Innovation and Entrepreneurship in the Energy Sector

David Popp[1,2]
Jacquelyn Pless[3]
Ivan Hascic[4]
Nick Johnstone[5]

December 6, 2019

Abstract: Innovation in the energy sector often proceeds slowly, and entrepreneurial start-up firms have historically played a minor role. We argue that this may be changing. Energy markets are going through a period of profound structural change. The rise of hydrofracturing lowered fossil fuel prices so much that natural gas is now the primary fuel for electricity generation in the US. Renewable energy technologies have also experienced significant cost and performance improvements. However, integrating intermittent resources creates additional grid management challenges requiring more innovation, which must be achieved quickly if climate policy goals are to be met. This chapter documents the evolving roles of innovation and entrepreneurship in the energy sector. First, we provide an overview of the energy industry, noting that many new energy technologies are smaller, more modular, and increasingly rely on innovation in other high-tech sectors where innovation typically moves more rapidly. We then conduct two descriptive data analyses, documenting a sharp decline in both clean energy patenting and start-up activity from about 2010 onwards. We discuss potential explanations and provide some evidence that innovation in existing technologies may simply have been successful, whereas continued innovation may be needed in enabling technologies that are more likely to depend on innovation in other sectors. We conclude that the increased complementarity of energy and high-tech innovations provides potential for faster paced energy innovation moving forward. However, understanding the impact of venture capital funding on such progress requires more rigorous evaluation.

[1]: Professor, Department of Public Administration and International Affairs, Center for Policy Research, The Maxwell School, Syracuse University, 426 Eggers Hall, Syracuse, NY 13244-1020, ph: 315-443-2482, fax: 315-443-1075, e-mail: dcpopp@maxwell.syr.edu, home page: https://dcpopp.expressions.syr.edu/.
[2]: Research Associate, National Bureau of Economic Research, Cambridge, MA.
[3]: MIT Sloan School of Management, 100 Main Street, Cambridge, MA 02142, email: jpless@mit.edu.
[4]: Senior Economist, Environment Directorate, Organisation for Economic Co-operation and Development (OECD), Paris, France.
[5]: Chief Statistician, Energy Data Centre, International Energy Agency (IEA), Paris, France.

Acknowledgements: We thank Julie Lassebie for helpful discussions on obtaining and working with Crunchbase data, Miguel Cárdenas Rodríguez for precious help with patent searches, and Myriam Gregoire-Zawilski for helpful research assistance. The views expressed in this paper are the authors' own and do not necessarily reflect those of the OECD, the IEA nor their member countries.

I. Introduction

Energy markets are going through a period of profound structural change. With significant cost declines and performance improvements in renewable energy technologies over the last decade, electricity grids must manage higher levels of generation from intermittent renewable energy resources. These resources lower greenhouse gas (GHG) emissions associated with the power sector, but creates new challenges for grid operators, who must balance supply and demand in real time. Furthermore, the rise of "unconventional" gas and oil in the past decade put downward pressure on fossil fuel prices, resulting in natural gas replacing coal as the primary fuel for electricity generation in the US.

Despite these advances, improving the environmental performance of the energy sector requires continued innovation. Limiting global warming to no more than 1.5° Celsius would reduce, but not eliminate, projected climate change impacts, but is only possible by limiting net carbon emissions to zero by mid-century (IPCC, 2018). Replacing vast amounts of fossil fuels with alternative, carbon-free energy sources such as solar and wind energy will require long-term energy storage solutions and smart grid technologies to integrate these intermittent energy sources into the grid (International Renewable Energy Agency 2017). These challenges must be overcome while also ensuring energy security in the face of rapidly changing market conditions.

Yet innovation in the energy sector often proceeds slowly. Energy firms invest less in R&D than almost all other sectors of the economy. Energy production is capital intensive, and especially long time horizons between initial idea and commercialization in the energy sector create a "Valley of Death" for energy innovation (e.g. Mowrey *et al*. 2010, Weyant, 2011). Such long time horizons also make energy firms less attractive to venture capitalists, who typically expect to see returns within 5-7 years. In addition, because the social benefits of clean energy associated with pollution reductions are not reflected in market prices without government intervention, the potential demand for clean energy technologies is dependent on effective environmental policy. As a result, while small, nimble start-ups are frequently the vehicle through which innovation reaches the market in many sectors, they have historically played a smaller role in the energy sector (Nanda *et al*. 2015, Gaddy *et al*. 2017).

However, given the changing nature of energy markets, the links between innovation and entrepreneurship in the energy sector warrant further analysis. Many of the latest energy technologies are smaller and more modular (e.g. solar panels, smart meters for homes) relative to conventional technologies. They also increasingly rely on advancements in other sectors. New smart grid technologies depend on software and information technology – a sector where entrepreneurial firms play important roles (e.g. Gaddy *et al*. 2017). How is the nature of innovation in energy changing? Are entrepreneurial firms now playing a larger role? Do more energy innovations contain a software or information technology component? Do energy start-ups with a high-tech component perform better than other energy start-ups?

We address these questions in three parts. We begin by providing an overview of the energy industry, focusing on how both unconventional natural gas and oil and increasingly affordable renewable energy sources are changing the industry and reviewing the current state of research on innovation in the energy industry. We then provide two new descriptive analyses on the changing nature of innovation in energy. First, we examine patenting activity for both clean energy and unconventional gas and oil, with a particular focus on contributions of knowledge that span multiple sectors, such as IT and energy. Despite rapid growth in the early 2010s, energy patenting activity has fallen in recent years. We consider possible explanations for this fall, such as the rise of hydraulic fracturing, changing regulations, diminishing returns to research, the existence of a cleantech bubble, and that innovation simply may have just worked. Second, we present data on start-up activity in the energy sector, with a similar focus on entrepreneurial energy firms that operate in high-tech fields. We document a similar decline in energy start-ups since about 2010. However, an increasing share of these start-ups are energy firms that are also high-tech. We show that high-tech energy start-ups are more likely to attract venture capital (VC) investments but they do not necessarily perform any better than non-high-tech energy start-ups. Conditional on receiving funding, energy start-ups generally do not perform better than the average funded firm, although there is some evidence of over-investment in clean energy corresponding with growth and subsequent fall in both patenting and VC funding during the 2006-2012 period.

The rest of this chapter proceeds as follows. In Section II, we provide industry background and a review of the energy innovation literature so far. Sections III and IV present our patenting and start-up analyses, respectively. We conclude with a discussion of emerging trends in the energy sector and suggestions for future research.

II. Industry Background

Our study of the energy industry focuses on the electricity sector, considering both the generation of electricity and the supply of fuel (e.g. coal and natural gas) to power plants. While we do not directly focus on energy in the transportation sector, there are technological needs that overlap both sectors, such as innovation in batteries either for energy storage on the power grid or for powering electric vehicles. These sectors play key roles in addressing future energy policy goals, as they include both the drilling and production of fossil fuel resources and potential gains from incorporating renewable energy technologies into electricity production. In 2016, fossil fuel combustion generated nearly 5 billion metric tons of greenhouse gases, accounting for 76 percent of all US emissions (US EPA, 2019). While electricity generation historically was the largest source of US greenhouse gas emissions, increased generation from natural gas and clean renewable energy resulted in emissions from the power sector falling below those of the transportation sector for the first time in 2016 (US EPA 2019).

[table 1 here]

Traditionally, innovation in the energy industry moved slowly. Compared to other industries, the energy industry invests little in R&D. Table 1 shows domestic R&D paid for and performed by U.S. companies in select industries, as a percentage of net sales. Over the past ten years, all US industries spent between 2.5 to 3.5% of sales on R&D. For manufacturing industries, this ranges from 3.1 to 3.9%. In R&D intensive industries such as pharmaceuticals or computers, the percentage is around 10%. In contrast, mining and extraction industries, which include the oil and gas sector, were spending less than one percent of sales on R&D until 2015. Utilities spend just 0.1% of sales on R&D. Only the engine and turbine manufacturing industry has R&D spending levels comparable to the rest of the manufacturing sector. Several key features make innovation in the energy industry different from other sectors:

1. Energy is a commodity. Consumers want the lights to go on when they flip a switch. While environmental considerations are becoming more important to consumers in many countries, most do not care about the source of that energy although environmental considerations are gaining ground in many countries. Successful entrepreneurs cannot fully capture the rents associated with

differentiating their product. Instead, reducing costs is the measure of successful innovation.

2. Regulation plays an important role in the industry. Electrical and gas service is usually distributed by regulated natural monopolies, and regulation of energy production varies across jurisdictions. Because consumers focus on cost rather than quality, until recently cleaner energy sources such as solar or wind were viewed as too expensive in the absence of interventions to address externalities. Unlike sectors where the government is a primary consumer (such as the military or space exploration), energy is somewhat unique in that government regulation shapes demand, but final consumption decisions are made in the private sectors. As a result, uncertainty over future policy can dampen incentives for R&D.

3. Energy generation is capital intensive. Economies of scale are pervasive in large power plants. For example, new natural gas-fired combined cycle plants are three times as large as similar plants built in the 1980s, leading to lower costs per kilowatt (EIA Today in Energy, 2019a). Demonstrating commercial viability of a new energy production technology requires hundreds of millions of dollars, making entry into the industry difficult for small start-up firms (Nanda *et al*. 2015).

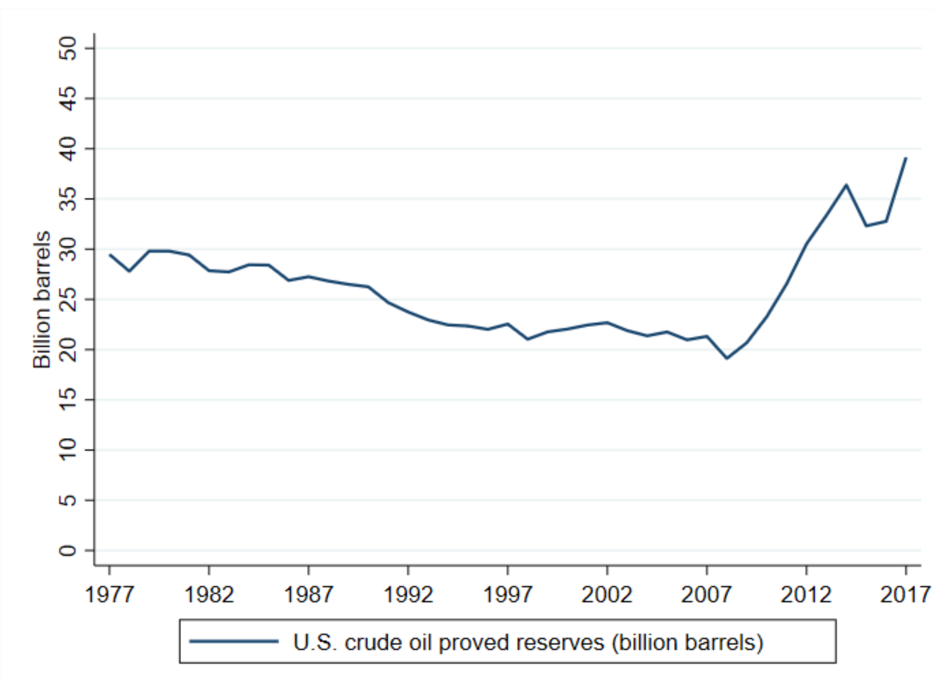
4. Long time horizons between initial idea and commercialization in the energy sector also make it more difficult for small start-up firms to raise capital (e.g. Popp 2016, Howell, 2017). Venture capital investors expect returns within three to five years of their investments. But the development and testing of new energy technologies takes longer (Gaddy *et al* 2017).

Measuring the returns to R&D in the energy sector is also challenging. Since energy is a commodity, reducing costs and environmental impacts matter more than increasing productivity. On these measures, the energy industry has seen remarkable changes in the 21st century. The rise of unconventional gas and oil sources obtained using hydraulic fracturing increased supplies and lowered prices of oil and gas. At the same time, costs of renewable energy sources fell to levels making them competitive with fossil fuels. Below we describe the impact of each of these technological advances on the energy industry.

A. The Rise of Shale Gas and Oil

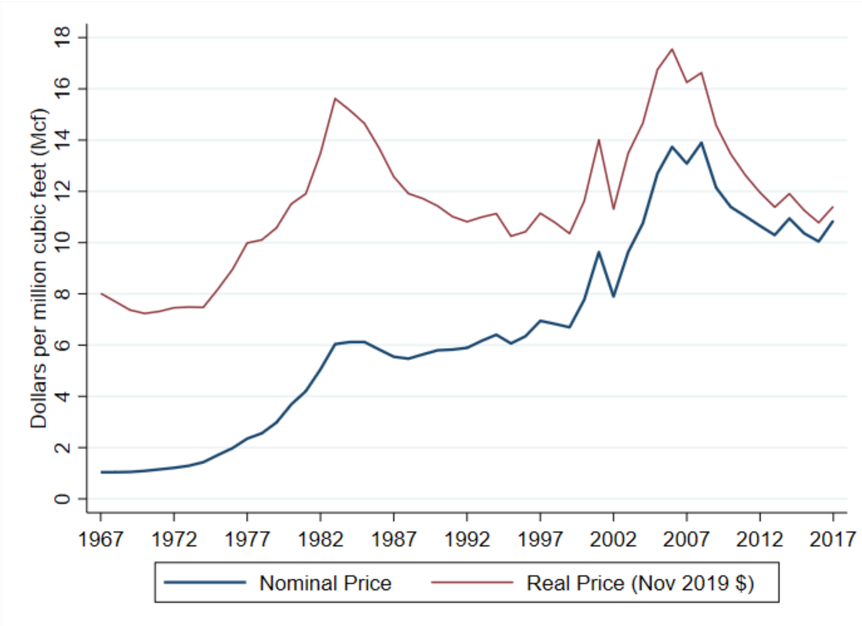
Economical access to natural gas and oil reserves in shale deposits has changed global energy markets. Shale deposits were too expensive to access until technological advances such as horizontal drilling and hydraulic fracturing (colloquially known as “fracking”) reduced drilling costs (Jacoby et al. 2012). These unconventional wells use a mixture of water, sand, and other chemicals to cause cracks and fissures in the rock formation that allow crude oil to escape (Fetter *et al*. 2018). Horizontal drilling is often used to widen access to shale plays. Improved access to shale gas and oil caused US crude oil reserves to grow (Figure 1), allowing the US to play a larger role in global oil markets. In September 2019, the US imported more petroleum than it imported for the first time since monthly recordkeeping began in 1973 (EIA Today in Energy 2019b). Domestically, increased access to natural gas lowered natural gas prices (Figure 2), leading to increased use of natural gas by electric utilities. Natural gas surpassed coal as the primary fuel source for US electric utilities in 2016 (Figure 3). Since 2010, US power plant emissions of sulfur dioxide (SO_2) fell by 75% and carbon dioxide emissions fell by over 25%. As a result, annual damages from emissions fell from \$245 billion to \$133 billion. Roughly \$60 billion of this reduction is due to changing shares of fuels in power generation (Holland *et al*. 2018).

Figure 1: U.S. Crude Oil Proved Reserves



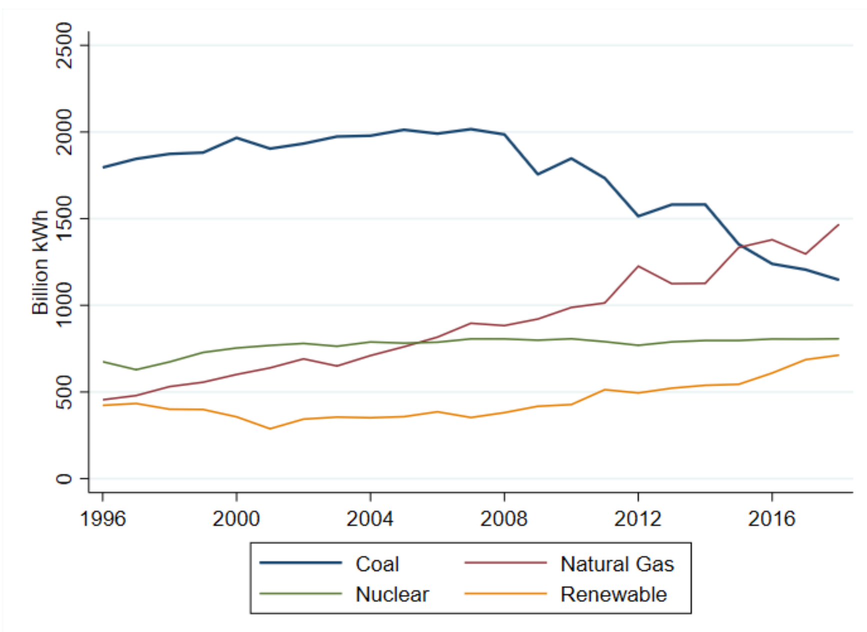
Notes: U.S. crude oil proved reserves, in billions of barrels. Source: U.S. EIA (2018).

Figure 2: Annual Residential Natural Gas Price



Notes: Average annual price of residential natural gas in the United States, in 2019 US dollars. Source: US.EIA Short-Term Energy Outlook, November 2019.

Figure 3: U.S. Electricity Generation by Fuel Source



Note: "Renewable" includes conventional hydropower, wind, wood biomass, waste biomass, geothermal, and solar. Source: U.S. Energy Information Administration (2019).

The rise in hydraulic fracturing began in the early 2000s, stimulated by the high price of conventional crude oil at the time. These higher prices made shale oil viable, and the initial activity in shale oil led to efficiency improvements that further reduced the costs (Killian 2016). Both private and public sector investments in the United States aided the development of shale gas technologies. The US invested in government R&D to develop unconventional natural gas, but oil industry innovations such as horizontal drilling and three-dimensional seismic imaging were also important. (Krupnick and Wang, 2017). In particular, Mitchell Energy, an independent natural gas firm, made large investments in shale gas development before it was proven profitable (Krupnick and Wang, 2017). Mitchell Energy had experimented with shale development for several years without finding a way to make it profitable. Their technological advance came in 1997, when they used new "slickwater" fracking treatments (Cahoy *et al*. 2013). In 2001, Devon Energy, an expert in horizontal drilling, acquired Mitchell Energy. Combining horizontal drilling and hydraulic fracturing led to the boom in shale gas production that would soon follow (Cahoy *et al*. 2013).

