivize incumbents up the financing chain to bridge the 'valley of death' also seem like possible solutions.

We should note that our analysis is not meant to suggest that process innovations are unimportant, or that the focus of VC on other aspects of clean tech is not valuable. Rather, our objective is to highlight the fact that the shifting focus of venture capital is likely to have an impact on both the rate and the characteristics of renewable energy innovation in the coming years. To the extent that there is still a need for experimentation with new technologies a desire to commercialize radical innovations in renewable energy, our work highlights that in addition to falling natural gas prices, there are structural factors about energy that make sustained experimentation by VCs difficult in renewable energy. Although it is still early in the life cycle of this industry, our discussion has outlined some specific factors that may facilitate the deployment of large amounts of risk capital that are necessary to finance renewable energy innovations.

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Figure 1: Source of Global Energy Consumed in 2010 (Total = 132,000 TWh)

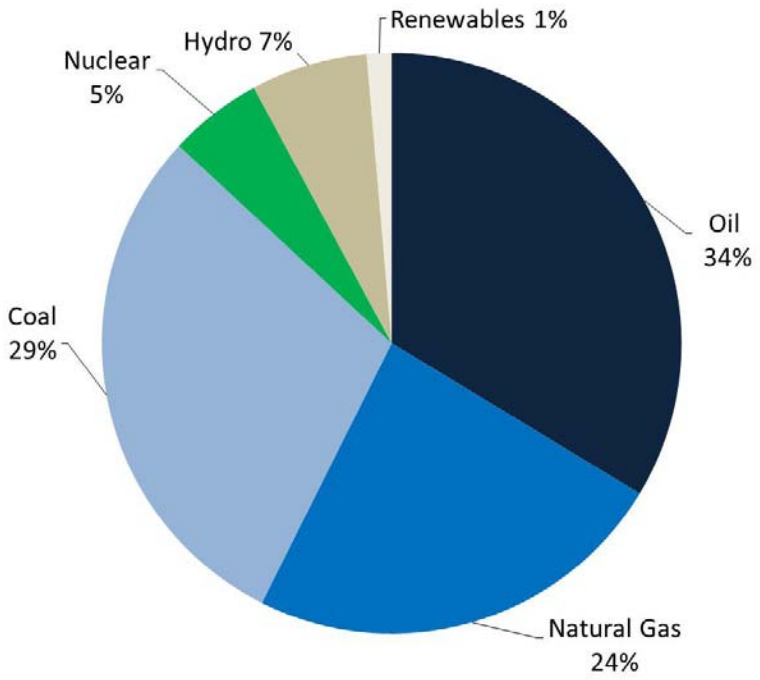


Figure 2A: Series A Financing for US-based startups in Solar, Wind and Biofuels

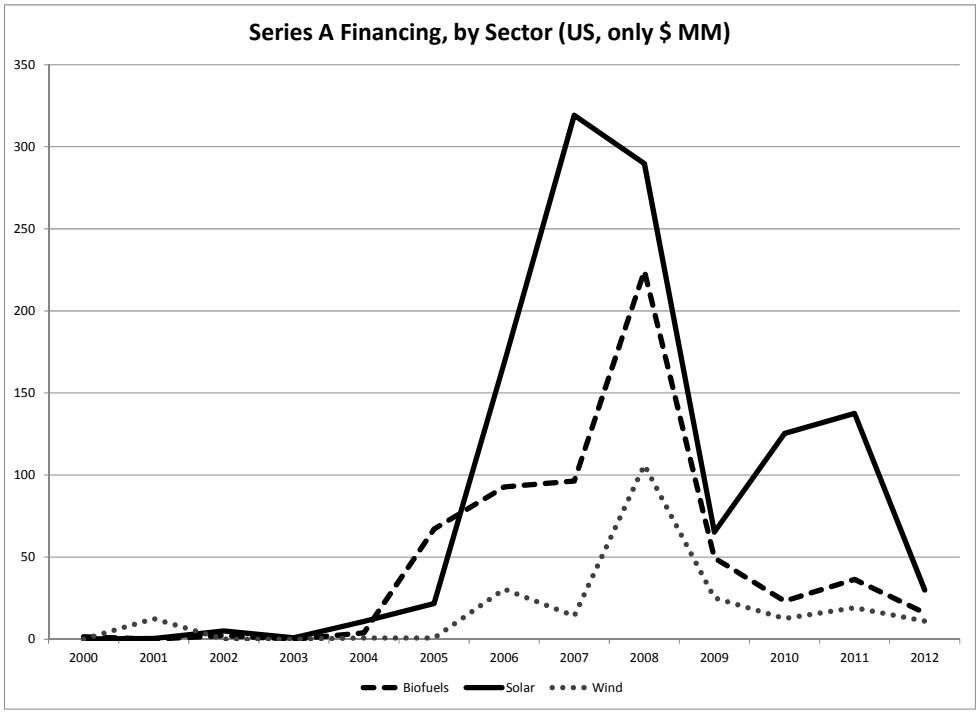


Figure 2B: Industrial / Energy Share of total VC investments (first series financings only)