[table 2 here]

Hydraulic fracturing has affected both energy markets and the environment in several ways:

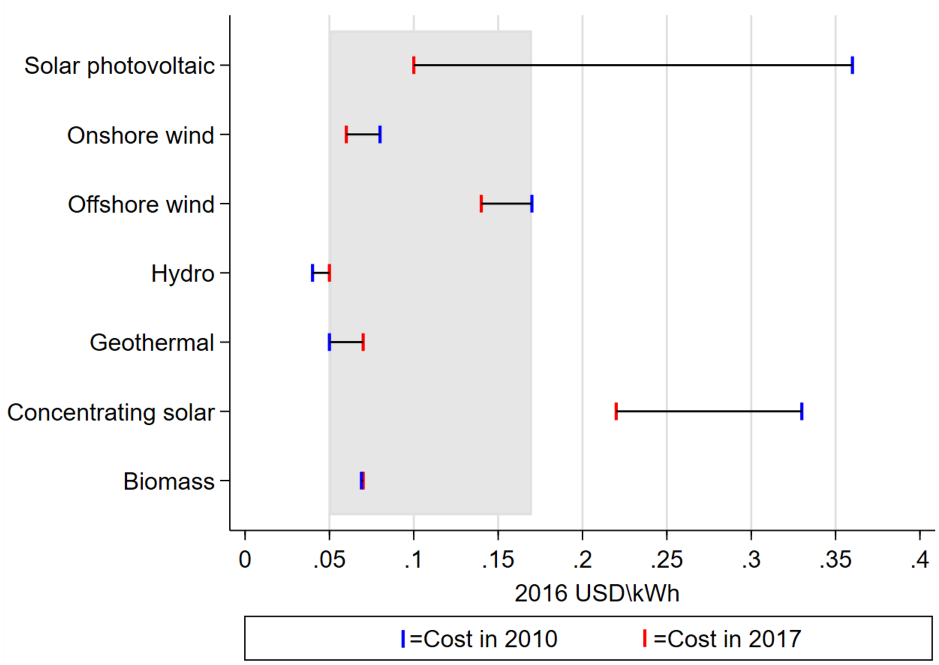
- Increased drilling has led to local economic booms. Employment in oil and gas extraction grew from nearly 74,000 workers in 2000 to over 113,400 workers in 2016 (Table 2). Communities in the top quartile of exposure to hydraulic fracturing experienced a 4.8% growth in employment and a 5.8% increase in household income (Bartik *et al*. 2019). Maniloff and Mastromonaco (2017) estimate the shale boom created about 550,000 local jobs. Feyrer *et al*. (2017) find that every million dollars of new oil and gas extracted creates 0.85 jobs within the county, and 2.13 jobs within 100 miles of the drilling site. To put this in perspective, $393 billion of new oil and gas production occurred between 2005 and 2014.

- At the same time, expansion of natural gas has hurt the coal industry. Employment in coal mining fell from a peak of 89,367 in 2012 to just 55,008 in 2016 (Table 2).

- Shale gas and oil reduce market volatility. While shale wells take longer to drill and reach production, they produce more per well and have less variation in production. Thus, shale gas is more responsive to market prices (Newell and Prest 2017).

- While the development of shale gas helped reduce air pollution from US power plants, it also raised new environmental concerns. Hydraulic fracturing requires several times more water than conventional drilling. Moreover, there are concerns that leaks and spills from hydraulic fracturing activity may contaminate groundwater. As a results, several countries and some US states have banned hydraulic fracturing while further study is conducted (Krupnick and Wang, 2017).

Figure 4: Costs of Electricity From Selected Sources

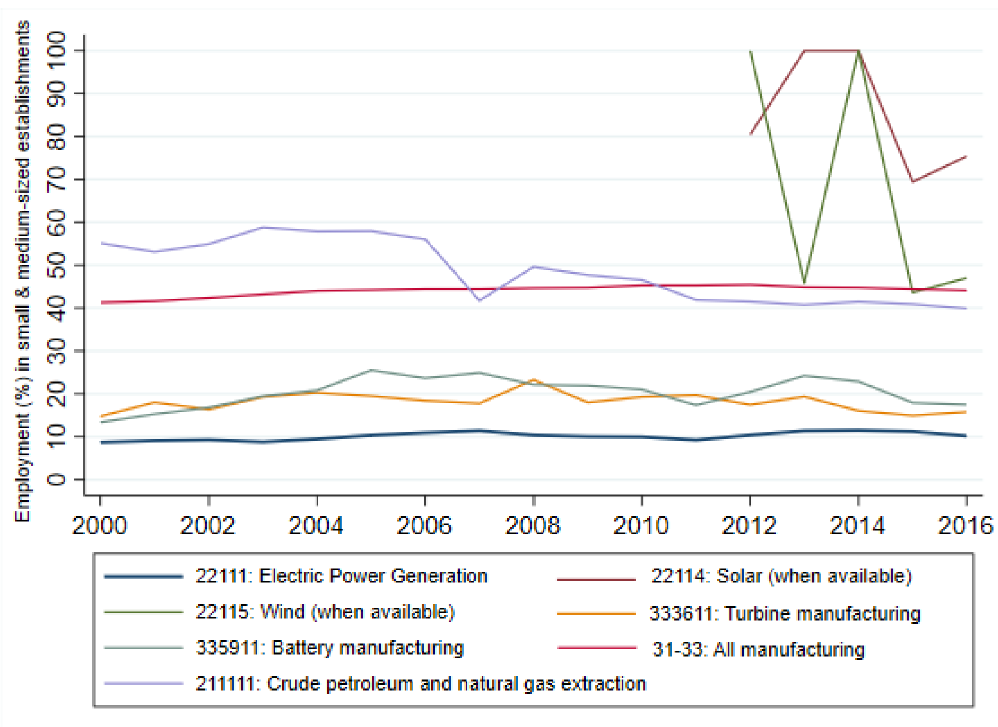


Notes: Figure shows the levelized cost of energy (LCOE) for various renewable energy sources. Data taken from Figure 2.1 in International Renewable Energy Agency (2018), which uses costs of individual projects in the IRENA Renewable Cost Database. Costs are the global weighted average of LCOE for newly commissioned projects in a given year, where the weights are based on capacity deployed by country/year. The gray shaded region shows the equivalent cost range for fossil fuels. Note that, by 2017, all renewable sources except concentrating solar power were competitive with fossil fuels.

B. Increased Penetration of Renewable Energy Sources

Increasing electricity generation from wind and solar energy pose a second opportunity for the energy sector, but it also comes with its set of challenges. The costs of electricity generated from solar photovoltaic (PV) and onshore wind turbines fell dramatically since 2010, making both competitive with electricity generated from fossil fuels (Figure 4). While renewable energy sources are still a small share of electricity generation in the US (17%), their use is growing rapidly (Figure 3). Solar and energy generation typically occurs at a smaller scale than fossil fuels. Figure 5 shows trends in the percentage of employment in small and medium-sized establishments for various industries. While the average for all manufacturing industries is just over 40 percent, power generation, turbine manufacturing, and battery manufacturing all have percentages around 20 percent or less. In contrast, most solar and wind energy generation occurs in small and medium sized establishments. Nonetheless, because solar and wind establishments are smaller and these enterprises still make up a small share of the overall power generation industry, the growth in renewable energy during the past decade did not lead to growth in employment in the power generation sector (Table 2).

Figure 5: Percentage of Employment in Small and Medium Enterprises, Select Industries



Notes: Figure shows the percentage of employees working in small and medium enterprises, which include establishments of 500 workers or less. Separate breakdowns for solar and wind are unavailable until 2011. Source: US Census Bureau: Statistics of US Businesses, various years.

Wind and solar energy are examples of *intermittent* sources of power, as the electricity generated depends on factors outside of the operator's control, such as wind speeds. Intermittent sources create challenges for managing the electricity grid (Borestein 2012). Because electricity is very expensive to store, what goes on the grid must match what comes off, requiring *balancing authorities* to equate power supply and demand in real time (EIA Today in Energy, 2016). To illustrate, consider the structure of the U.S. electricity grid. The continental United States electricity grid is divided into three mains sections: the Eastern Interconnection, the Western Interconnection, and the Electricity Reliability Council of Texas (ERCOT). Except for ERCOT, these interconnections are divided into smaller balancing authorities managing smaller regions. Some balancing authorities are independent utilities, such as the Tennessee valley Authority (TVA). Others are Regional Transmission Organizations – independent non-profit organizations, such as the Midwest Independent System Operator (MISO) or the New York Independent System Operator (NYISO) (EIA Today in Energy, 2011).

The increased penetration of intermittent renewable sources pose two additional challenges. First, because the marginal cost of renewables is 0, it is offered to wholesale markets at very low costs. At times when renewable energy generation is high, wholesale prices fall. In some cases, oversupply of electricity from mid-day solar energy created *negative* electricity prices – power producers were willing to pay grid managers to use the electricity they generate (Bajwa and Cavicchi 2017). Low wholesale prices have particularly hurt nuclear plants. While these plants also have low marginal costs, they have high fixed costs that are difficult to recover when wholesale prices are low. Nuclear plants are also costly to shut down and restart. As a result, competition from natural gas and wind is forcing some nuclear plants to retire early (Roth and Jaramillo, 2017) rather than accept low wholesale prices and operating at a loss. Second, modular sources such as solar photovoltaic (PV) panels exacerbate the fluctuations in electricity demand that occur during a typical day. As homeowners generate more of their own power during the day using solar photovoltaic panels, demand for electricity purchased from the grid falls but then picks up again in early evening as the sun sets and people return home for the day.

Addressing the challenges of grid integration requires both technological and management innovations. Cross-border power markets increase flexibility and make balancing supply and demand easier (Martinot 2016). Developing affordable energy storage options would reduce the need to instantaneously balance supply and demand. Currently, most electricity stored on the grid uses pumped hydro reserves: water is pushed to a higher elevation using excess electricity, where it can be released to generate electricity using hydropower when needed. The use of pumped hydropower storage is limited geographically. Technological advances such as better batteries could greatly expand the potential of energy storage (Greenblatt *et al.* 2017). Similarly, smart grid technologies allowing for automated demand-load management can better match supply and demand (Greenblatt *et al.* 2017). Smart grid technologies allow for two-way communication between customers and utilities, facilitating management strategies such as peak-load pricing, where electricity prices to consumers rise and fall based on market conditions. Consumers can, for example, then choose to run appliances at times when prices are lowest (US DOE, n.d.).

C. Innovation in the Energy Sector

The increased use of both hydraulic fracturing and renewable energy creates new technological challenges, but also creates new opportunities for innovation. New energy technologies are often smaller and modular (e.g. solar panels, smart meters for homes), reducing the need for large capital costs. While energy remains a commodity, the popularity of products such as Nest thermostats suggests that product differentiation is possible for end-use technologies that improve energy efficiency and potentially improve grid management. The rise of hydraulic fracturing depended in part on improved seismic imaging to help locate new shale resources (Krupnick and Wang, 2017). Today, energy companies are turning to data analytics and artificial intelligence (AI) to further improve their search for new energy (Anonymous, 2019).

Before turning to our analysis of the changing nature of energy innovation, we provide a brief review of evidence so far in the literature examining the effects of policies and regulations on energy innovation. See Popp (2019) for a more comprehensive review. There are several distinct features of energy innovation that make it particularly important to study today. First and foremost, addressing climate change and mitigating its potential harm in the time required will require significant innovation at speed and scale. Furthermore, in addition to the four challenges outlined at the beginning of this section, innovation in clean energy faces a "double-externality" challenge. As there are for any innovation, knowledge spillovers associated with clean energy innovative reduce private incentives for investing. However, the social benefits of clean energy associated with pollution reductions are also not reflected in market prices without government intervention. Thus, the potential demand for clean energy technologies is dependent on effective environmental policy. Policies addressing these *environmental externalities* increase the potential market size for clean energy innovation, and are often referred to as *demand-pull* policies in the literature. Policies supporting technology development directly are often referred to as *technology-push* policies.

These two market failures could, in principle, be addressed separately. Since knowledge market failures apply generally across technologies, economy-wide policies affecting all types of innovation could address knowledge market failures, leaving it to environmental policy to "get the prices right" to encourage green innovation. A carbon tax exemplifies the economist's goal of "getting prices right" by putting a price on emissions related to climate change. Evidence on the impact of market forces such as higher energy prices or price corrections from broad-based policies such as carbon taxes show that prices matter for innovation. Over the long term, a 10 percent increase in energy prices leads to a 3.5 percent rise in the number of U.S. patents in 11 different alternative energy and energy efficiency technologies (Popp 2002). Most of the response occurs quickly after a change in energy prices, with an average lag between an energy price change and patenting activity of 3.71 years. Verdolini and Galeotti (2011) find similar results using a multi-country sample from 1975 to 2000. Similarly, when facing higher fuel prices, firms in the automotive industry produce more innovations on clean technologies, such as electric and hybrid cars, and less in fossil-fuel technologies that improve internal combustion engines when facing higher fuel prices (Aghion et al. 2016). A 10 percent higher fuel price is associated with about 10 percent more low-emission energy patents and 7 percent fewer fossil-fuel patents. In contrast, energy prices are less effective for promoting innovation on home energy efficiency, particularly for less-visible technologies such as insulation that are installed by builders and are not easily modified. Instead, building code changes induce innovation for home energy efficiency (Noailly, 2012).

However, in addition to broad-based policies such as carbon taxes or cap-and-trade that target all greenhouse gas emissions, governments use a variety of targeted policies to promote clean energy and reduce emissions. Examples include energy efficiency standards, renewable energy mandates, tax incentives for purchasing rooftop solar photovoltaic equipment, and investment credits and subsidies for specific clean energy technologies. The type of policy support chosen also affects both the pace and direction of innovation. Policies to promote clean energy can either be *technology-neutral* or *technology-specific*. Technology-neutral policies provide broad mandates, such as reducing emissions to a certain level but leave it to consumers and firms to decide how to comply. Examples include a carbon tax, which targets all emissions equally, as well as more targeted policies such as renewable energy mandates. Such mandates can require that utilities generate a set portion of electricity from renewable energy, but they do not dictate what types of renewable sources be used. On the other hand, technology-specific policies stipulate the use of individual technologies. For example, tax credits for electric vehicles or rooftop solar energy are only available to consumers who purchase these products.

Technology-neutral policies promote technologies closest to being competitive in the market without policy support. Johnstone *et al.*'s (2010) study of renewable energy innovation is an example. Because wind energy was the closest to being competitive with traditional energy sources at the time of this study, innovation in countries with mandates to provide alternative energy focused on wind. In contrast, direct investment incentives such as feed-in tariffs supported innovation in solar and waste-to-energy technologies. These technologies were less competitive with traditional energy technologies and required the guaranteed revenue from a feed-in tariff to compete. Thus, although technology-specific policies may raise short-term costs, judicious use of them helps promote the development of low-emission technologies further from the market, such as offshore wind or carbon capture and sequestration.

Recent theoretical work provides support for the use of such targeted policies – particularly those technologies furthest from market. Other market failures such as learning-by-doing, path dependency, and capital market failures limit incentives to invest in these emerging technologies (Acemoglu *et al*. 2016, Fischer *et al*. 2017, Lehmann and Söderholm, 2018). Both learning-by-doing and path dependency justify technology-specific deployment policies such as feed-in tariffs or tax credits—most notably when the resulting cost-reductions benefit not only early adopters, but also those who wait to adopt until costs fall (e.g. Lehmann and Söderholm, 2018). However, the existing literature on learning-by-doing generally suggests that the benefits of learning-by-doing are not sufficient to justify current levels of deployment subsidies (e.g. Nemet 2012, Fischer *et al*. 2017, Tang, 2018). Empirical evidence on path dependency is slim. Path dependency creates a market failure if switching costs make it difficult for firms previously investing in one type of technology to switch to profitable opportunities in another. While some recent studies find evidence of path dependency in energy innovation (e.g. Aghion *et al*. 2016, Stucki and Woerter

2017), none of these studies tests whether the observed path dependency results from high switching costs or are simply a reaction to better research opportunities. More research on the relationship between switching costs and path dependency is needed.

In contrast, the evidence on capital market failures for energy is limited but suggestive of such market failures. In a study using financial microdata, Cárdenas Rodríguez *et al*. (2015) find that price-based policy instruments such as feed-in tariffs and tax credits have a positive effect on private investment for renewable energy. It is hypothesized that such instruments provide a more predictable revenue stream, potentially making them more suitable for alleviating the particular risk-return profile of renewable energy investments. In contrast, quota-based policy instruments, whose support levels are more difficult to ascertain ex ante, have no significant effect on private finance investment. Moreover, if credit markets are functioning well, price schemes will induce private finance for less mature technologies (e.g. solar PV), while a quota schemes will induce private finance for more mature technologies (e.g. onshore wind). However, if credit markets are not functioning well only price schemes will have an effect on private finance flows, and only for the case of onshore wind power.

In an evaluation of the US Department of Energy Small Business Innovation Research (SBIR) program, Howell (2017) provides evidence that early financing helps overcome capital market failures in clean energy. SBIR grants improve the performance of new clean energy firms, but are ineffective for older technologies such as coal, natural gas, and biofuels. Similarly, Popp (2017) provides evidence that bringing new energy technologies to market takes longer in clean energy than in other fields (e.g. Branstattter and Ogura 2005, Finardi, 2011), suggesting that the length of time necessary for commercialization of energy R&D creates a barrier to raising private sector financial support.

Given the importance of financing constraints, a recently emerging literature considers the role of venture capital for renewable energy. Nanda *et al*. (2015) provide descriptive data comparing clean energy innovations supported by venture capital to other clean energy innovations, showing patents from firms that received venture capital are cited more frequently. However, they argue that the nature of energy markets may reduce the potential of venture capital in clean energy. These concerns include the capital intensity of energy production, the long time frame, and the difficulty for successful ventures to find an "exit" strategy where they are purchased by a larger company. Similarly, comparing venture capital investments in clean energy, software, and medicine, Gaddy *et al*. (2017) find that clean energy ventures do not perform as well as software, but they do not perform worse than medicine. They also argue that their study suggests venture capital is poorly suited for clean technology. Cumming *et al*. (2017) consider crowdfunding as an alternative to venture capital. They collect data on crowdfunded projects from Indiegogo, with 7.4 % of projects pertaining to clean technology. While potential entrepreneurs are able to use the crowdfunding platform to reduce information asymmetries with investors, clean technology offerings are no more successful than other crowdfunded projects, and appear to be perceived as more risky.

Finally, climate change is a global problem. Innovators partake in global markets and are influenced by regulation not only at home, but in other countries where they do business. As such, policies in both local and foreign markets matter. Dechezleprêtre and Glachant (2014) compare wind energy patents across OECD countries, using data from 1991-2008. Their observations are country pairs, as they look at both the source (e.g. where the invention is developed) and destination (e.g. where patents are granted) of invention. Although the marginal effect of policies implemented at home is 12 times higher, the larger size of foreign markets make the overall impact of foreign policies twice as large on average as the overall impact of domestic policies on innovation. In a study of 15 OECD countries using patent data from 1978 to 2005, Peters *et al*. (2012) also find both domestic and foreign demand-pull policies (such as renewable portfolio standards or feed-in tariffs) are important for the development of solar PV technology. However, technology-push policies such as R&D subsidies only increase domestic innovation, as firms must be in the local market to take advantage of them. Fabrizio *et al.* (2017) find similar results for energy storage. In addition, as their sample includes patents from countries not directly regulating energy storage, they also show that demand-pull policies encourage innovation and increase technology transfer coming into the country, measured as domestic patent applications filed for technologies that originally filed for patent protection elsewhere.

III. Patenting in the Energy Sector

For an overview of trends in energy sector innovation, we present patent data for a range of energy technologies. We focus on technologies related to the changing nature of energy: clean energy technologies and hydraulic fracturing. A large literature on energy innovation has shown that clean energy patenting is responsive to both higher energy prices (e.g. Newell *et al*. 1999, Popp 2002, Verdolini and Gaelotti, 2011, and Aghion *et al*. 2016) and policy (e.g. Johnstone *et al*. 2010, Peters *et al*. 2012, Dechezleprêtre and Glachant, 2014, Nesta *et* al. 2014, Fabrizio *et al.* 2017). However, with a few exceptions, patent levels have fallen since a peak in the early 2010s. We explore possible explanations for this decline below.

Our patent data are taken from the European Patent Office World Patent Statistical Database (PATSTAT), which includes over 100 million patent applications from 90 patent authorities. To control for patent quality, we only include patent applications having two or more family members in different jurisdictions. Inventors must file a patent at each patent office for which they desire protection. Filing in multiple offices is a signal that the patented invention is of higher quality (e.g. Lanjouw *et al*. 1998, Harhoff *et al*. 2003). We use the European Patent Office's "Y scheme", which provides separate classifications for technologies pertaining to climate change mitigation and adaptation, to identify relevant patents. These classifications complement standard patent classification schemes such as the Cooperative Patent Classification (CPC) scheme, grouping together relevant technologies that may appear in a wide range of traditional patent classes (Veefkind *et al*. 2012, Angelucci *et al*. 2018).

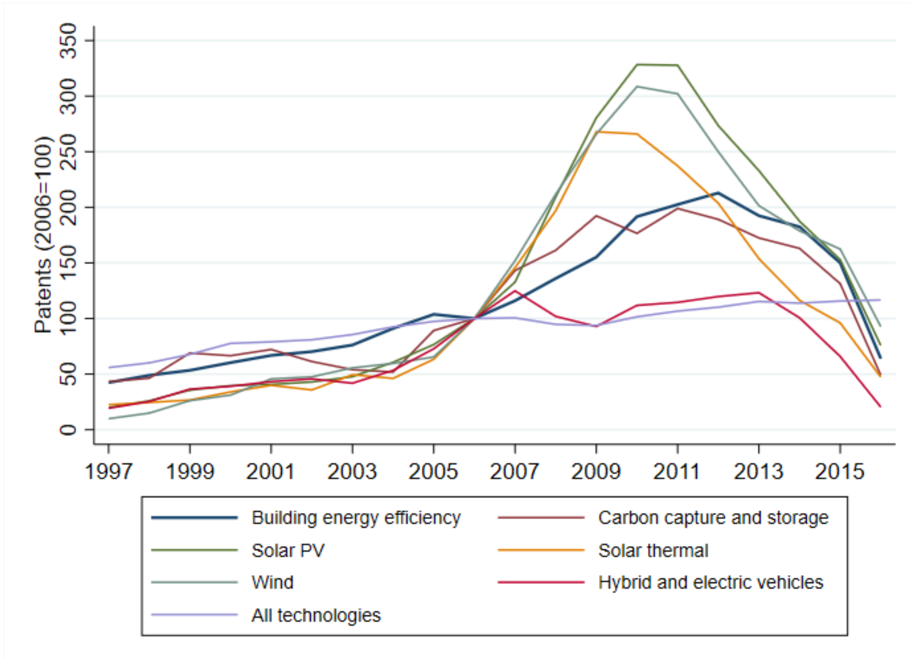
We first present data for eleven clean energy technologies, categorized in two main groups. Clean energy technologies include new or improved energy sources. Enabling technologies include those technologies that will help integrate a rapidly diversifying set of energy sources, such as energy storage, smart grids, and systems integration. Appendix Table A lists the patent classes used to identify each technology below.

Figures 6 through 8 present our patent data. The panels of Figure 6 show global trends for each group of patents. Our data include patents applied for between 1997 and 2015, so that our focus is on innovation since the Kyoto Protocol. Because the number of patents in each group varies, we normalize each patent series so that 2006 equals 100.[1] Two notable trends stand out. First, each energy technology experiences dramatic growth in the early 2010s. For most technologies, global patent counts increased by a factor of 3 or more from 2006 to 2011. Growth

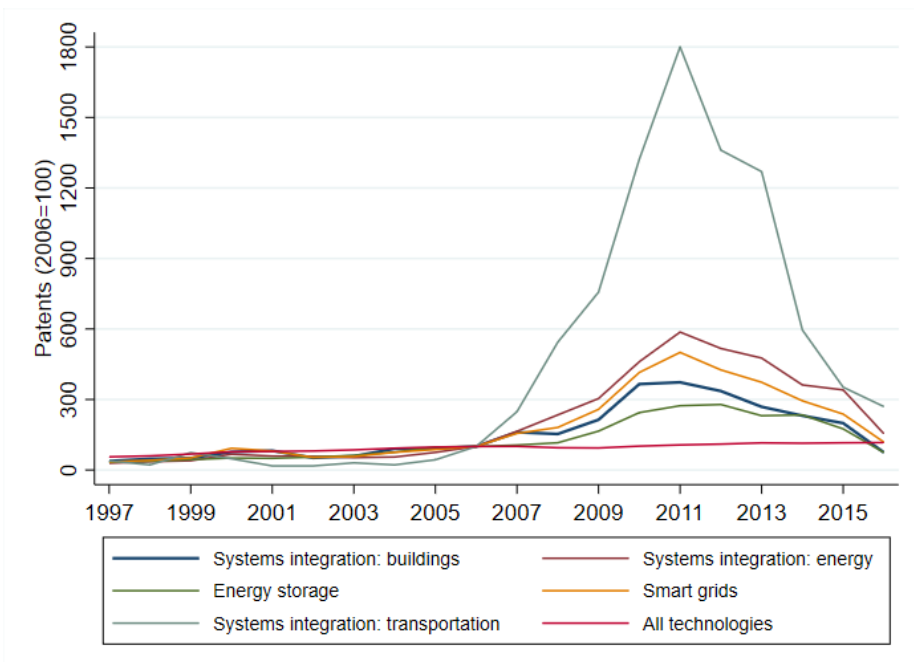
[1] We normalize in the middle of the sample, rather than in 1997, because some technologies have very few patents in the early years of the sample.

Figure 6: Global Energy Patents

A. Clean Energy Technologies



B. Enabling Energy Technologies



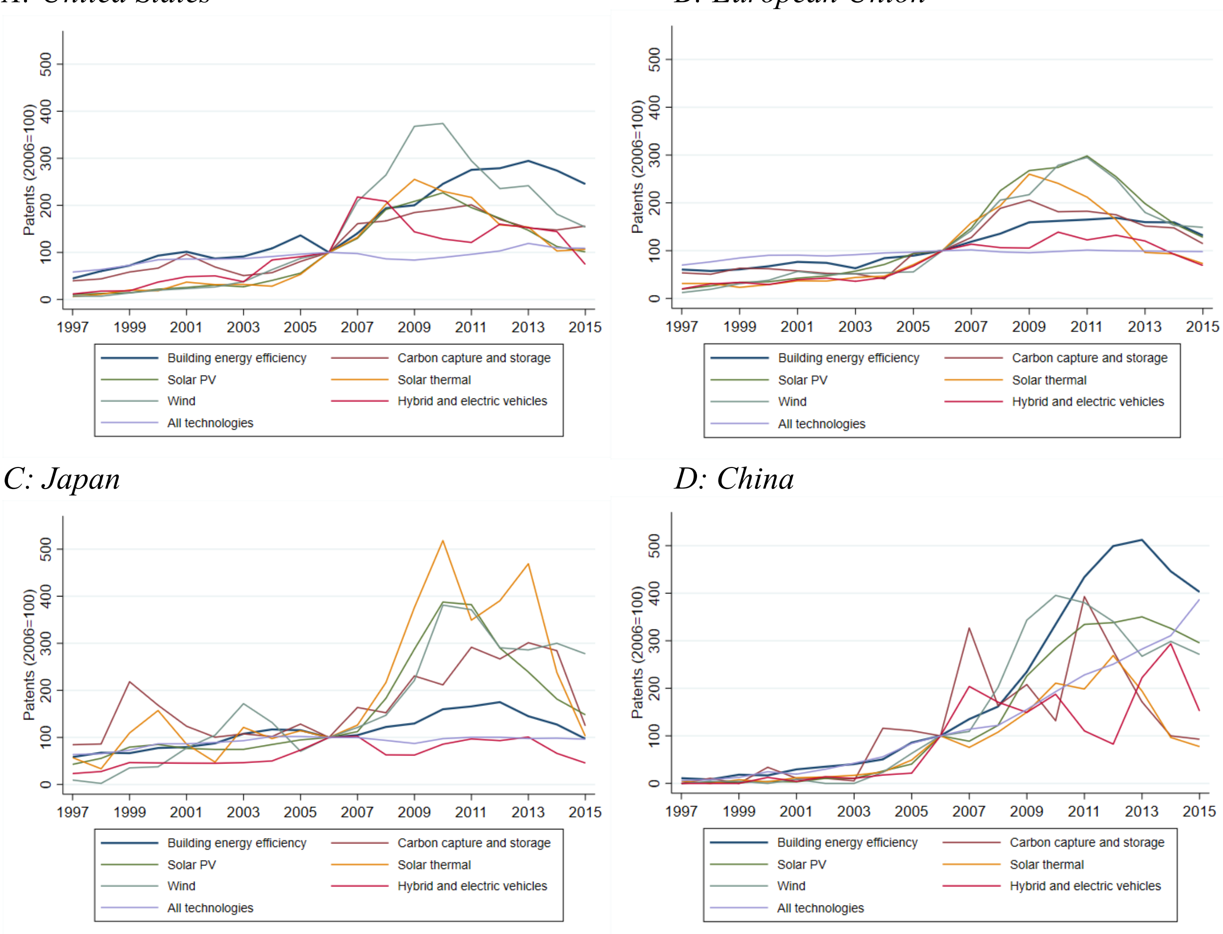
Notes: Figures show global counts of energy patents for patents filed in two or more countries. Patents are sorted by priority year. All counts normalized so that 2006 = 100. Patent extractions from the EPO World Patent Statistical Database (PATSTAT).

is larger for several of the enabling technologies, which are less mature. The only exception to this pattern is hybrid and electric vehicles, whose patent counts peak in 2007. For the remaining technologies, this sudden increase in clean energy patenting followed already significant growth in the early 21st century, as patent counts for most technologies doubled from 1997 to 2006. Second, this sudden increase in patenting was followed by a rapid decline. By 2015, patent levels were around half of what they were at the 2010-11 peak. This stands in contrast to the small, steady increases in patenting for all technologies.

Figure 7: Clean Energy Patents by Country

A: United States *B: European Union*

C: Japan *D: China*

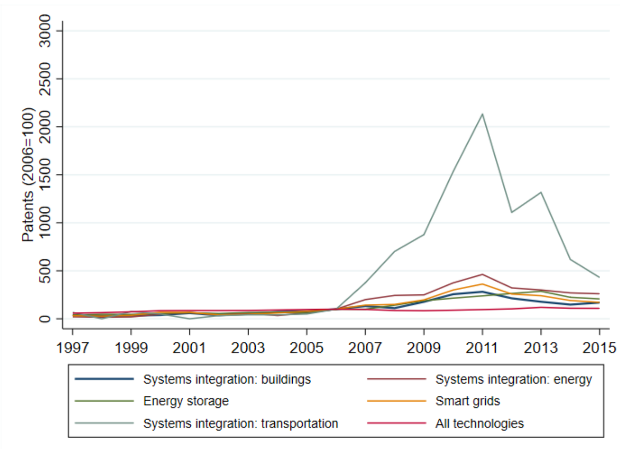


Notes: Figures show global counts of clean energy patents for patents filed in two or more countries. Patents are sorted by priority year. . Fractional counts used for patents with inventors from multiple countries. All counts normalized so that 2006 = 100. Patent extractions from the EPO World Patent Statistical Database (PATSTAT).

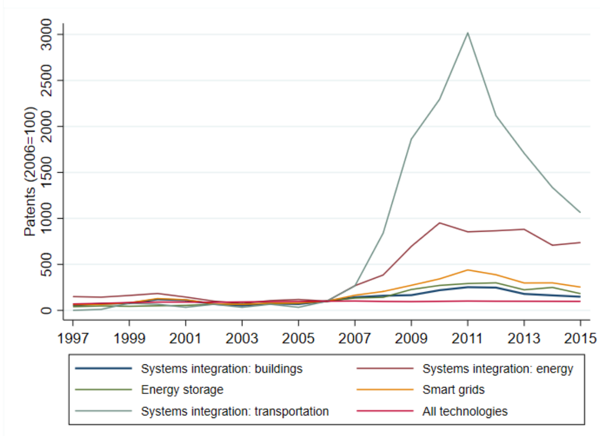
Figures 7 and 8 show that these trends are truly global. Based on the home country of each inventor, we present clean energy patents and enabling technology patents from inventors from the United States, the European Union, Japan, and China. While the downturn is not as noticeable for China (or perhaps begins a year or two later), overall patenting is also increasing more rapidly in China, so that much of the growth in energy patenting in China simply corresponds to an overall increase in patenting activity. With few exceptions, such as building energy efficiency patents in the U.S. and EU, similar peaks and declines are observed for clean energy technologies in the US, EU, and Japan.

Figure 8: Enabling Energy Technology Patents by Country

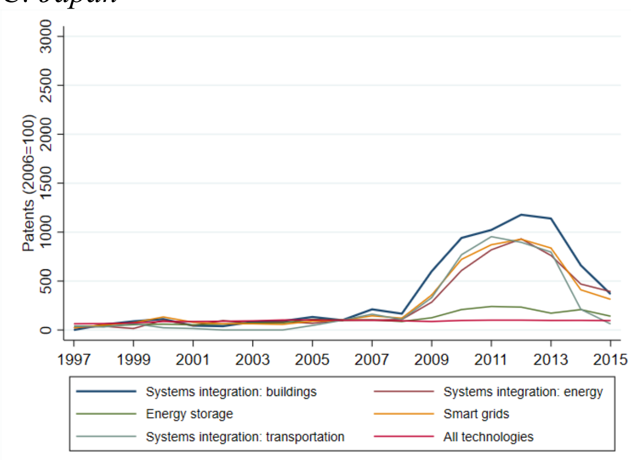
A: United States



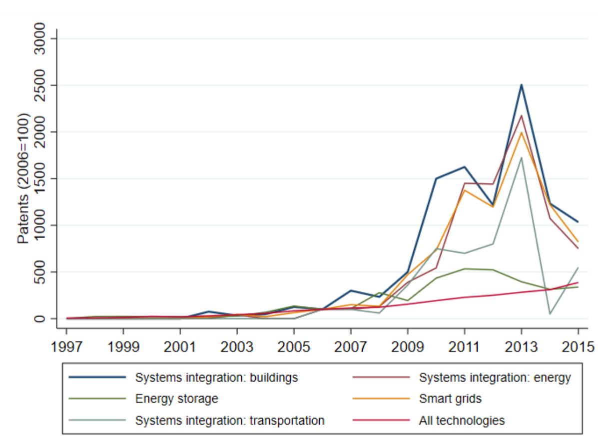
B: European Union



C: Japan



D: China



Notes: Figures show global counts of enabling energy technologies for patents filed in two or more countries. Patents are sorted by priority year. Fractional counts used for patents with inventors from multiple countries. All counts normalized so that 2006 = 100. Patent extractions from the EPO World Patent Statistical Database (PATSTAT).

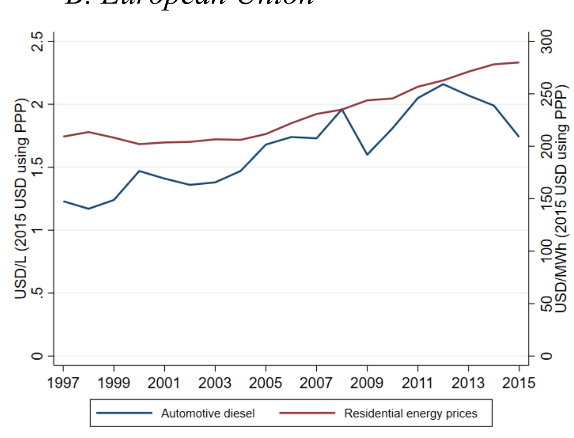
A. Why Has Clean Energy Patenting Fallen?

While it is beyond the scope of this chapter to provide definitive evidence on any one possible explanation for the recent decline in clean energy patenting, we suggest several possible explanations below. When relevant, we cite evidence from recent working papers that have begun exploring this decline. In other cases, we provide our own descriptive data to look for correlations between potential mechanisms that might explain the decline.

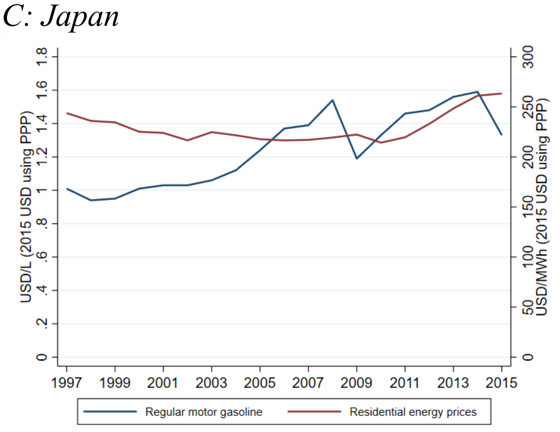
Figure 9: Energy prices, selected countries

A: United States

B. European Union



C: Japan



Notes: Figures show gasoline and residential electricity prices for select countries, in 2015 US Dollars. *Source*: IEA (2019) Energy Prices and Taxes Statistics.

1. The rise of hydrofracturing

The decline in clean energy patenting comes soon after the expansion of US natural gas production due to hydrofracturing. Recall that natural gas prices in the US began to decline after 2007. Similarly, increased oil supply and decreased demand after the global recession led to decreased oil and gasoline prices (e.g. Figure 9). Acemoglu *et al*. (2019) posit that the shale boom caused energy innovation to shift from clean energy to fossil fuels.