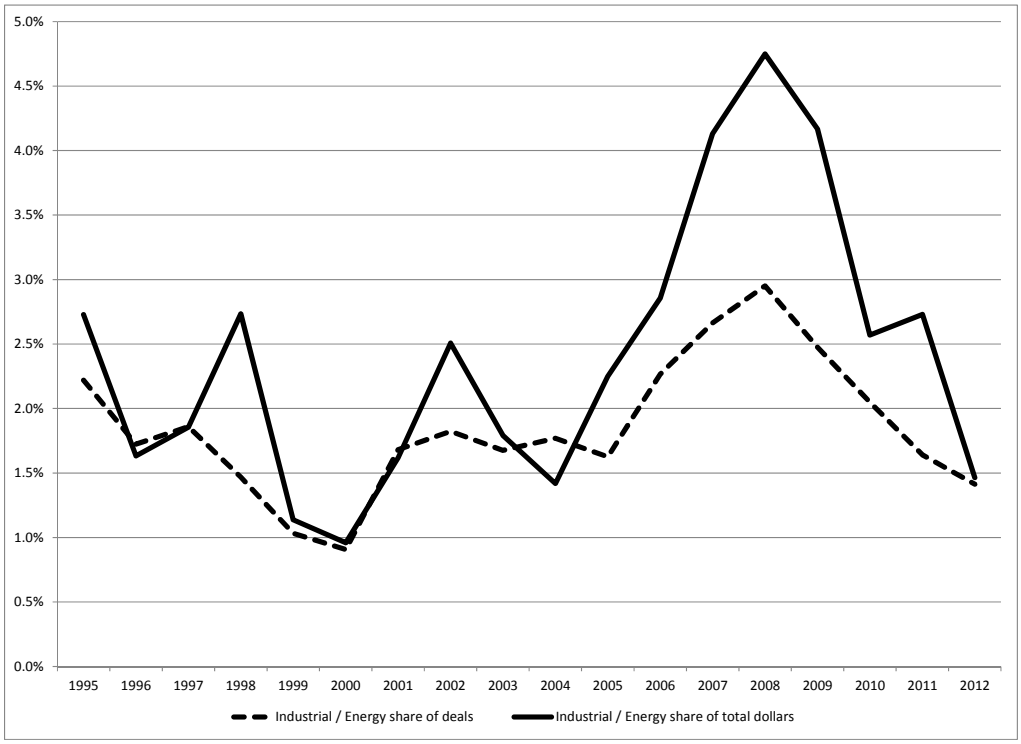
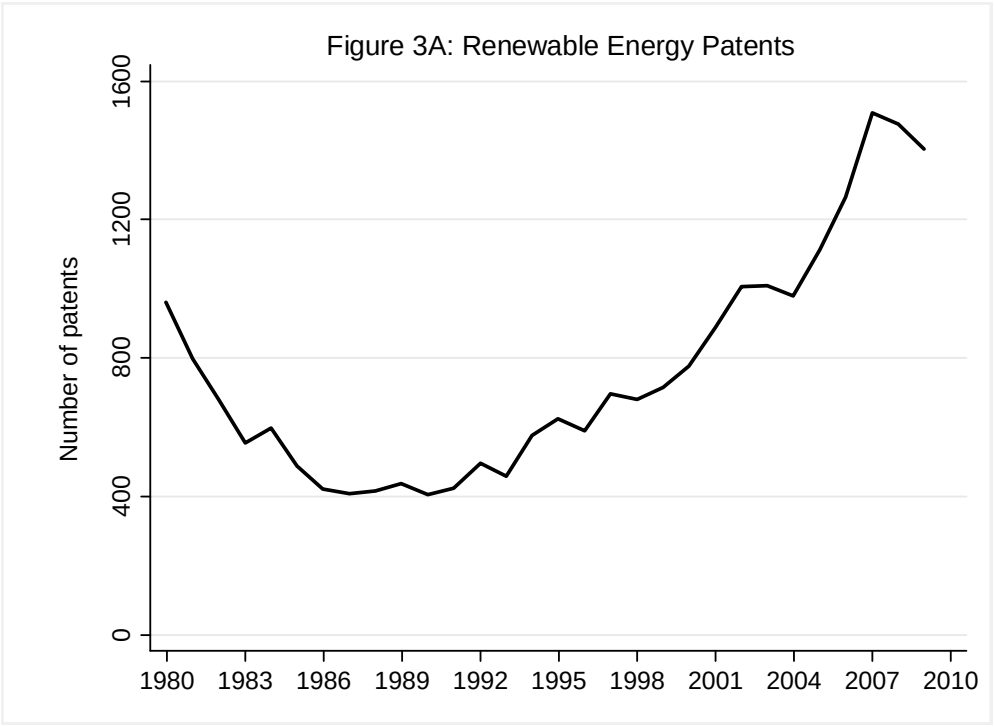
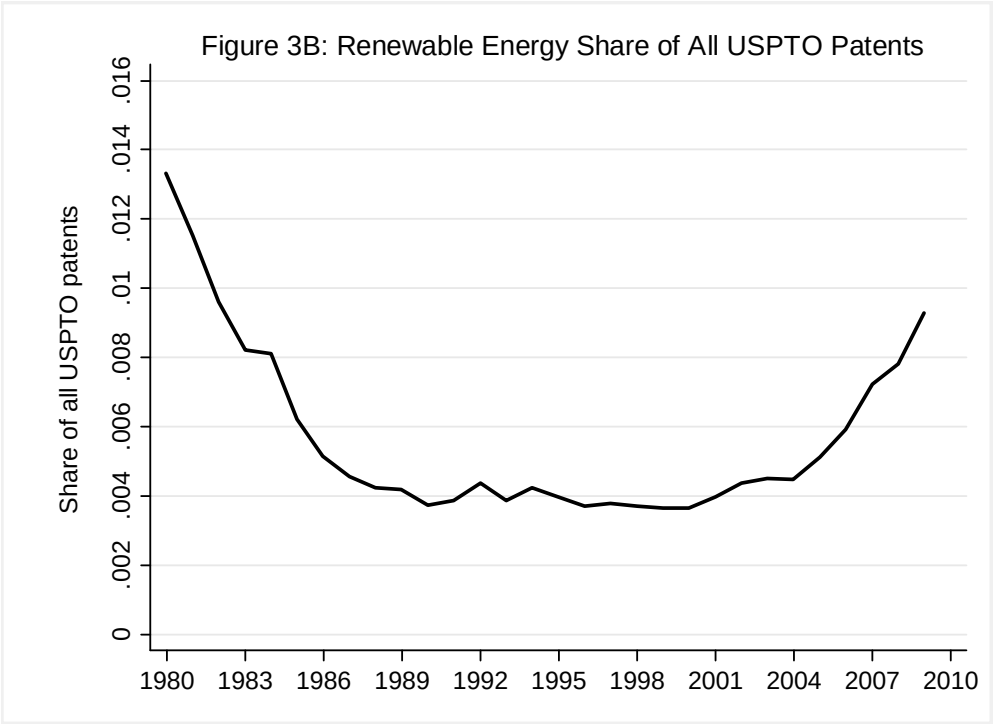
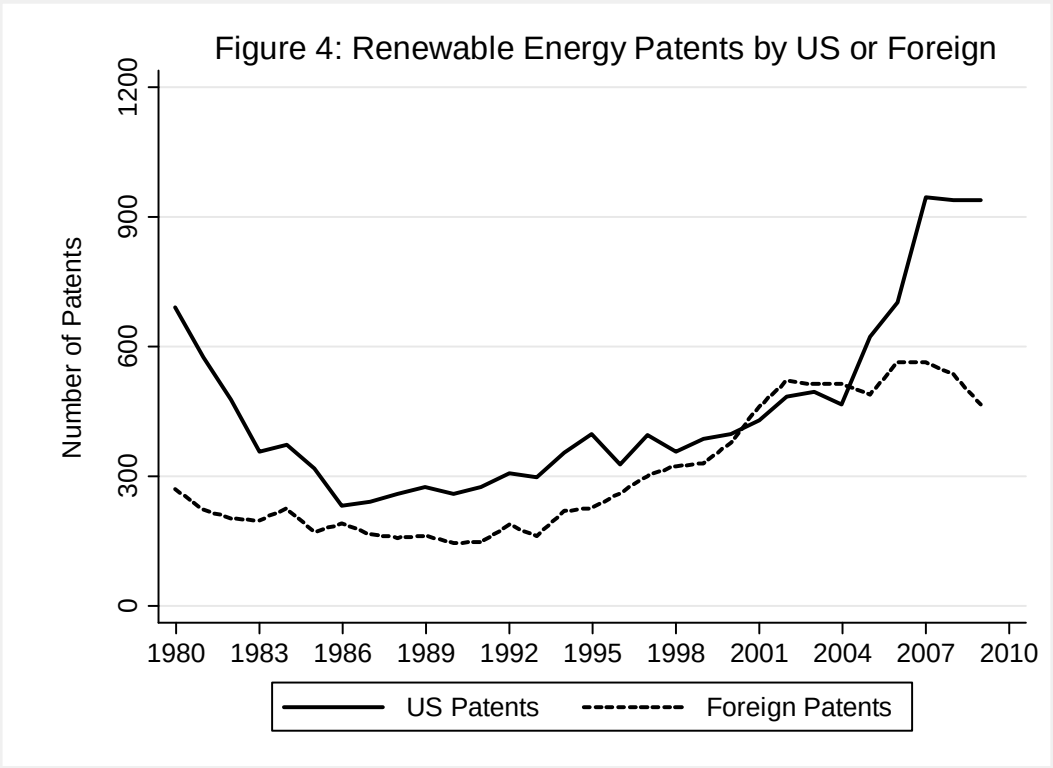