[table 3 here]

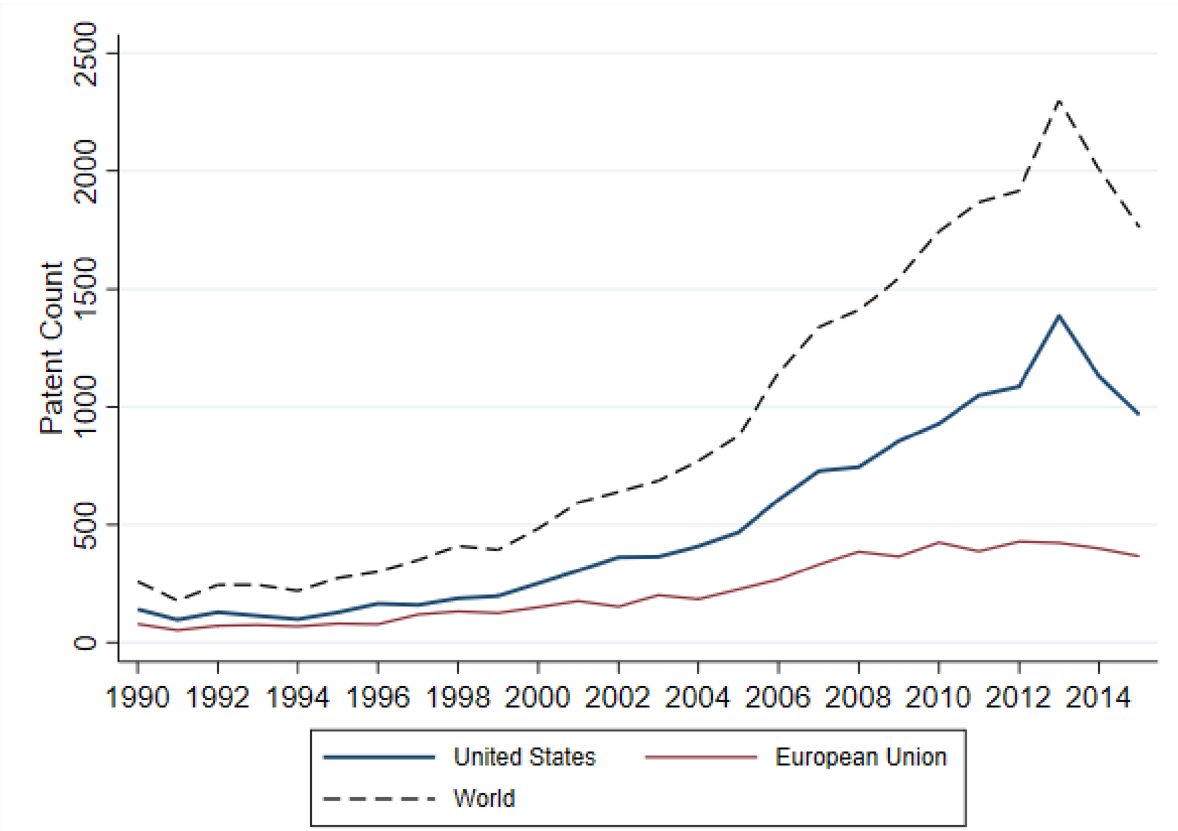
Data on hydraulic fracturing patents provide some support for this argument. Figure 10 shows patent counts related to hydrofracturing for the world, the United States, and European Union.[2] Together the US and EU account for 79% of these patents. Two trends emerge. First, after a period of relatively flat innovation, hydrofractruring innovation took off during the first decade of the 21st century. Between 1990 and 1999, fracking patents grew by just over 50%. From 2000 to 2009, they grew by more than a factor of 3. While they do not grow as fast as most clean energy patents, hydraulic fracturing patents do not peak until 2013.

Second, recent innovations in hydrofracturing are dominated by the United States, as nearly all the growth during the 2000s comes from US inventors. Fracking faces strong public opposition in Europe due to concerns over surface water diversion, groundwater quality, and consistency with climate policy goals (Krupnick and Wang 2017) While the US is responsible for about 20 to 30% of most energy inventions (Table 3), it is responsible for over 50% of fracking patents. Nonetheless, the fall in clean energy patenting has occurred globally. Moreover, while hydrofracturing contributed to the fall in oil and gas prices during this time period, electricity prices are a more important driver of innovation for renewable technologies such as solar and wind energy. Trends in electricity prices vary across countries (Figure 9). Electricity prices were relatively stable in the US, thanks in part to lower natural gas prices, but steadily increasing in the

[2] As in other figures, data includes patents with applications in two or more countries, sorted by priority year and inventor country. As the patent classes used to identify these innovations are limited in scope, we also perform a robustness check using a broader set of classes which may however include un-related technologies. For this reason they are combined with a keyword search on patent titles and abstracts using the terms hydraulic fracturing, horizontal drilling, well completion (following Cahoy et al. 2013). These counts are not directly comparable to our other patent trends, as the keyword searches are only possible for patents applications registered at granted by the US and European Patent Offices. Although the resulting patent counts are much lower, the trends for those patents are similar, with a three-fold increase during the 2000s and dominance by U.S. inventors. Search terms for both search strategies are listed in Appendix A.

EU and began to rise in Japan after bottoming out in 2010. As such, the rise of hydrofracking offers at best a partial explanation for the decline in clean energy patents.

Figure 10: Hydrofracturing patents, 1990-2015



Notes: The figure shows hydrofracturing patents with applications in two or more countries, sorted by priority year and inventor country. Fractional counts used for patents with inventors from multiple countries. Patent extractions from the EPO World Patent Statistical Database (PATSTAT).

2. Weakened regulations

Because market prices do not internalize environmental externalities for clean energy versus other energy sources, regulatory support is an important driver of innovation in the energy sector. Both weakened regulation and uncertain regulation dampen incentives to innovate. Some regulatory changes that occurred as renewable energy reached its peak include:

- The election of President Barack Obama in the United States increased expectations that the U.S. would enact nationwide climate legislation. While several proposals were considered – most prominently the American Clean Energy and Security Act, more commonly known as the Waxman-Markey bill, which would have instituted a cap-and-trade system for U.S. carbon emissions – health care was the first priority of the new administration, and prospects for nationwide climate policy fell once Republicans took control of the Senate in 2010.

- The initial run-up of clean energy innovation coincides with the beginning of the European Union's Emissions Trading Scheme (EU-ETS), an EU-wide cap-and-trade program for carbon emissions. Phase I of EU-ETS began in 2005. This pilot phase lasted until 2007. Phase II, which began in 2008, lowered the supply of allowances available. While allowance prices initially rose to 30 Euros as a result, they fell to below 10 Euros after the financial crisis in late 2008 (Ellerman *et* al. 2016). Allowance prices would not reach pre-crisis levels again until phase IV began in 2018.[3]
- As the cost of renewable energy technology fell, government support also began to decline. Germany, Spain, and Italy – three major supporters of solar PV, all cut subsidies to PV after the financial crisis. While Spain cut subsidies to PV in September 2008, Germany announced cuts in late 2010 – right at the peak of patenting activity. Italy announced cuts to subsidies beginning in 2012. Moreover, Spain's subsidy cut was retroactive, increasing uncertainty among investors. A working paper by Ko and Simons (2019) argues that these subsidy cuts affected innovation not only domestically, but abroad as well. They link the subsidy cuts to a decline in R&D by South Korean manufacturers, who exported seventy percent of PV production..

Weakened regulations are a plausible explanation for the worldwide decline in clean energy innovation. Both energy supply technologies and the enabling technologies needed to complement these technologies peak after 2010, corresponding with when the US election reduced the likelihood of climate policy in the US and Germany reduced solar subsidies. In contrast, technologies less directly linked to these policies, such as building energy efficiency and hybrid vehicles, peak at different times. That global innovation fell as a result is consistent with studies

[3] https://sandbag.org.uk/carbon-price-viewer/, accessed November 14, 2019.

such as Dechezleprêtre and Glachant (2014) and Peters *et al*. (2012), who demonstrated the importance of global markets for wind and solar innovation respectively.

3. Was there a clean technology bubble?

While most discussions of the recent decline in clean energy patents attempt to explain the decline, perhaps instead it is the rapid growth in clean energy patenting around 2010-11 that requires an explanation. Clean energy patenting has fallen from its peak, but it still witnessed impressive growth compared to overall technological progress since 2006. Except for hybrid/electric vehicles and solar thermal, growth in patenting 2006-2015 is still greater for energy patents than for all patents in general. For instance, by 2015, overall patent counts are 16 percent higher than they were in 2006. In contrast, solar PV patent counts are 53 percent higher, wind energy patents 62 percent higher, energy storage patents 74 percent higher, and smart grid patents 138 percent higher. Perhaps investors were overly optimistic about the future potential of clean energy, leading to a cleantech bubble. Our venture capital data allow us to explore this possibility further, by looking for evidence of a clean technology bubble in venture capital around the same time.

4. Diminishing returns to research

Both demand-side and supply-side pressures affect energy innovation (Popp 2002). As research in a field progresses, promising opportunities may be used up, making it harder for further progress. Given how quickly clean energy patenting increased in the early 2010s, might promising avenues of research simply dried up?

Popp (2002) uses forward citations made to patents in a given year to assess the quality of innovation from a given year. However, that requires several years of patent data to assess, which is not possible for the recent decline in patents. Instead, we present data on two measures of patent quality that make use of data on *backward* citations – citations made by a given patent to the prior art:

- *Radicalness*, first proposed by Shane (2001), measures the extent to which patents are building upon ideas outside the patented technological domain. For a given patent, p, it is the count of the number of IPC classes included in patents cited by patent *p* that are not included in the classifications of patent *i* itself. It is calculated as:

$$Radicalness_p = \sum_j^{n_p} {CT_j}/{n_p}, \text{ for } IPC_{pj} \neq IPC_p,$$

where CT_j is the count of IPC 4-digit classifications IPC_{pj} cited by patent *p* that are not assigned to patent *p*, and n_p represents the total number of IPC classes in the prior art cited by patent *p* (Squicciarini *et al*. 2013).

- *Originality*, first proposed by Trajtenberg *et al*. (1997), measures the breadth of technology fields on which a patent relies. It also relies on backwards citations, but is based on the percentage of citations made by patent *p* to each possible IPC 4-digit patent class. Patents building on a more diverse set of knowledge are more original. We calculate originality as:

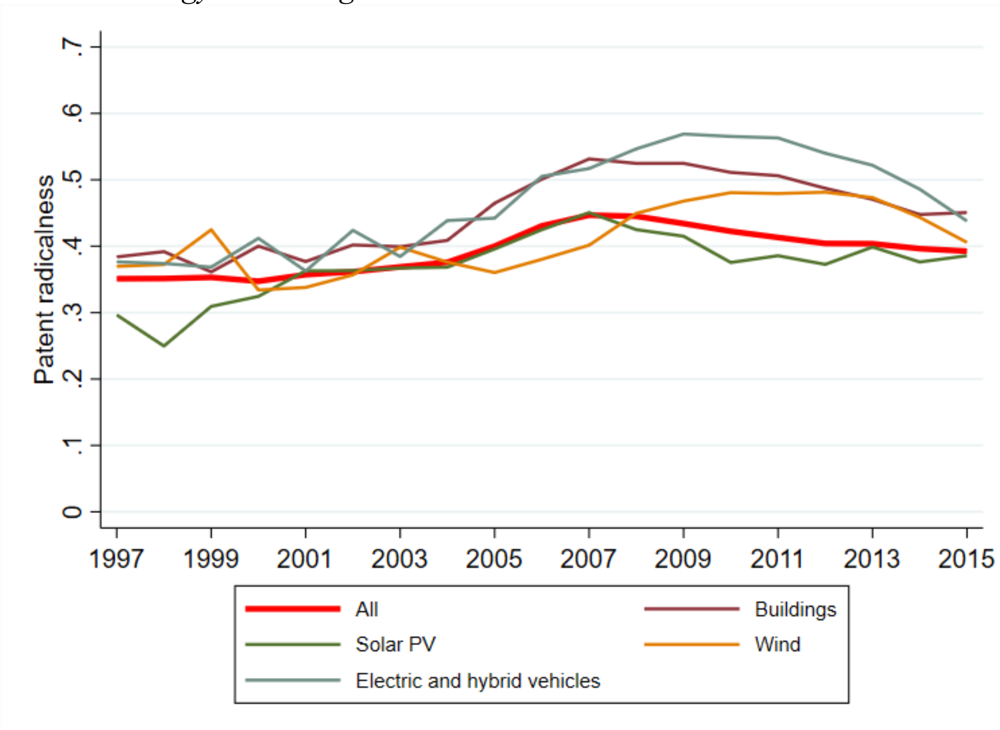
$$Originality_p = 1 - \sum_j^{n_p} s_{pj}^2,$$

where s_{pj} is the percentage of citations made by patent *p* to patent class *j* out of the n_p IPC 4-digit classifications in all patents cited by patent *p* (Squicciarini *et al*. 2013).

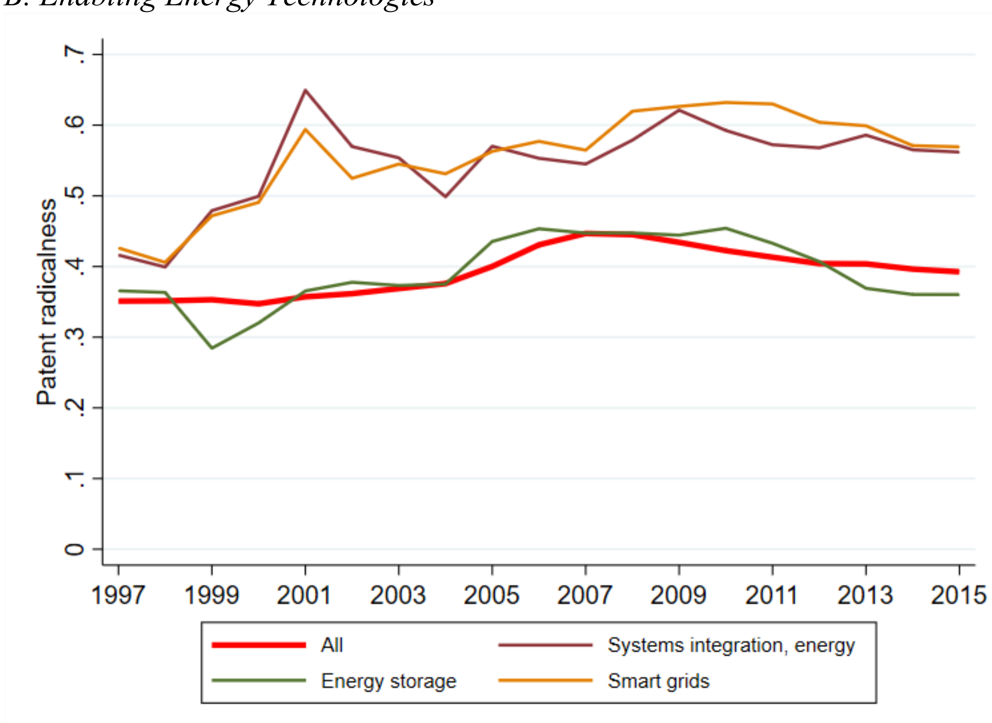
Figures 11 and 12 present radicalness and originality for a select set of our energy patent technologies, as well as all patents (in red) for comparison. Because the annual averages for small technological fields are noisy, we present the data as three-year moving averages. In each figure, the top panel includes “traditional” clean energy technologies such as renewables and electric and hybrid vehicles. A few things stand out here. Among these technologies, there are some noticeable peaks for radicalness, although this appears to coincide with a similar peak for all technologies. Only wind has a notable peak for originality, although after holding steady for several years, the originality of solar PV has also fallen since 2009. That said, both originality and radicalness for wind peak at the same time that wind patenting peaks, providing suggestive evidence of diminishing returns in that field. Electric and hybrid vehicles are both more radical and more original than either other clean energy technologies or all technologies in general. Nonetheless, while their originality is fairly constant over time, the radicalness of EHV peaks in 2009, which is just after EHV patenting peaks. In contrast, radicalness building energy efficiency technology also peaks in 2009, although patenting doesn’t peak until 2012. Solar PV is nearly always less radical and less original than the average technology. Finally, note that by 2015, wind and solar are no

Figure 11: Radicalness

A. Clean Energy Technologies



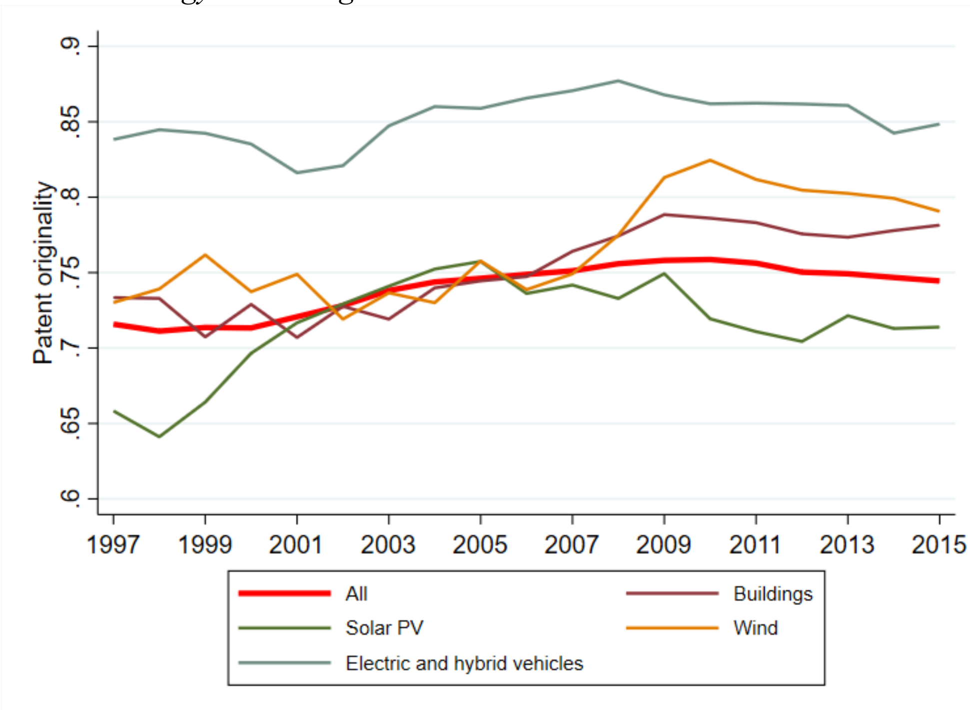
B. Enabling Energy Technologies



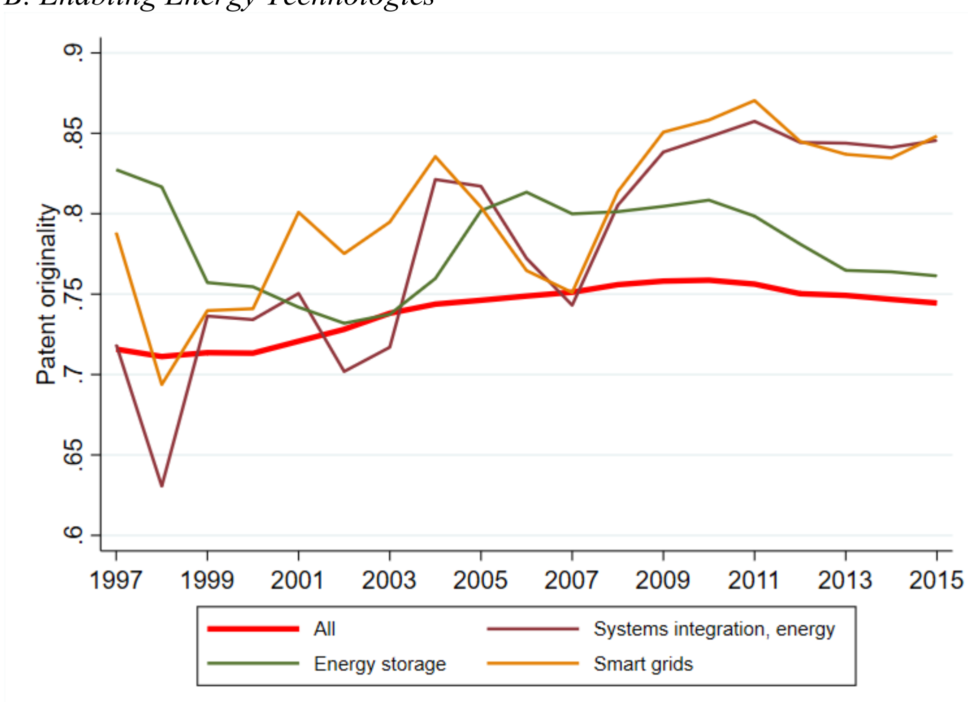
Notes: Figures show the three-year moving average of radicalness for selected energy technologies. Source: authors' calculations using data from the EPO World Patent Statistical Database (PATSTAT).