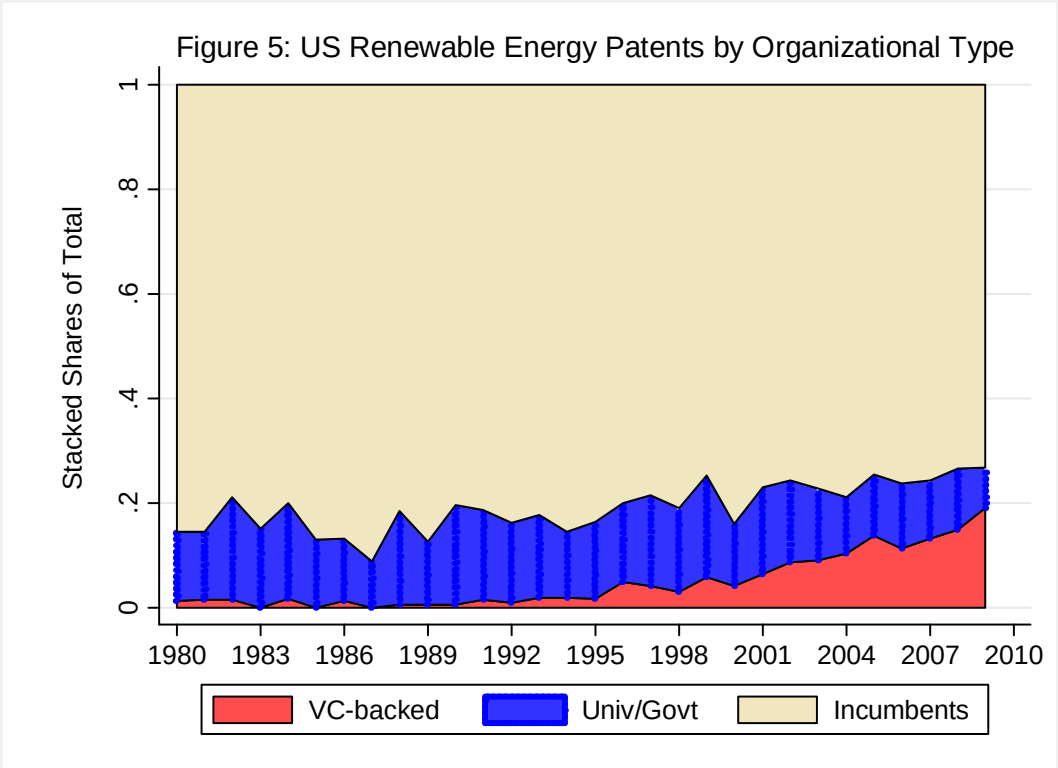
Figure 2C: Share of Series A Clean-tech financings by VCs going to solar, wind and biofuels startups




Figure 3A: Renewable Energy Patents
Number of patents
0
400
800
1200
1600
1980
1983
1986
1989
1992
1995
1998
2001
2004
2007
2010


Figure 3B: Renewable Energy Share of All USPTO Patents
Share of all USPTO patents
0
.002
.004
.006
.008
.01
.012
.014
.016
1980
1983
1986
1989
1992
1995
1998
2001
2004
2007
2010


Figure 4: Renewable Energy Patents by US or Foreign
Number of Patents
0
300
600
900
1200
1980
1983
1986
1989
1992
1995
1998
2001
2004
2007
2010
US Patents
Foreign Patents


Figure 5: US Renewable Energy Patents by Organizational Type
Stacked Shares of Total
0
.2
.4
.6
.8
1
1980
1983
1986
1989
1992
1995
1998
2001
2004
2007
2010
VC-backed
Univ/Govt
Incumbents

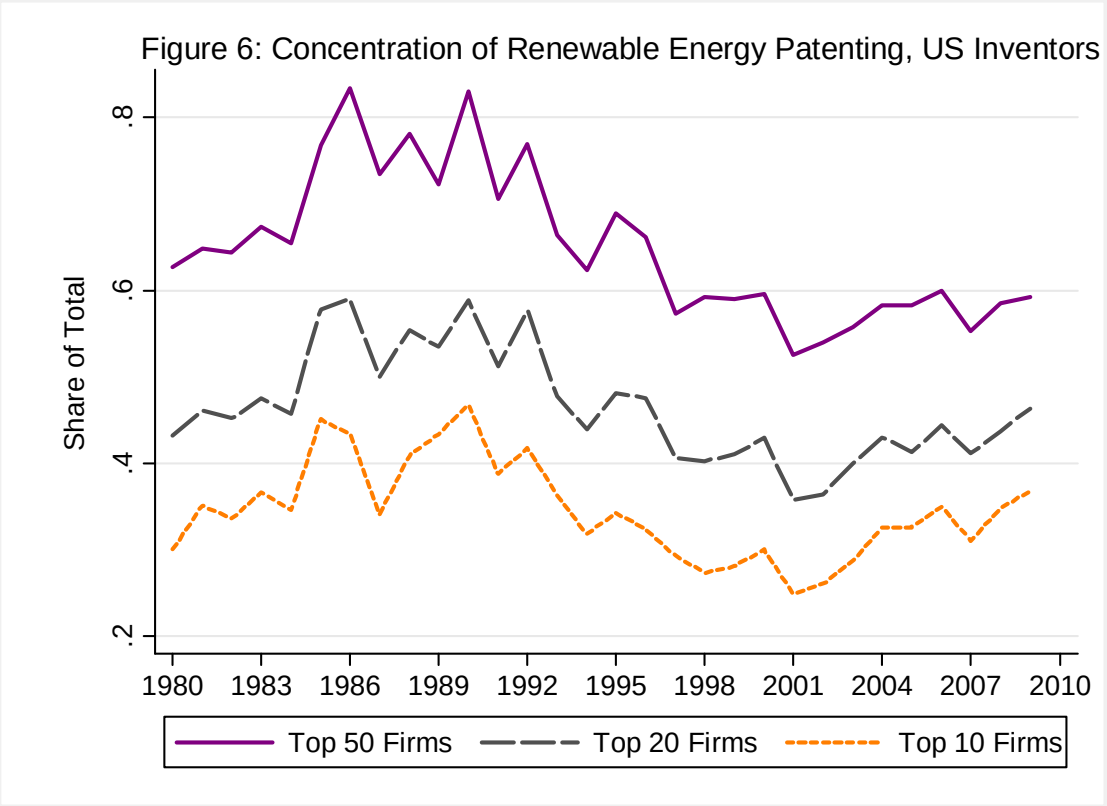


Figure 7: Funding Gaps and the "Valley of Death"