Figure 12: Originality

A. Clean Energy Technologies



B. Enabling Energy Technologies



Notes: Figures show the three-year moving average of originality for selected energy technologies. Source: authors' calculations using data from the EPO World Patent Statistical Database (PATSTAT).

more radical than the average technology, although wind is slightly more original. This result also suggests that the era of "peak patenting" for wind and solar PV may be ending.

The bottom panel of each figure presents radicalness and originality for three enabling energy technologies: systems integration, energy storage, and smart grids. While originality has fallen for energy storage, all three are more original than the average technology, suggesting that advances in these types of technologies may be increasingly important for driving the energy transition and integration of new resources. Interestingly while both systems integration and smart grids technology are more radical than the average technology, the radicalness of energy storage almost perfectly follows the trends for the average technology. Energy storage appears to build off a diverse range of technologies (i.e., it is more original), but not necessarily technological classes outside of its own domain (i.e., it is not more radical).

The measures for enabling technologies are inconsistent with diminishing returns as an explanation for decreasing patenting in these technologies. Particularly for systems integration and smart grid technology, the patented applications being filed are still radical and original. It may be that the fall in patenting for these technologies has occurred because they are complements to intermittent renewable energy sources such as wind and solar. Decreased patenting in those technologies may have been seen as a sign of reduced opportunities for smart grids and systems integration. However, diminishing returns appears to be only a partial explanation at best for decreased clean energy patenting.

5. Innovation has worked

Related to the possibility that research has hit diminishing returns is the possibility that clean energy research in existing technologies has been a success, so that less research is needed. Recall from section II that the costs of wind and solar PV have fallen to levels that make them competitive with traditional sources of electricity. In fact, by 2017 solar PV costs had fallen below what experts had earlier predicted for the year 2030 (Nemet, 2019)! Clean energy innovation peaking at the point where costs become competitive is consistent with innovation on other clean technologies. For instance, Popp (2006) shows both how innovation on sulfur dioxide and nitrogen oxide pollution control quickly increased soon after the passage of regulations in the US, Japan, and Germany, and returned to pre-peak levels once the goals of the regulation were met.

But unlike these examples, more innovation is still needed—urgently—to enable the clean energy transition in the time required. Wind and solar energy still make up just a small fraction of electric generation. Complementary technologies to integrate rising shares of wind and solar into the grid are needed. Electric vehicles must improve to be widely accepted by consumers. Innovation in new technologies altogether—such as long-term storage solutions for seasonal balancing—are needed in some regions. That innovation, at least as measured by patent counts, is falling may suggest a challenge for business and policy makers moving forward. At the same time, it may be that these trends do not fully capture some innovation that is crucial for the clean energy transition. Cost-effective integration of clean energy resources increasingly relies on innovation in other high-tech sectors, like IT, and it may be that traditional measures of energy patenting and innovation do not reflect the benefits that these advances bring to the energy sector. Further development of measures and methods for capturing these innovations is needed.

B. The Challenges of New Energy Technologies

For many reasons, the remaining technological needs for a clean energy transition will be more challenging to meet and are likely to require additional government support. First, the next wave of energy innovation will emphasize public infrastructure such as smart-grid technologies, the integration of intermittent renewable energy technologies into the grid, the adoption of connected vehicle infrastructure, and charging infrastructure for electric vehicles. How will private sector innovation respond when the demand for new equipment comes from the government itself in the form of infrastructure investment, rather than from the private sector?

Second, if successful, these emerging technologies will generate large spillovers. Much of their social value comes from making it easier to use complementary technologies such as intermittent renewables. For example, as the share of electricity generated by intermittent renewable power grows, advances in energy storage would greatly improve grid management. Energy storage breakthroughs leading to better batteries would also make electric vehicles more attractive to consumers, both by reducing costs and increasing vehicle range. Because of its novel nature, Dechezleprêtre *et al*. (2017) find evidence of large spillovers in many areas of clean energy research.

Third, the value of energy storage also depends on the cost of solar and wind generation. Complementarities among technologies make future benefits from innovation uncertain. The potential private sector rewards from energy storage innovation are connected to progress in intermittent renewables. As the cost of solar and wind falls, so must the cost of storage to continue to add value (Braff *et al*. 2016). This interdependency raises uncertainty about the future profits from innovation.

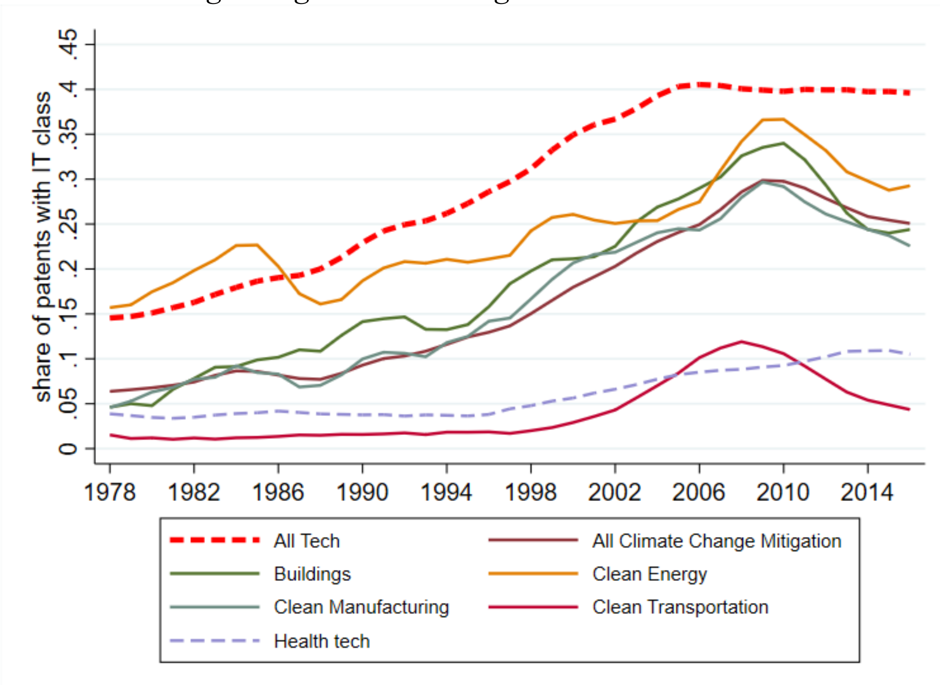
Finally, grid integration and energy storage innovations also provide examples of how the building blocks of energy innovation are changing. The high radicalness and originality of both smart grids and system integration technologies suggest technologies will require more innovation across different businesses and different lines of technology. As an example of the changing nature of energy technology, we look at the extent to which information and communication (ICT) technology has permeated both energy and other sectors.

Figure 13 illustrates the penetration of digital technology in different technological domains, measured as the three-year moving average of the percentage of patents in different fields that also have an ICT patent classification. Overall, the share of patents also having an ICT class rose through the end of the 20th century, plateauing around 40% by 2006. Trends in ICT penetration among climate mitigation technologies is similar (panel A), although a bit lower. For climate mitigating energy and building technologies, ICT penetration is just a few percentage points below all technologies, and follows similar trends. ICT penetration is a bit lower for climate mitigation technologies in the manufacturing sector, and much lower in the transportation sector.

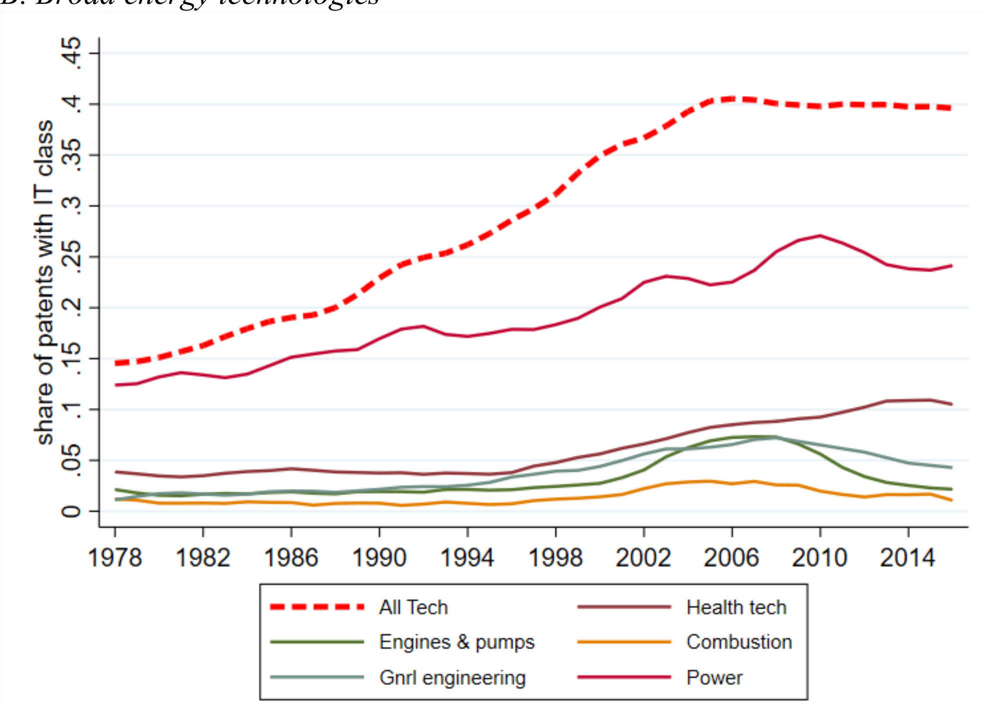
Panel B provides evidence from other energy and engineering technologies (panel B). Compared to these technologies, ICT penetration appears more important for climate mitigation. ICT penetration for power technologies plateaus at around 25%. In patents related to general engineering, engines, or combustion patents have ICT penetration rates below 10 percent.

Figure 13 – Penetration of digital technologies in various technologies

A. Climate change mitigation technologies



B. Broad energy technologies



Note: 3 year moving average of % of "claimed priorities" (i.e. patent family size > 1) in the different fields which also have an ICT co-class. Patent extractions from EPO World Patent Statistical Database (PATSTAT) by OECD/ENV and IEA/EDC (2019).

As energy innovation moves forward, bringing in new knowledge from disparate sectors such as ICT could change the nature of energy R&D. Traditionally, energy R&D has been dominated by large firms that move slowly. While redesigning a turbine requires the physical transformation of equipment, improvements in software and information technology can be made more quickly (Branstetter *et al*. 2019a). ICT improvements are also modular. Software components can be developed remotely and integrated into larger systems, allowing R&D to be done in more locations, both domestically and abroad (Branstetter *et al*. 2019b). These changes suggest that innovation in other sectors, especially those that are high-tech, is likely to become more important during the next wave of energy innovation. To examine this possibility, we turn next to data on venture capital in the energy industry

IV. Early-Stage Financing for Start-ups in the Energy Sector

Start-ups historically played a minor role in the energy sector (Nanda et al., 2015; Gaddy et al., 2017). Existing distribution systems and regulatory frameworks were designed for a centralized system, and combined with high capital costs, there were significant barriers to entry. However, the transition towards a more decentralized energy system characterized by increasing levels of renewable energy and storage technologies may change the role of energy start-ups. Furthermore, the successful integration of these resources relies on progress and innovation in other sectors as well, where entrepreneurial firms do play a larger role. For example, information technology (IT) and blockchain technology are further helping to facilitate this transition to a more decentralized energy system and becoming increasingly abundant. Blockchain energy startups are multiplying, raising more than 265 million euro for applications in the energy sector in 2017 (European Commission, 2018).

At the same time, start-ups need to raise capital to survive or successfully exit, but venture capital (VC) investments for clean energy firms have fallen in recent years after large investments through the 2000s. There are multiple potential explanations for this perceived failure of the VC model for clean energy. Some point to inadequate risk-return profiles (Gaddy et al., 2017). Long time horizons between technology idea, development, and commercialization in the energy sector offer an alternative explanation, whereby firms may have achieved the desired returns but on a time-scale that is typically not attractive to VCs. This suggests a different form of more patient capital may be needed. If high-tech is becoming more important in the energy sector, it also could be that it is just increasingly difficult to evaluate energy start-ups as they become increasingly complex and perhaps difficult to evaluate *ex ante*. While Nanda et al. (2015) and Gaddy et al. (2017) provide initial explorations of venture capital in the energy sector, the changing nature of energy markets in recent years suggests further investigation is warranted to better understand the historical and potential role of start-ups in enabling and driving the clean energy transition.

In this section, we explore trends in the types of companies founded since the year 2000 as well as the funding raised by different start-ups. We also examine the performance of different types of energy firms, such as whether they raised funding, whether they had a successful exit (i.e., as measured by an acquisition or initial public offering (IPO)), and the time to exit conditional on a successful exit. While the analysis remains purely descriptive and does not attempt to estimate any causal relationships, our exploration of heterogeneous correlations reveals a few key insights that warrant more rigorous evaluation in future research.

A. Data Overview

We gather firm-level data on start-up companies and VC activity from Crunchbase, a commercial database of innovative companies.[4] Crunchbase provides detailed information on organizations—such as their founding date, headquarter country, funding raised (with detailed funding round information), and exits—generating real-time updates from a community of partners and machine learning algorithms. It has become a leading provider of data on startups and investment activity, especially for the U.S., and it has been embraced by the investor community as a leading platform for discovering and connecting with innovative companies.

With that said, the data comes with its limitations. There are certainly selection concerns, for instance, as more innovative companies are more likely to appear in the data. There is also increasing coverage over time but with less comprehensive coverage in the final year or two given time lags. Furthermore, some firms may misleadingly indicate that they operate in a certain sector for self-promotion purposes in an effort to attract more funding, as sector categories are not cross-

[4] The database can be accessed at www.crunchbase.com. Crunchbase was created in 2007, however the data cover firms that were founded in preceding years as well.

checked against traditional sectoral classifications. Lastly, the coverage for firms in some countries, such as China, is very low, which may be particularly important for the energy context.

We do not attempt to address these selection biases from a statistical perspective. However, we do try to engage with some of the concerns descriptively when we graphically explore trends and outcomes of firms across sectors by using *shares* of total firms founded and total funding allocated each year per sector in addition to the totals. We also focus mainly on comparisons across sectors and across energy types (rather than changes over time) in our correlation analysis and discussion. Insofar as the selection biases impacting performance metrics are not systematically different across sectors or firms of different energy types within the energy sector, our analyses still provide some meaningful insight about energy start-ups that is new to the literature.

We link several Crunchbase datasets in order to compile our dataset for analysis. First, we start with the full cross-section of 733,133 organizations.[5] We keep only those that were founded in 2000 or later and those that indicated their primary business as operating as a company (as opposed to an investor, for instance). We match this organization-level data to funding round-level data, and we convert all funding amounts (in USD) to real 2010 dollars using the consumer price index from the World Bank. The funding deal dataset includes 268,774 observations with about 71k missing actual funding amount information, so the totals used throughout the analysis are lower bounds for this sample of firms.[6] We find each firm's total funding raised and the number of successful funding rounds (where each observation in the funding deal dataset is defined as a funding round) and match these data to the organization-level cross-sectional data. We also match this to Crunchbase's data on firm exits (i.e., acquisitions and initial public offerings (IPOs)). After dropping duplicate observations, the datasets include information on about 87 thousand acquisitions and 17 thousand IPOs.

Perhaps most interestingly for our analysis, Crunchbase sector classifications allow us to identify start-ups that operate in multiple (and possibly complementary) fields, such as IT. We classify firms based upon whether they indicate that they are in the energy sector, and separately

[5] We accessed the data in Summer 2019.
[6] These also are lower bounds from the perspective of firms not appearing in Crunchbase at all. When examining the impact of this funding on various outcomes, these correlations will embed selection bias, such as endogeneity associated with these firms perhaps being more visible (and thus perhaps more successful) than those that do not appear in the data or do not have fully populated funding data.

firms also indicating that they operate in a high-tech sector. Table 4 provides a summary of how we classify different types of firms and the number of observations we have for each category. Our final sample consists of 604,884 firms founded from 2000 through 2018, including 13,515 energy firms. Panel A provides the breakdown of firms based upon high-level sectors. We classify different types of energy firms in Panel B, and in Panel C, we further breakdown the energy firms based upon whether they also operate in a high-tech sector. Of the 13,515 energy firms, 10,129 are energy-only (e.g. not also high-tech) versus 3,386 being energy as well as high-tech. Panel C also shows the number of firms that are also high-tech by energy type.

[Table 4 here]

B. Trends in Companies Founded and Funding Raised

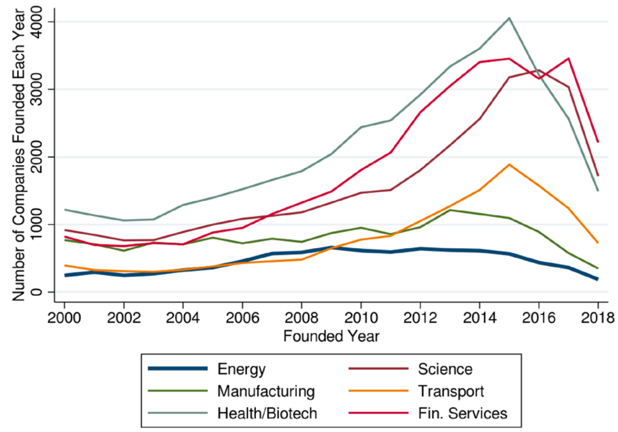
We begin by graphically exploring trends in companies founded each year and funding raised for energy firms relative to those in manufacturing, science, health and biotech, transportation, and financial services.[7] Figure 14 illustrates these trends from 2000 through 2018 in four panels. First, in Panels A and B, we plot the total number of companies founded each year and the share of companies founded each year by sector, respectively. The number of energy firms founded appears to peak in the year 2012, which is a little later than when it peaks when measured as a share of founded firms. This suggests that founding energy firms was still on the rise throughout the great recession, but not as quickly relative to firms in other sectors. Furthermore, the number and share of start-ups in financial services, science and engineering start-ups all increase more quickly than energy following the recession, with the share of firms founded that are energy-related falling from about 2007 onwards.

Panels C and D illustrate similar patterns for the share of total funding each year allocated to each sector (Panel C) and the share of total funding deals by sector (Panel D).[8] These figures also clearly illustrate the "bubble" of investments flowing to energy at different times. There are two spikes in the share of energy funding levels—in 2008 and 2012—and also a spike in the share

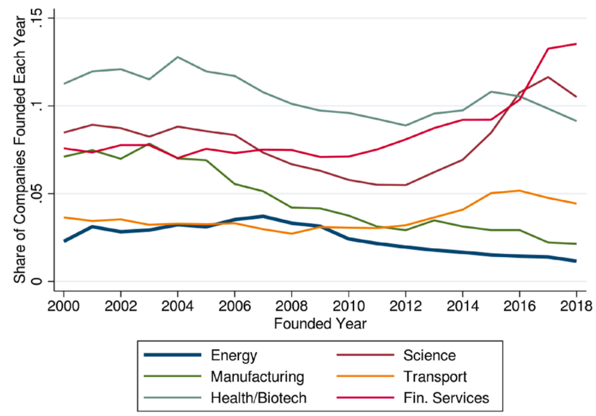
[7] Note that because some firms may participate in multiple sectors, some firms and their associated funding are double-counted.
[8] A share of funding deals refers to the share of the total number of VC funding rounds completed each year that go to each sector.