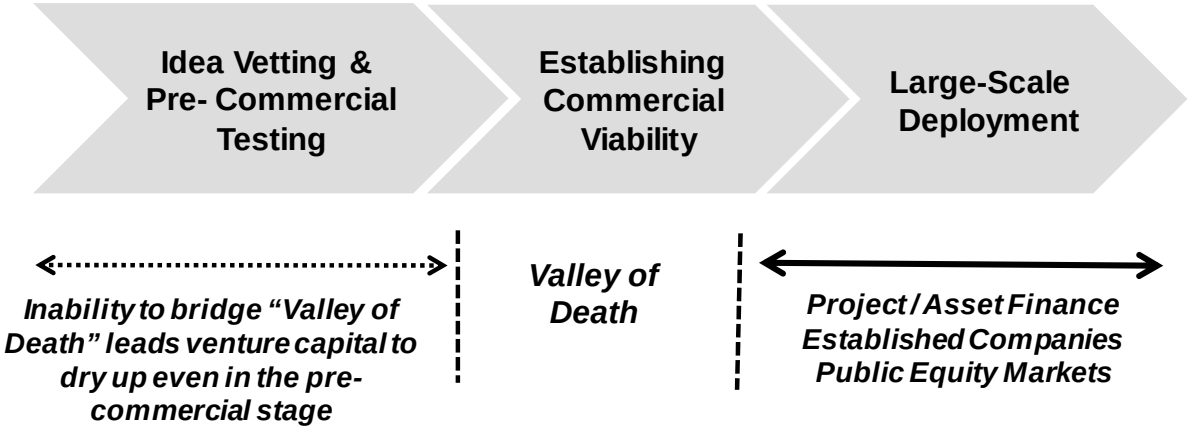


Table 1

Patenting rates in renewable energy, by technology and organization type

This table reports the breakdown of 22,869 renewable energy patents at the USPTO that were granted between 1980 and 2009. Panel A provides a breakdown for the entire sample and Panel B provides a breakdown for US-based inventors. Venture backed startups refer to patents where the assignee was matched to a firm that received Venture Capital finance (identified using data from Cleantech i3 and Bloomberg New Energy Finance). Patents granted to academic institutions or government labs were identified using a text-matching algorithm followed by manual review. Incumbent firms refer to the residual category of assignees who were not classified as either VC-backed or from academia / government. Unassigned patents are those not affiliated with any organization and are typically seen as independent inventors.

PANEL A: ALL RENEWABLE ENERGY PATENTS AT USPTO (1980-2009)

	Venture-backed Startups	Incumbent Firms	Academia and Government	Un-assigned	Total	Percent
Solar	473	5,937	732	2,502	9,644	42%
Wind	169	1,679	70	1,129	3,047	13%
Biofuels	177	4,995	884	778	6,834	30%
Hydro-electric	78	1,132	107	1,058	2,375	10%
Geothermal	52	597	54	266	969	4%
Total	949	14,340	1,847	5,733	22,869	100%

PANEL B: US-BASED INVENTORS ONLY

	Venture-backed Startups	Incumbent Firms	Academia and Government	Un-assigned	Total	Percent
Solar	402	2,797	482	1,884	5,565	41%
Wind	71	689	39	693	1,492	11%
Biofuels	143	2,987	659	513	4,302	32%
Hydro-electric	41	643	68	757	1,509	11%
Geothermal	29	431	42	219	721	5%
Total	686	7,547	1,290	4,066	13,589	100%

Table 2

Assignees with five or more patents to US-based inventors

Rank	Solar	Patent Count	Bio	Patent Count	Wind	Patent Count	Hydro	Patent Count	Geothermal	Patent Count
1	Applied Materials, Inc	56	Stine Seed Company	212	GE	204	GE	16	Kelix Heat Transfer Systems	7
2	SunPower Corporation	35	DuPont	78	Genedics Clean Energy, LLC	9	Ocean Power Technologies	12	Earth To Air Systems, LLC	5
3	Solopower	33	Merschman Seeds	76	Clipper Windpower Technology	8	Alticor Corporate Enterprises	11	GE	5
4	GE	31	Novo Group	30	Northern Power Systems, Inc.	6	Lockheed Martin	6		
5	Boeing	25	UOP	30	FloDesign Wind Turbine Corp.	5	Verdant Power	6		
6	Konarka Technologies	24	Chevron	29	Frontier Wind, LLC	5				
7	Stion Corporation	24	Monsanto	29	RenScience IP Holdings Inc.	5				
8	IBM	20	Syngenta AG	25						
9	DuPont	18	M.S. Technologies LLC	22						
10	Emcore Solar Power, Inc.	17	Dow	21						
11	Nanosolar, Inc.	17	Michigan State University	17						
12	Guardian Industries Corp.	16	ADM	13						
13	Xerox	13	University of Illinios	13						
14	Solyndra LLC	12	University of Wisconsin	13						
15	TE Connectivity	12	Amyris	12						
16	Twin Creeks Technologies	12	Royal DSM	12						
17	Lockheed Martin	11	NewMarket Corporation	11						
18	Miasole	11	U.S. Department of Agricultur	11						
19	Solaria Corporation	9	GE	10						
20	UTC	9	University of California	10						
21	Energy Innovations, Inc.	8	Battelle Memorial Institute	9						
22	GM	8	Ceres, Inc.	8						
23	Solexel, Inc.	8	University of Southern Californ	7						
24	Solfocus, Inc.	8	BASF	6						
25	University of California	8	ConocoPhillips Company	6						
26	World Factory, Inc.	8	ExxonMobil	6						
27	Foxconn	7	ZeaChem Inc.	6						
28	Iostar Corporation	7	Agritope/Aventis	5						
29	North Carolina State Univer	7	Battelle	5						
30	University of Central Florida	7	Catalytic Distillation Technolog	5						
31	Xantrex Technology Inc.	7	Coskata, Inc.	5						
32	Chevron	6	LUCA Technologies, Inc.	5						
33	Genedics Clean Energy, LLC	6	LenLo Chem, Inc.	5						
34	Qualcomm Inc.	6	Pennsylvania State University	5						
35	NASA	6	Rice University	5						
36	United Solar Ovonic LLC	6	Syntroleum Corporation	5						
37	Varian Semiconductor	6	Xyleco, Inc.	5						
38	AMPT, LLC	5								
39	Advanced Energy Industries	5								
40	Alcatel-Lucent	5								
41	Apple Inc.	5								
42	Architectural Glass and Alur	5								
43	Batelle/MRIGlobal	5								
44	Plextronics, Inc.	5								
45	Primestar Solar Inc.	5								

Table 3
Citations to patents

This table reports the results from Negative Binomial regressions where the dependent variable is the count of cumulative citations received by each patent five years from the patent's application. Column (1) reports results for the full sample. Columns (2) and (3) exclude patents with no assignees. Column (3) looks only at the latter half of the thirty-year period, from 1995-2009. Columns (4), (5) and (6) are the equivalent to Columns (1), (2) and (3) respectively but for the subsample of US-based inventors only. All regressions include fixed effects for the patent's grant year as well as a technology fixed effect (for Solar, Wind, Biofuels, Hydro and Geothermal). Parentheses report robust standard errors, clustered by assignee. *** p<0.01, ** p<0.05, * p<0.1

	Full Sample			US-based Inventors only		
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Venture Capital Backed Startup	0.606***	0.639***	0.672***	0.601***	0.641***	0.670***
	(0.165)	(0.158)	(0.177)	(0.181)	(0.173)	(0.199)
(b) Incumbent firms	0.118	0.113	0.099	0.163*	0.164*	0.143
	(0.073)	(0.075)	(0.108)	(0.087)	(0.089)	(0.132)
(c) Unassigned	-1.365***			-1.472***		
	(0.176)			(0.175)		
P-value on Chi2 test for difference between (a) and (b)	0.002***	<0.001***	<0.001***	0.011**	0.003***	0.002***
Patent application year fixed effects	Y	Y	Y	Y	Y	Y
Technology fixed effects	Y	Y	Y	Y	Y	Y
Observations	22,869	17,136	11,611	13,589	9,523	6,155

Table 4
Share of patents with at least one citation

This table reports the results from OLS regressions where the dependent variable takes a value of one if the patent received at least one citation and zero otherwise. Results are robust to running logit regressions. Column (1) reports results for the full sample. Columns (2) and (3) exclude patents with no assignees. Column (3) looks only at the latter half of the thirty-year period, from 1995-2009. Columns (4), (5) and (6) are the equivalent to Columns (1), (2) and (3) respectively but for the subsample of US-based inventors only. All regressions include fixed effects for the patent's grant year as well as a technology fixed effect (for Solar, Wind, Biofuels, Hydro and Geothermal). Parentheses report robust standard errors, clustered by assignee. *** p<0.01, ** p<0.05, * p<0.1

	Full Sample			US-based Inventors only		
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Venture Capital Backed Startup	0.105***	0.130***	0.136***	0.077*	0.114***	0.123***
	(0.034)	(0.027)	(0.029)	(0.040)	(0.030)	(0.032)
(b) Incumbent firms	0.055***	0.053***	0.058***	0.061***	0.063***	0.070***
	(0.016)	(0.014)	(0.017)	(0.019)	(0.018)	(0.022)
(c) Unassigned	-0.353***			-0.381***		
	(0.018)			(0.020)		
P-value on Wald test for difference between (a) and (b)	0.126	0.002***	0.003***	0.643	0.059*	0.058*
Patent application year fixed effects	Y	Y	Y	Y	Y	Y
Technology fixed effects	Y	Y	Y	Y	Y	Y
Observations	22,869	17,136	11,611	13,589	9,523	6,155