Figure 14: Comparison of Energy Firms to Other Sectors

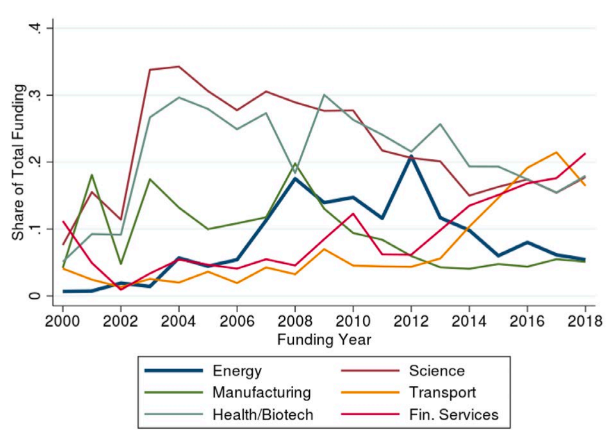
A: Number of Companies Founded Each Year



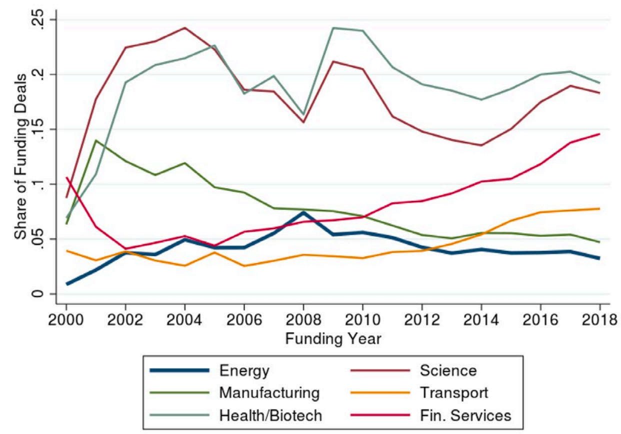
B: Share of Companies Founded Each Year



C: Share of Total Funding by VCs Each Year



D: Share of Total Funding Deals by VCs

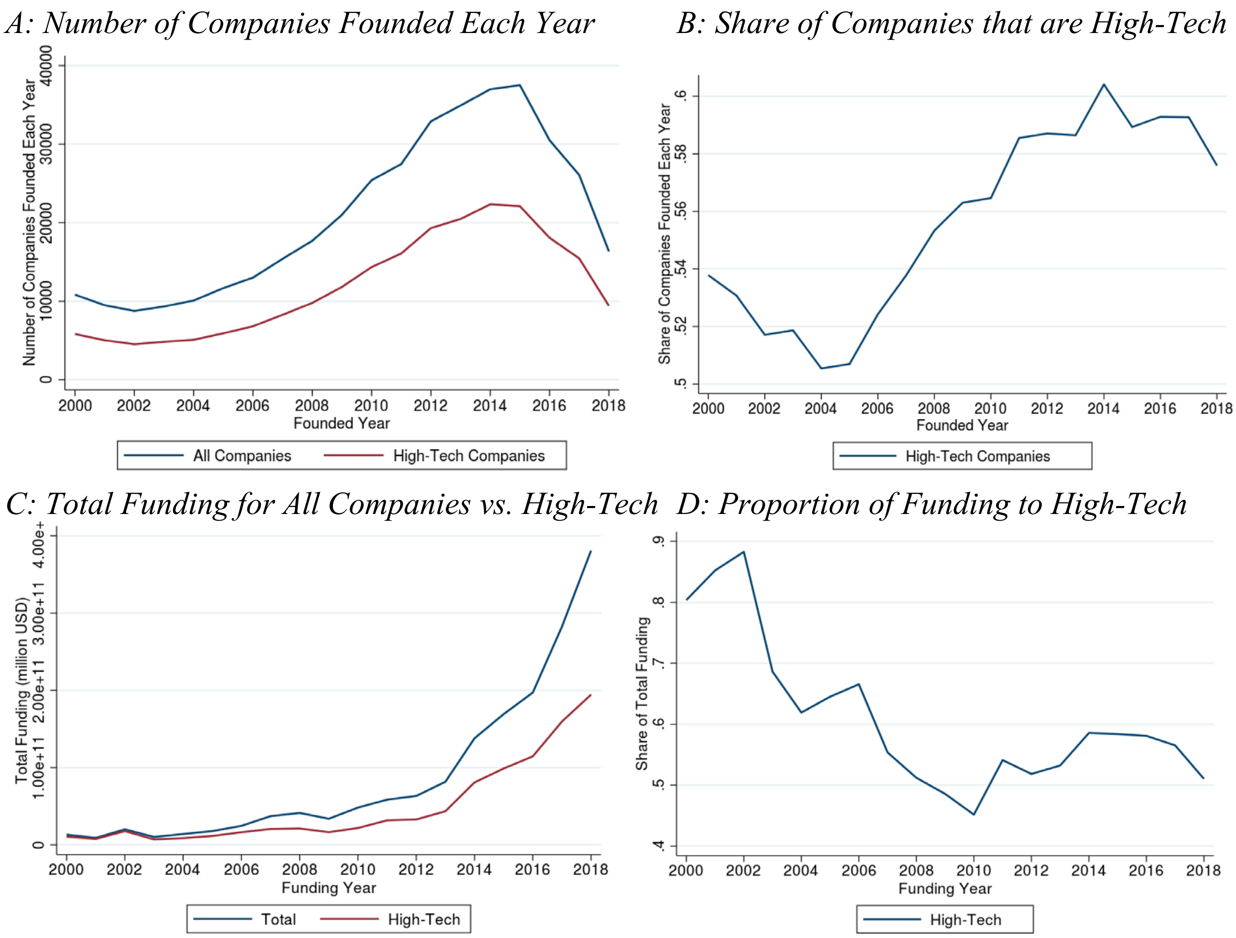


Notes: Panel A compares the number of firms founded each year. Panel B compares the share of firms founded each year as a proportion of all firms. Panel C is the share of total VC funding going to each sector, and Panel C is the share of total number of completed VC rounds going to each sector.

of funding deals for energy firms in the year 2008. This aligns with energy firm founding year peaks, descriptively suggesting that such funding may be correlated with the successful start-up of energy firms. The decrease in funding for energy firms corresponds with decreases in science and health/biotech as well, whereas funding to financial services and transportation are on the rise following the great recession. We will explore the relationship between funding and start-up performance in Section IV.C.

The rise and fall of the share of VC funding going to energy firms also closely mirrors the trends in patenting presented in Section III. In both cases, rapid growth begins in the mid-2000s. While the peak in venture capital funding comes slightly later than the peak in many clean energy patents, both drop significantly after 2012, and both remain above the levels achieved prior to the initial increase in 2006. While these data are only suggestive, it does appear that the rise and fall in patenting seen during the 2006-2012 period may be indicative of broader trends in energy investment.

Figure 15: Growing Share of Companies Founded are High-tech from 2005-2014

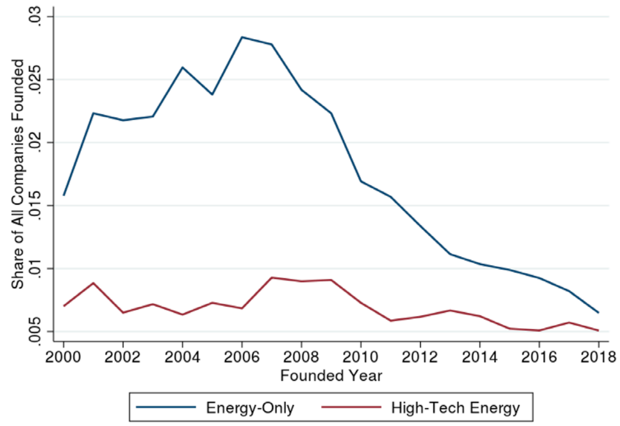


Next, given the increasing penetration of high-technology innovations broadly over the past decade—combined with the need for high-tech innovations in the energy sector for the integration of variable renewable energy resources—we explore trends in high-tech companies as well as energy firms that are either energy-only or high-tech energy. We first compare high-tech companies to all companies in Figure 15. Panel A plots the number of companies (total and high-tech) over time and Panel B plots the share of companies founded each year that are high-tech. These figures illustrate how the share of companies that are high-tech has risen starkly from about

2006 onwards. Panels C and D explore VC funding allocated, revealing that the majority of funds do go to firms that are high-tech. The share of funds going to high-tech firms fell in the years leading up the recessing and through 2010, but then rose again quickly from 2010 onwards, suggesting that VCs may be particularly drawn to firms reporting to operate in high-tech sectors.

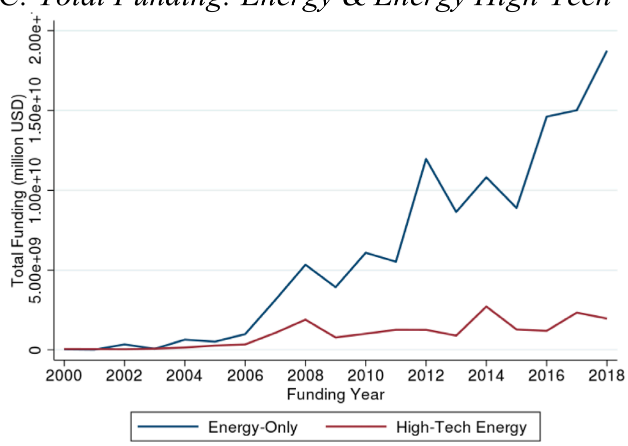
Figure 16: Energy-only and High-Tech Energy Companies

A: Share energy-only vs. energy and high-tech

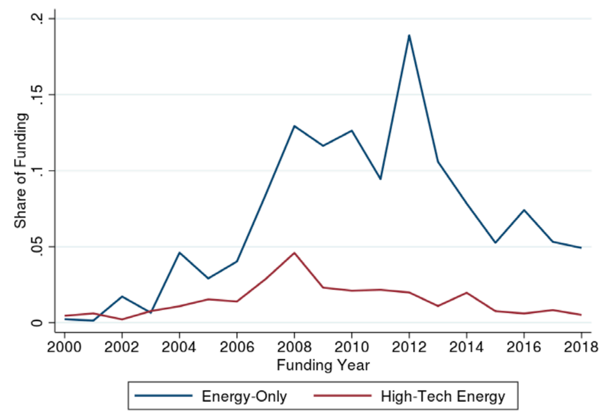


B: Increasing share of high-tech energy cos.

C: Total Funding: Energy & Energy High-Tech



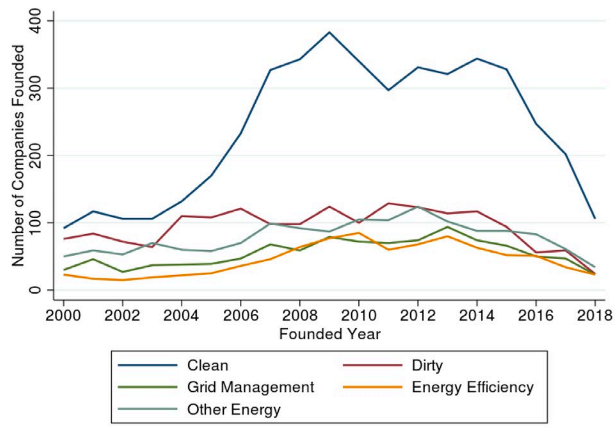
D: Share of Funding: Energy & Energy HT



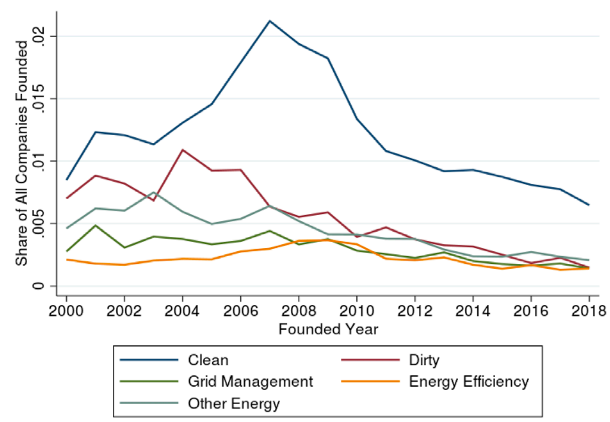
We explore this further to see if a similar relationship holds in the energy sector specifically (Figure 16). Panel A of Figure 16 plots the share of all companies founded that are energy firms also categorized as high-tech versus those that are energy-only (i.e., not also operating in the high-tech space), and Panel B plots the share of energy firms founded each year that are also high-tech. While the overall number of energy-only start-ups has been falling since about 2006, the number of energy firms that are also high-tech rose sharply after 2006 and plateaued throughout the great recession, falling again from 2009 onwards (but then leveling off from about 2012 onwards). The proportion of energy start-ups that are also high-tech have therefore been rising quickly. Comparing these findings with funding towards these types of firms in Panels C and D, we can see that the spike in the number of high-tech energy start-ups around the year 2008 also aligns with a spike in funding (both in totals and in shares) around the same time.

Figure 17: Energy Companies Founded Each Year by Energy Type

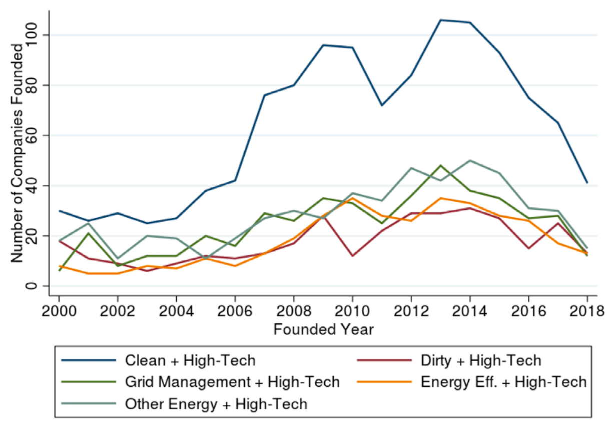
A: Number of Companies by Energy Type



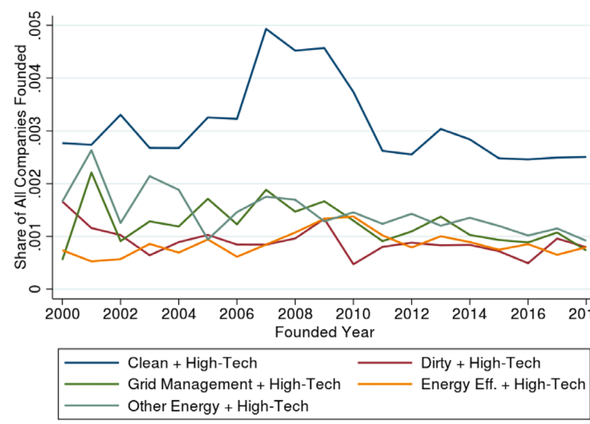
B: Share of All Companies by Energy Type



C: Number of Companies by Energy Type



D: Share of All Companies by Energy Type



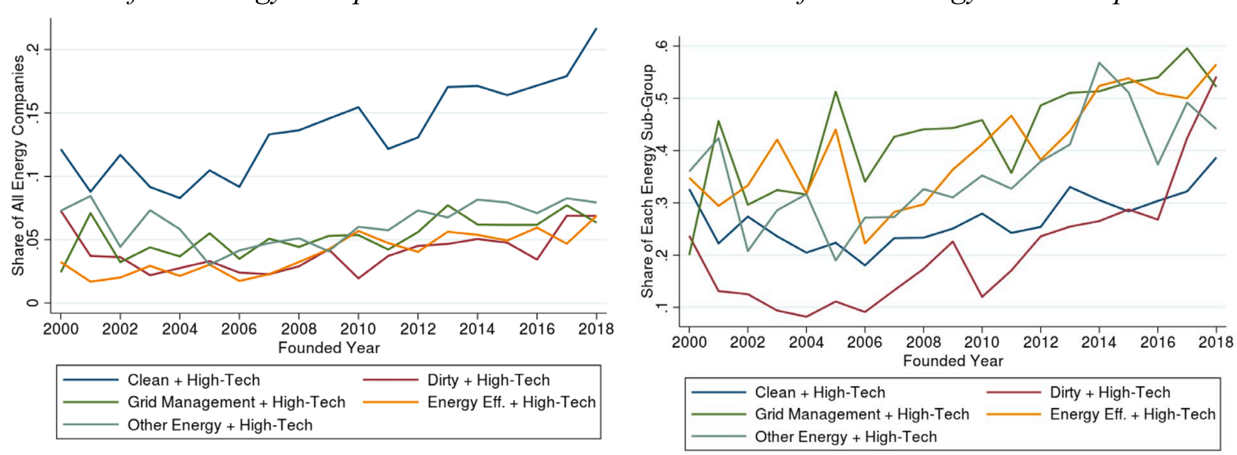
Notes: Shares (Panel B and Panel D) are proportions of all companies founded in a given year.

We explore this distinction between energy-only and high-tech energy firms by energy type as well (see Figure 17). Panel A plots the number of companies by energy type (clean, dirty, grid management, energy efficiency, and other) and Panel B plots the share of all firms that fall into each category. These figures very clearly show the "bubble" of clean energy firms that emerged through the great recession: while the number of firms in dirty energy, grid management, etc. remained relatively flat (or increased slightly), there was a major spike in clean energy from about 2004 to 2008, with the proportion of firms in clean energy then falling sharply from about 2009 onwards. When examining firms that specifically are also high-tech in these energy sub-categories in Panels C and D, we can see that these trends may have been at least partially driven by high-tech energy firms. The proportion of firms that are high-tech clean energy firms jumped sharply from 2005 to 2007, and then began to fall from 2008 onwards before leveling off in 2011.

As one final exploration of whether energy start-ups are increasingly also high-tech, we examine the share of *energy* firms (rather than of total firms) that are also high-tech by energy type. Panel A of Figure 18 plots energy firms that are also high-tech by energy sub-group as shares of all energy companies founded each year, and Panel B of Figure 18 plots firms that are also high-tech as shares of their own sub-group. In other words, in Panel A, high-tech clean firms are plotted as a proportion of all energy firms, in Panel B, high-tech clean firms are plotted as a proportion of all clean energy firms. The story is clear: across all energy sub-groups, start-ups are increasingly either claiming to be high-tech or actually are high-tech. This growth is similar to the growth observed in the share of energy patents also classified as high-tech, as well as supporting the anecdotal evidence presented in Section II that IT is also of growing importance in the search for new energy resources.

Figure 18: Increasing Trends in Energy Firms that are Also High-Tech

A: Share of All Energy Companies Founded *B: Share of Each Energy Sub-Group Also HT*



Notes: All shares are of totals corresponding to all energy firms.

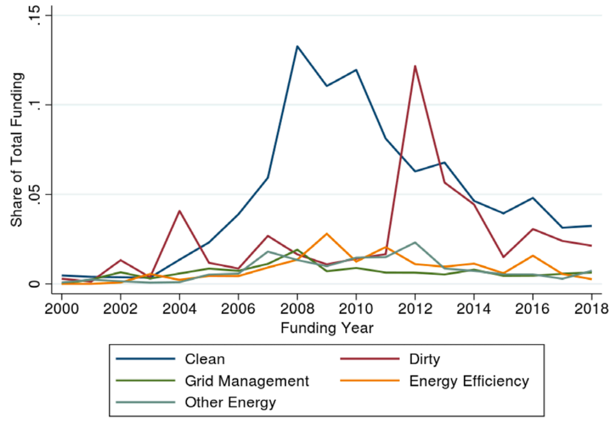
Lastly, we examine whether these trends are correlated with VC funds flowing to energy firms that are also high-tech, as this could provide some insight into one potential explanation of why VC funding has not performed as well in the energy sector relative to others. That is, it could be that being labeled or marketed as "high-tech" helps these firms attract VC, but they may not actually end up performing any better than energy-only firms. This could be for several reasons. High-tech energy firms may be particularly complex and difficult to assess, or such firms could take longer to commercialize their products or exit if they are working on a more complex technology. It also could be that some firms simply claim to be high-tech when they are not as a means for attracting VC—a hypothesis that's been posed in light of Crunchbase being used as a platform by VCs. This could mean that VCs over-value them, or alternatively, that they just don't perform as well as energy-only firms. We explore firm performance in the next section, but first we present graphical evidence of funding trends for these types of firms.

Figure 19 plots the share of total funding (Panels A and C) and the share of successful funding deals each year (Panels B and D) by energy sub-category (Panels A and B) and then by energy sub-category for firms that are also high-tech. Panels A and B illustrate the clean energy funding "bubble" that occurred around the year 2008, where there is a large spike in the share of funding that goes to clean energy relative to other types of energy in terms of both levels of funding and the number of funding deals. Interestingly, there is also a spike in funding allocated to dirty energy around 2012-13, which is likely driven by the fracking revolution. Panels C and D specifically look at high-tech energy firms by sub-category. Despite there only being a spike in funding for clean energy firms in general around the year 2008, it appears as though there is a spike in funding for *all* energy types that are also at least labeled as "high-tech", and this is particularly pronounced for clean energy and grid management firms.

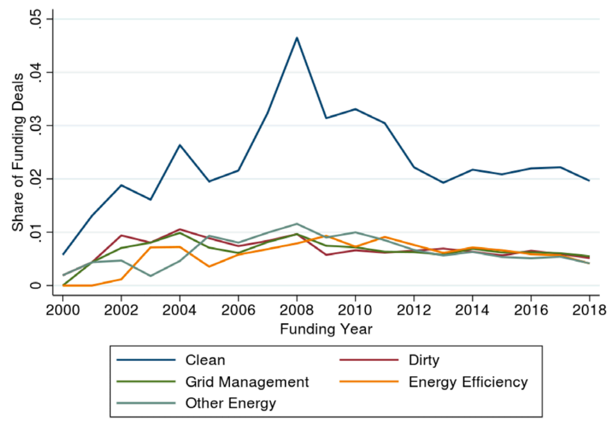
Taken together, these findings suggest that at least part of the explanation for changes in clean energy VC funding is that energy firms are increasingly high-tech. The energy transition requires complementary high-tech endeavors, such as innovation in smart technologies, platforms, and the AI required for managing a more complex and distributed system. However, this may present new challenges for VCs. It may be that "high-tech" firms are more attractive to VCs, but they may not necessarily perform better (which we explore in the next section). It also could be that the firms in our data are actually not necessarily in high-tech industries but rather just claiming to be in an effort to attract funding. Any of these stories could at least partially explain unexpectedly low returns to investments in the clean energy sector so far.

Figure 19: Share of Funding Going to Energy Firms

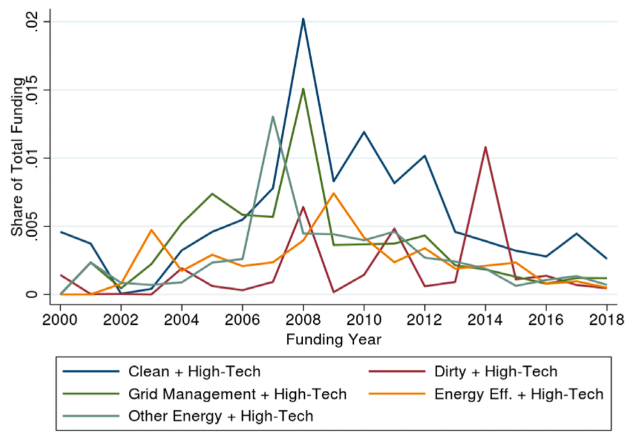
A: Share of Total Funding by Energy Type



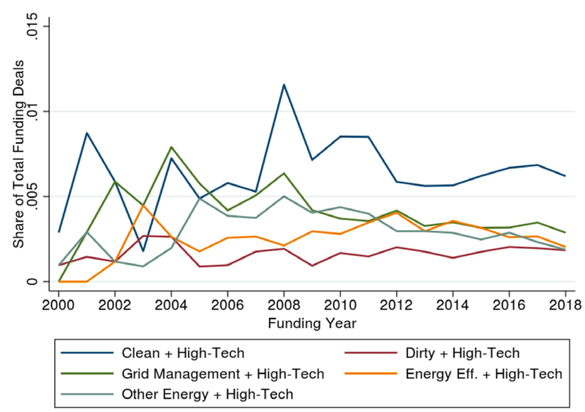
B: Share of Funding Deals by Energy Type



C: Share of Total Funding by Energy Type



D: Share of Funding Deals by Energy Type



Notes: Energy Funding as Shares of Total Funding (Panels A and C) and Shares of Funding Deals (Panels B and D). Panels C and D show Shares by Energy Type for energy firms that are also high-tech.

This also presents a new challenge for researchers studying energy innovation: studying firms or patents that are only identified as being in the energy sector will vastly under-estimate innovation and start-up activity that is relevant for advancing the clean energy transition. Accounting for innovation in high-tech sectors that are also applicable for the exploration, integration, and management of new energy systems and resources is more important than ever for fully understanding the energy innovation landscape.

C. The Performance of Energy Firms

Insufficient returns to investments are often pointed to as the key explanation for why VC funding has not been as successful in the clean energy sector relative to other sectors. This could be due to low returns—or lower returns than expected—or it could be that the time horizons for achieving returns are just longer than average and thus the returns have not yet been realized. A third hypothesis is that it is difficult to identify promising energy VCs that are increasingly complex and operating not just in the energy sector but also often in other high-tech sectors, or that VCs over-value such firms. To explore these potential explanations, we explore the success of energy firms relative to average firms and other high-tech firms, as well as performance metrics across energy types as measured by whether they had a successful exit (i.e., acquisition or IPO), whether they ever raised funds, the amount raised conditional on raising funds, and the time to exit as measured by the difference between the founding and exit year. In each, case we regress these outcomes on indicators of firm types, along with founded year fixed effects and a dummy variable indicating whether the firm is located in the U.S. We also cluster our standard errors by founding year. We focus on two broad sets of questions:

1. Are energy start-ups more or less likely to raise funds and/or successfully exit via acquisition or IPO? Does this vary by the time of energy firm? (Tables 5-8).
2. Conditional on having received funds, are energy start-ups more or less likely to successfully exit? While differences in the likelihood of receiving funding may occur if the expected potential returns differ across sectors, conditional on receiving funding, any differences across sectors observed are suggestive evidence that investors are not valuing expected returns across sectors correctly (Table 9).

Since the firms who decide to list in Crunchbase are not a random sample of start-ups, our results should not be interpreted as causal. However, they reveal correlations in the data worthy of exploration in future research

We begin by examining all firms and comparing the relative performance of energy firms (of any type) as a baseline. Table 5 presents the correlation between being an energy firm and the five measures of firm performance, conditional on founding year fixed effects and as well as a dummy for whether the firm is headquartered in the US. Across all metrics, energy firms perform better than the average firm in our sample. They are 4.2%, 6.3%, and 14.5% more likely to be acquired, go public, or raise funds over their lifetimes, respectively. They also raise more money conditional on raising any funds (column 4), and they take 0.85 fewer years on average to exit conditional on either being acquired or going public.

[table 5 here]

Given that VC has been considered an inappropriate model for the energy sector after some investments did not provide the expected returns, it is interesting that the energy start-ups listed in Crunchbase perform relatively *better* than the average start-up. One potential explanation motivated from our graphical analysis is that investors may place a premium on firms that are both energy and high-tech relative to those that are uniquely energy. Indeed, Table 6 presents evidence suggesting that high-tech energy firms raise more funds than non-high-tech energy firms, yet they perform far worse on other metrics. The estimates provide correlations between various performance metrics and indicator variables for whether firms operate in both the energy and high-tech spaces versus only operating in the energy space or only operating in the high-tech space.[9] While firms that operate *only* in the energy space do better than the average firm on every measure, high-tech energy firms are no more likely to be acquired or go public than the average firm and far less likely to do so relative to energy-only firms (Columns 1 and 2). They also do not take any less time to exit relative to the average firm but take longer to exit relative to energy-only firms (Column 5). Yet high-tech energy firms are 11% *more* likely to raise funds relative to energy-only firms (Column 3).[10]

[table 6 here]

We also consider whether the performance of energy start-ups varies by the type of energy, as much of the discussion around the perceived failure of the VC model has centered around clean energy. For instance, do clean energy firms perform worse or take longer to exit (than the average firm or relative to other types of energy firms), thus making VC a poor vehicle for financing clean

[9] Note that these categories are mutually exclusive, so that the coefficients are, for example, the share of firms of each type that are acquired or have an IPO. The differences between the correlations for energy-only and high-tech energy firms are statistically significant in all cases (at the 10% level in Column 1, at the 5% level in Columns 2 and 5, and at the 1% level in Columns 3 and 4).

[10] This is significant at the 1% level. Conditional on raising funds, energy plus high-tech firms raise fewer funds relative to energy-only funds (Column 4), but this could be an artefact of the data. The graphical analysis demonstrated that the amount of funding per round decreased in later years, and this is also when the number of energy plus high-tech firms is increasing.

energy? The evidence presented in Table 7 suggests that this is not the case.[11] Clean energy firms are less likely to be acquired relative to the average firm as well as energy firms (column 1), but they are more likely to go public (column 2) and raise funds (on both the extensive (column 3) and intensive margins (column 4)) relative to the average firm. They also take less time to exit (column 5). At the same time, relative to dirty energy firms and other "general" energy firms, they are less likely to go public and take slightly longer to exit. Taken together, these correlations may suggest that slightly longer time horizons relative to other energy firms may partially explain insufficient VC investment returns if expectations were incorrect. That is, if investors assumed that the exit time for clean energy firms would be the same as dirty energy firms, they would have (just slightly) under-estimated the amount of time it would take for clean firms to exit. But, nonetheless, clean firms do exit much faster than the average firm and perform better on most measures.

[table 7 here]

Finally, in Table 8 we examine the same correlations for energy firms only operating in the energy space and those that also operate in the high-tech space. These correlations are conditional on being some type of energy firm, so that the omitted category is the average "general" energy firm. Once again we find that venture capital investors appear to place a premium on energy firms that are also high-tech. With the exception of energy efficiency, energy firms that are also high-tech raise more funds than their energy-only counterparts. The chances of raising funds are negative for dirty energy-only and grid management-only relative to the average "general" energy firm (and there is zero correlation between being clean energy-only and raising funds), whereas they are positive for all three energy types when the firm is also high-tech. At the same time, the high-tech energy firms do not perform better (and actually perform worse on occasion) across the other performance metrics. Clean and dirty high-tech energy firms are less likely to go public, and high-tech dirty energy firms are also less likely to be acquired. Being high-tech also increases the time to exit for dirty, grid management, and energy efficiency firms.

[table 8 here]

A core remaining question is whether differences in returns to energy investments relative to investments in other firms can at least partially explain the fall in energy funding (and founding

[11] Each of these categories is mutually exclusive.

of energy start-ups) over time. Our data do not allow us to directly examine *returns* to energy investments. However we can compare the performance of energy firms that are funded relative to the average funded firm to better assess how well VC *investments* in energy fare. We test the likelihood of exit (either through acquisition or IPO) *conditional on receiving funding*. Correlation comparisons conditional on funding also at least partially account for selection bias associated with being more likely to receive funding. While energy firms in the Crunchbase dataset may do better than other firms on some measures of performance, selection into Crunchbase is not random.

We estimate the correlations across the full sample, as well as when splitting the sample into thirds based on each firm's founding year (2000-2005, 2006-2012, and 2013-2018), in order to test whether there may have been a "bubble" in clean energy finance. The years chosen correspond to the boom-and-bust period observed in clean energy patenting.[12] Lerner (2011) notes that venture capital funding is often cyclical, with investors overreacting to both good and bad news. Moreover, he finds that clean energy investment grew rapidly, albeit from a very low base, in the early 2000s. Overall returns on these investments were high, but primarily due to two very successful companies. He notes that the patterns observed in his data suggest overfunding may have occurred in the clean energy sector. If such a "bubble" exists, we expect firms funded during bubble years (i.e., roughly 2006-2012 in the clean energy investment context) to perform worse than those funded in other years, as clean energy investor expectations may have been unreasonably high.

[table 9 here]

Table 9 presents the results. Column 1 uses the full sample. We see that clean energy and "other" energy firms are about 2.5 percentage points less likely to exit than the average firm. As the sample mean is just 11.6 percent, this is a substantial difference. Unlike the estimates for the full sample in Table 7 that do not condition on receiving funding, in no cases do we see that funded energy firms are *more* likely to exit. Recall that energy firms in Crunchbase are more likely to receive funding (Table 7), so that overall they exit more frequently than other firms. However, conditional on funding, energy firms do no better than other firms, and clean energy firms do worse. Understanding why energy firms are more likely to receive funding is left for future

[12] We do not include separate categories for high-tech energy firms in this table, as the small number of firms in each cell lead to imprecise estimates when splitting the sample. Overall, we find similar patterns for non-high tech energy firms, but with nearly all coefficients insignificant when splitting the sample.

research. It may be that there are differences in the types of firms selecting into Crunchbase, or it may be that because entrepreneurs do not see venture capital as an appropriate model for energy, only relatively more promising energy companies choose to seek out venture capital.

Why do some funded energy firms fare worse than non-energy funded firms? We provide suggestive evidence of a "bubble" in clean energy and energy efficiency investments that coincides with the peak patenting and VC period of 2006-2012. While energy firms funded in the early period perform just as well as the average firm across all energy types, clean energy, energy efficiency, and "other" energy firms perform worse during the boom-and-bust period of 2006-2012. These firms are 25 to 30 percent less likely to exit than funded non-energy firms. Consistent with the "bubble" hypothesis, the share of total funding going to both clean energy and energy efficiency firms has a notable peak between 2006 and 2009 (Figure 19). Also consistent with a boom and bust story, energy efficiency firms are 30 percent more likely to exit during the prior 2000-2005 period, although this estimate is imprecise, with a p-value of 0.12. Dirty energy funded firms are still just as likely to exit as non-energy firms during this period, further suggesting that this boom-and-bust period was truly unique to investments in clean energy, energy efficiency, and "other" energy firms. In the 2013-2018 period, only "other" energy firms remain less likely to exit.

These results partially corroborate the possibility of a clean-tech bubble, although we cannot rule out other potential explanations. If investors are overly exuberant about clean energy during the boom period, and invested too much into clean energy relative to other sectors, we would expect to see poorer performance of funded energy firms founded during that time. Of course, this need not imply a bubble. Actual returns are uncertain. Investors may hold a portfolio of investments with negatively correlated risks to hedge against losses in any one sector. Investors may have acted rationally, only to see clean energy firms experience unexpectedly bad outcomes, such as because of changing regulations. Moreover, our analysis only looks at binary outcomes. We do not calculate a rate of return by comparing the valuation of these firms on exit to the amount raised. Exploration of competing explanations is left for future research.

D. Summary of Findings on Start-Ups

To summarize our findings on venture capital in the energy sector, we find a growing interest in energy firms that also operate in the high-tech space. These firms are more likely to raise funds than other types of energy firms, even though they are not more likely to exit than energy firms not also in high-tech. In general, all types of energy firms in the Crunchbase dataset perform better than the average firm on most performance metrics. However, once conditioning on having received funding, energy firms generally do not perform better than the average funded firm. There is some evidence of over-investment in clean energy during the 2006-2012 period, but more research is needed.

One caveat worth noting is that we are unable to decipher whether these firms are *actually* working on high-tech technologies or whether they just claim to be doing so on the Crunchbase platform, perhaps in an effort to attract more funding. To truly measure the importance of high-tech activity we would need a better measure of actual business activities. At a minimum, we provide evidence that energy firms claiming to be high-tech seem to attract more funding. This suggests that VCs may place a premium on these types of firms, which could be explained either by the fact that they are high-tech or by being high-quality if the savviness of claiming to be high-tech is correlated with other measures of firm quality.

V. Conclusions

As our chapter has documented, the nature of innovation in the energy sector is changing. Within the past decade, the use of hydrofracturing technology in the U.S. increased the prominence of natural gas. Increased usage of natural gas reduced carbon emissions as it replaced coal as the dominant fuel for electricity, but brought with it new environmental questions. The costs of wind and solar energy fell to levels making them competitive with fossil fuels. Innovative activity in the energy sector is also increasingly high-tech across all energy types.

The patent data presented in section III highlights the role of innovation promoting these trends. Patents for wind, solar, and hydrofracturnig all peaked in the early 2010s. The data also illustrate the challenges faced by the industry moving forward. As electricity generation from wind and solar energy grows, integrating these intermittent energy sources into the electricity grid will become more challenging. Unfortunately, not only has patenting in clean energy technologies such as wind and solar energy fallen from their early 2010s peak, but so has patenting in enabling technologies such as grid integration, smart grids, and energy storage.

Our chapter posits several possible explanations for the fall of clean patenting over the past decade. While we leave it for future research to identify the relative contributions (if any) of the various explanations proposed in section III, it is undoubtedly the case that innovation in the energy industry is changing in ways never seen before. Traditionally, energy R&D has been dominated by large firms that move slowly. But increasingly, new energy innovation depends, at least in part, on high tech innovations such as IT. IT innovation moves much more quickly, is modular, and sees greater participation from smaller firms. Our venture capital data back this up. Energy start-ups attract funding at higher rates relative to the average firm, and energy firms with a high-tech component attract funding even more often. However, once conditioning on receiving funding, energy firms generally do not perform better than the average firm.