Table 5
Share of patents that are highly cited

This table reports the results from OLS regressions where the dependent variable takes the value of one if the patent was above the 90th percentile in terms of citations received, and zero otherwise. Results are robust to running Logit regressions. Percentiles are calculated relative to citations received by other patents in the same technology and application year and are based on cumulative citations received by each patent five years from the patent's grant. Column (1) reports results for the full sample. Columns (2) and (3) exclude patents with no assignees. Column (3) looks only at the latter half of the thirty-year period, from 1995-2009. Columns (4), (5) and (6) are the equivalent to Columns (1), (2) and (3) respectively but for the subsample of US-based inventors only. Since percentiles are calculated with a technology-year cell, all regressions implicitly include fixed effects for the patent's application year as well as a technology fixed effect (for Solar, Wind, Biofuels, Hydro and Geothermal). Parentheses report robust standard errors, clustered by assignee. *** p<0.01, ** p<0.05, * p<0.1

	Full Sample			US-based Inventors only		
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Venture Capital Backed Startup	0.075***	0.075***	0.083***	0.086***	0.086***	0.101***
	(0.026)	(0.026)	(0.027)	(0.028)	(0.028)	(0.028)
(b) Incumbent firms	0.018	0.018	0.015	0.037**	0.037**	0.031*
	(0.013)	(0.013)	(0.014)	(0.016)	(0.016)	(0.016)
(c) Unassigned	-0.125***			-0.114***		
	(0.015)			(0.015)		
P-value on Wald test for difference between (a) and (b)	0.018**	0.018**	0.008***	0.054*	0.054*	0.009***
Patent application year fixed effects	Y	Y	Y	Y	Y	Y
Technology fixed effects	Y	Y	Y	Y	Y	Y
Observations	22,869	17,136	11,611	13,589	9,523	6,155

Table 6
Degree of self citation

This table reports the results from Negative binomial regressions where the dependent variable is the number of number of backward citations that are self-citations. All regressions control for the total number of backward citations, so the coefficients reflect the share of prior art being cited that is self-citation. They can therefore be interpreted as the degree to which the assignee is engaged in incremental or exploitative innovation. Column (1) reports results for the full sample. Columns (2) and (3) exclude patents with no assignees. Column (3) looks only at the latter half of the thirty-year period, from 1995-2009. Columns (4), (5) and (6) are the equivalent to Columns (1), (2) and (3) respectively but for the subsample of US-based inventors only. All regressions include fixed effects for the patent's application year as well as a technology fixed effect (for Solar, Wind, Biofuels, Hydro and Geothermal). Parentheses report robust standard errors, clustered by assignee. *** p<0.01, ** p<0.05, * p<0.1

	Full Sample			US-based Inventors only		
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Venture Capital Backed Startup	-0.340	-0.338	-0.213	-0.135	-0.130	-0.146
	(0.266)	(0.266)	(0.281)	(0.296)	(0.296)	(0.308)
(b) Incumbent firms	0.405**	0.405**	0.466**	0.379**	0.380**	0.307
	(0.188)	(0.188)	(0.232)	(0.181)	(0.181)	(0.219)
(c) Unassigned	-5.259***			-5.283***		
	(1.045)			(1.082)		
P-value on Chi2 test for difference between (a) and (b)	0.007***	0.007***	0.013**	0.056*	0.057*	0.087*
Patent application year fixed effects	Y	Y	Y	Y	Y	Y
Technology fixed effects	Y	Y	Y	Y	Y	Y
Observations	22,869	17,136	11,611	13,589	9,523	6,155

Table 7
Characteristics of innovation: patent novelty

This table reports the results from OLS regressions where the dependent variable is the novelty of the patent claims, calculated as described in the appendix. Column (1) reports results for the full sample. Columns (2) and (3) exclude patents with no assignees. Column (3) looks only at the latter half of the thirty-year period, from 1995-2009. Columns (4), (5) and (6) are the equivalent to Columns (1), (2) and (3) respectively but for the subsample of US-based inventors only. Since the Novelty measure is calculated for each focal patent at a given point in time, relative to patents from the three previous years in the same technology area, all regressions implicitly include fixed effects for time and technology. Parentheses report robust standard errors, clustered by assignee. *** p<0.01, ** p<0.05, * p<0.1

	Full Sample			US-based Inventors only		
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Venture Capital Backed Startup	-0.020	-0.017	-0.022*	0.003	0.011	-0.000
	(0.014)	(0.015)	(0.012)	(0.018)	(0.022)	(0.017)
(b) Incumbent firms	-0.039***	-0.039***	-0.052***	-0.050***	-0.049***	-0.068**
	(0.012)	(0.012)	(0.017)	(0.019)	(0.018)	(0.029)
(c) Unassigned	-0.009**			-0.005		
	(0.004)			(0.005)		
P-value on Wald test for difference between (a) and (b)	0.380	0.352	0.222	0.121	0.117	0.10*
Patent application year fixed effects	Y	Y	Y	Y	Y	Y
Technology fixed effects	Y	Y	Y	Y	Y	Y
Observations	22,869	17,136	11,611	13,589	9,523	6,155

Appendix

Assignees with the most patents between 2000-2009, including US and Foreign inventors

Rank	Incumbents	Patent Count	VC-backed firms	Patent Count	Academia and Government	Patent Count
1	GE	541	Konarka Technologies, Inc.	52	Industrial Technology Research Institute	38
2	DuPont	235	Solopower, Inc.	33	University of California	36
3	Stine Seed Company	213	LM Glasfiber A/S	30	University of Wisconsin	27
4	Vestas	136	Repower Systems AG	30	Michigan State University	22
5	Canon	131	Nanosolar, Inc.	29	U.S. Navy	21
6	Siemens	92	Stion Corporation	24	U.S. Department of Agriculture	19
7	Boeing	88	Clipper Windpower Technology, Inc.	18	North Carolina State University	18
8	Mitsubishi Group	88	PowerLight Corporation	14	Fraunhofer Society	17
9	Novo Group	83	Miasole	13	University of Illinios	17
10	Merschman Seeds	81	Solyndra LLC	12	Institut Francais du Petrole	16
11	Sanyo	79	Twin Creeks Technologies, Inc.	12	NASA	15
12	BASF	76	Xantrex Technology Inc.	11	University of Central Florida	15
13	Sharp	68	Energy Innovations, Inc.	10	University of Florida	14
14	ExxonMobil	65	Hansen Transmissions International NV	9	Princeton University	13
15	DKB Group	64	Ocean Power Technologies, Inc	9	Massachusetts Institute of Technology (MIT)	12
16	Applied Materials, Inc	61	Solaria Corporation	9	National Institute of Advanced Industrial Science and Technology	12
17	Chevron	60	Ceres, Inc.	8	Battelle Memorial Institute	11
18	Monsanto	56	Nanosys, Inc	8	U.S. Army	10
19	Samsung	52	Solexel, Inc.	8	Iowa State University	9
20	Nordex Energy GmbH	48	Solfocus, Inc.	8	California Institute of Technology	8
21	SunPower Corporation	45	ZeaChem Inc.	8	Korea Advanced Institute of Science and Technology	8
22	Kaneka Corporation	44	Metabolix Inc.	7	Pennsylvania State University	8
23	Lockheed Martin	42	Oryxe Energy International, Inc.	7	University of Southern California	8
24	Dow	39	SunPower Corporation, Systems	7	National Research Council of Canada	7
25	Sumitomo	39	Converteam Ltd	6	National Taiwan University	7
26	Gamesa	38	Enlink Geoenergy Services, Inc.	6	U.S. Department of Energy	7
27	RAG Foundation	37	Tigo Energy, Inc.	6	University of Arizona	7
28	Schott AG	37	Verdant Power	6	Clemson University	6
29	CSIR	34	Coskata, Inc.	5	Queen's University at Kingston	6
30	BP	33	FloDesign Wind Turbine Corp.	5	Rice University	6
31	Royal DSM	32	Kior Inc.	5	Swiss Federal Institute of Technology (EPFL)	6
32	UTC	32	LUCA Technologies, Inc.	5	University of Colorado	6
33	IBM	31	Marine Current Turbines Limited	5	University of Michigan	6
34	Royal Dutch Shell	31	Plextronics, Inc.	5	University of Toledo	6
35	Sony Corporation	31	Primestar Solar Inc.	5	Atomic Energy Council	5

Appendix 2: New Measure of Novelty

We have developed a new measure of Novelty that is not based on citation-measures. Instead, we draw on a textual analysis of patent applications to look at the similarity of patent claims and descriptions for patents in a given technology-area. Intuitively, our definition is such that patents with greater textual similarity to neighboring patents are considered to be less novel. Our measure of novelty should be particularly useful in the context of science-based patenting, where technical terms are more unique and therefore more likely to signal differences in the characteristics of innovation, and for more recent time periods, where initial forward citations may be a noisy predictor of ultimate outcomes.

While a more complete exposition and validation of the measure of Novelty is being developed elsewhere (see Younge, 2013 - ready this fall), the general outline for the calculation of the measure is as follows:

First, the calculation algorithm reviews every patent claim and description in the sample to build a list of all terms used; the list of terms constitutes a high-dimensional positive space wherein each term represents a dimension into that space. Second, the algorithm positions each patent in the vector space by assigning it a set of coordinates where the magnitude of each dimension is calculated as the "term frequency inverse document frequency" (TF-IDF) of each term in the patent. Intuitively, TF-IDF gives a greater weight to a dimension when a term occurs more frequently in the patent, and gives a lesser weight to a dimension if the word is frequently observed in other patents as well. Third, the algorithm calculates the “similarity” between every possible combination of two patents, by calculating the cosine of the angle formed between their vectors. The measurement of similarity is bounded [0,1], with a measurement of 1 representing a perfect similarity between two patents.

Having thus arrived at a pair-wise list of similarity comparisons, between every possible combination of patents in the sample, the algorithm then calculates a measurement of Novelty for each focal patent by examining the distribution of similarities relative to a comparison set of patents. The comparison set is draw from the prior three years and from the same technology area as the focal patent (e.g., “Solar”). To assess the “novelty” of a patent – a concept connoting few neighbors in the technology landscape – we take the 5th percentile of the rank-ordered distribution of similarities tied to the comparison set. For ease of interpretation, we reverse the novelty measure by subtracting it from 1, arriving at a measurement for Novelty that is bounded [0,1], where 1 represents a patent that is entirely dissimilar from all other patents. When needed, we average patent-level measures of novelty up to the firm or category level.