While our work is descriptive, not causal, it does raise several questions, both for research and for the industry moving forward. One is how to promote innovative solutions to technical challenges such as grid integration that incorporate high tech solutions. Do existing energy firms have the capability to incorporate high-tech solutions into their products, or will collaborative research become more important? While there is scant evidence on the role of collaborative research in the energy sector, the work that does exist suggests government intervention can facilitate collaboration. However, this research primarily focuses on flows of knowledge across borders (e.g. Hascic *et al*. 2012, Conti *et al*. 2018) or across institutions. For alternative energy technologies, both scientific articles and patents with authors from multiple types of institutions (e.g., university and corporations) are cited more frequently, suggesting that collaborations may have positive impacts on research quality (Popp 2017). Within the European Union, research networks enhance the effect of demand-side policies, particularly when high scientific profile network members, such as universities, are included in the network (Fabrizi *et al.* 2018). There is less research on promoting collaborations across fields. As the decline in patenting for enabling technologies suggests, such research is needed. For example, do patents combining energy and high-tech come from incumbent firms or new entrants to the field? Are they more likely to be collaborative?

Better understanding the role that smaller firms, particularly those operating in the high-tech space, can play moving forward is also important. Howell (2017) finds that Small Business Innovation Research (SBIR) funding from the Department of Energy has been effective, particularly for clean energy technologies. That support was most important for clean energy raises two points. First, it highlights that economies of scale may be less prominent for clean energy technology than for traditional energy technologies, so that smaller firms may play a more important role in clean energy innovation. Second, it raises the question of the extent to which financial constraints hinder clean energy investment, relative to a lack of demand for emerging clean technologies that historically have not been cost-effective without government support. That is, is the Valley of Death for energy research really due to the special characteristics of energy innovation, or simply a result of historically underpriced environmental externalities reducing demand for cleaner technology? Both falling costs and increased policy support from governments may provide future researchers evidence needed to better identify the effects of financial constraints from other market failures holding back clean technology. Similarly, linking patent data with data on venture capital could provide new insights. For instance, how prominent were start-up firms in the energy patenting boom of the early 2010s? Were their patents heavily cited? That is, did start-ups provide new insights to a changing field?

Finally, while start-up firms may play a larger role for growing modular technologies such as solar PV or emerging needs with a high-tech component such as grid integration, much of the energy industry is still characterized by large firms with economies of scale. Even if fossil fuel plants are all replaced, large nuclear plants are likely to remain. Offshore wind technology, if successful, will also be capital intensive. The power grid itself is a natural monopoly. The challenge for both industry and policy makers moving forward is identifying when smaller, modular technologies are likely to be successful and when large-scale, capital intensive technologies are needed (e.g. Nemet, 2019, chapter 11), and to devise policy solutions that recognize the different needs of each type of technology. The climate problem is too large and complex for a one-size-fits-all solution, and so is the energy system on which solving the climate problem depends.

Appendix Table A: CPC classifications for energy technologies

<u>Clean Energy Technologies</u>

Building Energy Efficiency	
Y02B 20/00-70/00	Aspects of energy efficiency related to lighting, appliances, etc…
Y02B 80/00	Aspects of energy efficiency related to building envelope
Carbon capture and storage	
Y02C	Capture, storage, sequestration or disposal of greenhouse gases
Solar photovoltaic (PV)	
Y02E 10/50	Photovoltaic (PV) energy
Solar thermal energy	
Y02E 10/40	Solar thermal energy
Wind energy	
Y02E 10/70	Wind energy
Hybrid and Electric Vehicles	
Y02T 10/62	Hybrid vehicles
Y02T 10/64	Electric vehicles

<u>Enabling Technologies</u>

Energy storage	
Y02E 60/10	Energy storage
Smart grids	
Y04S	Systems integrating technologies related to power network operation, communication or information technologies for improving the electrical power generation, transmission, distribution, management or usage, i.e. smart grids
Systems integration: building	
Y02B 70/30-346	Systems integrating technologies related to power network operation and ICT for improving the carbon footprint of the management of residential or tertiary loads, i.e. smart grids as CCMT in the buildings sector or as enabling technology in buildings sector.
Y02B 90/20-2692	Systems integrating technologies related to power network operation and communication or information technologies mediating in the improvement of the carbon footprint of the management of residential or tertiary loads, i.e. smart grids as enabling technology in buildings sector
Systems integration: energy	
Y02E 40/70-76	Systems integrating technologies related to power network operation and ICT for improving the carbon footprint of electrical power generation,

	transmission or distribution, i.e. smart grids as CCMT in the energy generation sector or as enabling technology in the energy generation sector
Y02E 60/70-7892	Systems integrating technologies related to power network operation and communication or information technologies mediating in the improvement of the carbon footprint of electrical power generation, transmission or distribution, i.e. smart grids as enabling technology in the energy generation sector

Systems integration: transportation

Y02T 90/167-169	Systems integrating technologies related to power network operation and ICT for supporting the interoperability of electric or hybrid vehicles, i.e. smart grids as interface for battery charging of electric vehicles [EV] or hybrid vehicles [HEV]

Hydrofracturing

CPC codes included in Figure 10:

C10G 1	Production of liquid hydrocarbon mixtures from oil-shale, oil-sand, or non-melting solid carbonaceous or similar materials, e.g. wood, coal
E21B 43	Methods or apparatus for obtaining oil, gas, water, soluble or meltable materials or a slurry of minerals from wells

The robustness check in footnote 2 includes the above CPC codes and additional CPC codes in combination with keyword searches:[13]

E21B 36	Heating, cooling, insulating arrangements for boreholes or wells, e.g. for use in permafrost zones
C10G 2300	Aspects relating to hydrocarbon processing covered by groups C10G 1/00 - C10G 99/00
Y10T 29	Metal working
C09K 8	Compositions for drilling of boreholes or wells; Compositions for treating boreholes or wells, e.g. for completion or for remedial operations
E21B 47	Survey of boreholes or wells
B32B 15	Layered products comprising a layer of metal
E21B 7	Special methods or apparatus for drilling
B32B 1	Layered products having a general shape other than plane

[13] The patent search strategy follows Apenteng (2016). Keywords include “hydraulic fracturing”, “horizontal drilling” and “well completion” following Cahoy et al. (2013).

References

Acemoglu, D., P. Aghion, L. Barrage, and D. Hémous. 2019. "Climate Change, Directed Innovation, and Energy Transition: The Long-run Consequences of the Shale Gas Revolution," working paper, available at https://scholar.harvard.edu/aghion/publications/climate-change-directed-innovation-and-energy-transition-long-run-consequences, last accessed November 7, 2019.

Acemoglu, D., U. Akcigit, D. Hanley, and W. Kerr. 2016. "Transition to Clean Technology." *Journal of Political Economy*. 124(1): 52–104.

Aghion, P., A. Dechezleprêtre, D. Hemous, R. Martin, and J. Van Reenen. 2016. "Carbon Taxes, Path Dependency and Directed Technical Change : Evidence from the Auto Industry." *Journal of Political Economy.* 124: 1-51.

Angelucci, S., F.J. Hurtado-Albir and A. Volpe. 2018. "Supporting Global Initiatives on Climate Change: The EPO's "Y02-Y04S" Tagging Scheme." *World Patent Information*. 54: 585-592.

Anonymous 2019. "Oil rush." *The Economist*. March 16, 2019: 57.

Apenteng, Seth O., 2016. "Patent Analysis of Shale Gas Technology to Identify the U.S. Government's Role in its Development", A Thesis in Energy and Mineral Engineering, *The Pennsylvania State University*.

Bajwa, Maheen and Joseph Cavicchi 2017. "Growing Evidence of Increased Frequency of Negative Electricity Prices in U.S. Wholesale Electricity Markets." *IAEE Energy Forum*, 37-41.

Bartik, Alexander W., Janet Currie, Michael Greenstone, and Christopher R. Knittel. 2019. "The Local Economic and Welfare Consequences of Hydraulic Fracturing." *American Economic Journal: Applied Economics* 11(4): 105-155.

Borenstein, Severin. 2012. "The Private and Public Economics of Renewable Electricity Generation." *Journal of Economic Perspectives*, 26(1), 67-92.

Braff, William A., Joshua M. Mueller, and Jessika E. Trancik. 2016. "Value of storage technologies for wind and solar energy." *Nature Climate Change* 6: 964-969.

Branstetter, Lee G. Matej Drev, and Namho Kwon. 2019a. "Get with the Program: Software-Driven Innovation in Traditional Manufacturing." *Management Science*. 65(2): 541-558.

Branstetter, Lee G., Britta Glennon and J. Bradford Jensen. 2019b. “The IT Revolution and the Globalization of R&D.” *Innovation Policy and the Economy: Volume 19*. Josh Lerner and Scott Stern, eds., University of Chicago Press, Chicago, IL.

Branstatter, L., Ogura Y., 2005. “Is Academic Science Driving a Surge in Industrial Innovation? Evidence from Patent Counts.” *NBER Working Paper #11561*.

Cahoy, Daniel R., Joel Gehman, and Zhen Lei. 2013. “Fracking Patents: The Emergence of Patents as Information-Containment Tools in Shale Drilling.” *Michigan Telecommunications and Technology Law Review* 19: 279-330.

Cárdenas Rodríguez M., I. Haščič, N. Johnstone, J. Silva and A. Ferey (2015), "Renewable Energy Policies and Private Sector Investment: Evidence from Financial Microdata," *Environmental & Resource Economics*. 62(1): 163-188.

Conti, C., M.L. Mancusi., F. Sanna-Randaccio, R. Sestini, and E. Verdolini. 2018. “Transition Towards a Green Economy in Europe: Innovation and Knowledge Integration in the Renewable Energy Sector.” *Research Policy*. 47: 1996-2009.

Cumming, D.J., G. Leboeuf and A. Schwienbacher. 2017. “Crowdfunding Cleantech.” *Energy Economics*. 65: 292-303.

Dechezleprêtre, A. and M. Glachant. 2014. “Does Foreign Environmental Policy Influence Domestic Innovation? Evidence from the Wind Industry.” *Environmental and Resource Economics*. 58 (3): 391-413.

Dechezleprêtre, A., R. Martin, and M. Mohnen, M. 2017. “Knowledge Spillovers from Clean and Dirty Technologies: A Patent Citation Analysis.” Grantham Research Institute on Climate Change and the Environment Working Paper No. 135.

EIA Today in Energy 2019a. “More new natural gas combined-cycle power plants are using advanced designs,” https://www.eia.gov/todayinenergy/detail.php?id=39912, last accessed October 17, 2019.

EIA Today in Energy 2019b. “US petroleum exports exceeded imports in September,” https://www.eia.gov/todayinenergy/detail.php?id=42176, last accessed December 6, 2019.

EIA Today in Energy 2016. “U.S. electric system is made up of interconnections and balancing authorities,” https://www.eia.gov/todayinenergy/detail.php?id=27152, last accessed November 22, 2019.

EIA Today in Energy 2011. "About 60% of the U.S. electric power supply is managed by RTOs," https://www.eia.gov/todayinenergy/detail.php?id=790, last accessed November 22, 2019.

Ellerman, Denny, Claudio Marcantonini and Aleksandar Zaklan (2016), "The EU ETS: Eight Years and Counting," *Review of Environmental Economics and Policy*, 10(1), 89-107.

European Commission (2018). "10 Trends Reshaping Climate and Energy," European Political Strategy Centre. Available at: https://ec.europa.eu/epsc/sites/epsc/files/epsc_-_10_trends_transforming_climate_and_energy.pdf)

Fabrizi, A., G. Guarini, and V. Meliciani. 2018. "Green Patents, Regulatory Policies and Research Network Policies." *Research Policy*. 47: 1018-1031.

Fabrizio, K.R., S. Poczter, and B.A. Zelner. 2017. "Does innovation policy attract international competition? Evidence from energy storage." *Research Policy*. 46: 1106-1117.

Fetter, T.R., A.L. Steck, C. Timmins, and D. Wrenn. 2018. "Learning by Viewing? Social Learning, Regulatory Disclosure, and Firm Productivity in Shale Gas." *NBER Working Paper #25401*.

Feyrer, James, Erin T. Mansur and Bruce Sacerdote. 2017. "Geographic Dispersion of Economic Shocks: Evidence from the Fracking Revolution." *American Economic Review* 107(4): 1313-1334.

Finardi, U. 2011. "Time Relations between Scientific Production and Patenting of Knowledge: The Case of Nanotechnologies." *Scientometrics*. 89(1), 37-50.

Fischer C., L. Preonas, and R. Newell R. 2017. "Environmental and Technology Policy Options in the Electricity Sector: Are We Deploying Too Many?" *Journal of the Association of Environmental and Resource Economists*. 4(4): 959-984.

Gaddy, B.E., V. Sivaram, T.B. Jones and L. Wayman. 2017. "Venture Capital and Cleantech: The Wrong Model for Energy Innovation." *Energy Policy*. 102: 385-395.

Greenblatt, Jeffrey B., Nicholas R. Brown, Rachel Slaybaugh, Theresa Wilks, Emma Stewart, and Sean T. McCoy. 2017. "The Future of Low-Carbon Energy.' *Annual Review of Environment and Resources* 42: 289-316.

Harhoff, D., F. M. Scherer, and K. Vopel (2003), "Citations, Family Size, Opposition and the Value of Patent Rights", *Research Policy*, 32(8): 1343-1363.

Hascic, I., N. Johnstone, and N. Kahrobaie. 2012. "International Technology Agreements for Climate Change: Analysis Based on Co-Invention Data." *OECD Environment Working Papers No. 42*.

Holland, Stephen P., Erin T. Mansur, Nicholas Muller, and Andrew J. Yates. 2018. "Decompositions and Policy Consequences of an Extraordinary Decline in Air Pollution from Electricity Generation." *NBER Working Paper #25339*.

Howell, S.T. 2017. "Financing Innovation: Evidence from R&D Grants." *American Economic Review*. 107(4): 1136-1164.

International Renewable Energy Agency. 2018. *Renewable Power Generation Costs in 2017*, International Renewable Energy Agency, Abu Dhabi.

International Renewable Energy Agency. 2017. *Accelerating the Energy Transition Through Innovation,* International Renewable Energy Agency, Abu Dhabi.

IPCC, 2018: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. In Press.

Jacoby, Henry D., Francis M. O'Sullivan and Sergey Palstev. 2012. "The Influence of Shale Gas on U.S. Energy and Environmental Policy." *Economics of Energy and Environmental Policy*. 1(1): 37-51.

Johnstone, N. I. Hascic and D. Popp. 2010. "Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts." *Environmental and Resource Economics.* 45(1): 133-155.

Killian, Lutz. 2016. "The Impact of the Shale Oil Revolution on U.S. Oil and Gasoline Prices," *Review of Environmental Economics and Policy*, 10(2), 188-205.

Ko, Yu-li and Kenneth L. Simons. 2019. "The Cross-Border Impact of Demand-Pull Policies on R&D: A Firm-Level Analysis." working paper available at http://homepages.rpi.edu/~simonk/pdf/photovoltaicResearchAndSubsidies.pdf, last accessed December 10, 2019.

Krupnick, Alan and Zhongmin Wang. 2017. "Lessons from the U.S. Shale Gas Boom." In Ian Parry, Karen Pittel, and Herman Vollebergh (eds.) *Energy Tax and Regulatory Policy in Europe: Reform Priorities*. MIT Press, Cambridge, MA, 223-253.

Lanjouw J. O., A. Pakes, and J. Putnam (1998), "How to Count Patents and Value Intellectual Property: The Uses of Patent Renewal and Application Data", *Journal of Industrial Economics*, 46(4): 405-432.

Lehmann, P. and P. Söderholm 2018. "Can Technology-Specific Deployment Policies Be Cost-Effective? The Case of Renewable Support Schemes." *Environmental and Resource Economics*. 71: 475-505.

Lerner, J. 2011. "Venture Capital and Innovation in Energy." In *Accelerating Energy Innovation: Insights from Multiple Sectors*, edited by Rebecca M. Henderson and Richard G. Newell, 225–260. University of Chicago Press.

Maniloff, Peter and Ralph Mastromonaco. 2017. "The local employment impacts of fracking: A national study." *Resource and Energy Economics* 49: 62-85.

Martinot, Eric. 2016. "Grid Integration of Renewable Energy: Flexibility, Innovation, and Experience." *annual Review of Environment and Resources* 41: 223-251.

Mowrey, D.C., R.R. Nelson, and B.R. Martin. 2010. "Technology Policy and Global Warming: Why New Policy Models are Needed (or Why Putting New Wine in Old Bottles Won't Work)." *Research Policy*. 39: 1011-1023.

Nanda, R., K. Younge and L. Fleming. 2015. "Innovation and Entrepreneurship in Renewable Energy," chapter 7 in *The Changing Frontier: Rethinking Science and Innovation Policy*, A.B. Jaffe and B.F. Jones (eds.), University of Chicago Press, Chicago, IL, pp. 199-232.

Nemet, G.F. 2019. *How Solar Energy Became Cheap: A Model for Low-Carbon Innovation*. Routledge Press, New York.

Nemet, G.F., 2012. "Knowledge Spillovers from Learning by Doing in Wind Power." *Journal of Policy Analysis and Management*. 31(3): 600-621.

Newell, R. A.B. Jaffe and R. Stavins. 1999. "The Induced Innovation Hypothesis and Energy-Saving Technological Change." *The Quarterly Journal of Economics.* 114(3), 941-975.

Newell, Richard G. and Brian C. Priest. 2017. "How the Shale Boom has Transformed the US Oil and Gas Industry," *Resources for the Future Issue Brief 17-11*.

Nesta, L., F. Vona, and F. Nicolli. 2014. "Environmental Policies, Competition, and Innovation in Renewable Energy." *Journal of Environmental Economics and Management*. 67: 396-411.

Noailly, J. 2012. "Improving the Energy Efficiency of Buildings: The Impact of Environmental Policy on Technological Innovation." *Energy Economics*. 34: 795-806.

Peters, M., M. Schneider, T. Griesshaber and V.H. Hoffman. 2012. "The impact of technology-push and demand-pull policies on technical change–Does the locus of policies matter?" *Research Policy*. 41 (8):1296-1308.

Popp, D. 2019. "Environmental Policy and Innovation: A Decade of Research." *International Review of Environmental and Resource Economics*. 13(3-4): 265-337.

Popp, D. 2017. "From Science to Technology: The Value of Knowledge From Different Energy Research Institutions." *Research Policy*. 46(9): 1580-1594.

Popp, D. 2006. "International Innovation and Diffusion of Air Pollution Control Technologies: The Effects of NO_X and SO_2 Regulation in the U.S., Japan, and Germany." *Journal of Environmental Economics and Management*. 51(1): 46-71.

Popp, D. 2002. "Induced Innovation and Energy Prices." *American Economic Review*. 92(1): 160-180.

Roth, Michael Buchdahl and Jaramillo, Paulina 2017. "Going nuclear for climate mitigation: An analysis of the cost effectiveness of preserving existing U.S. nuclear power plants as a carbon avoidance strategy." *Energy*: 131: 67-77.

Shane, S. (2001), "Technological Opportunities and New Firm Creation", *Management Science*, 47 (2): 205–220.

Squicciarini, Mariagrazia, Hélène Dernis and Chiara Criscuolo. 2013. "Measuring Patent Quality: Indicators of Technological and Economic Value." OECD Sciece, Technology and Industsry Working Papers 2013/03.

Stucki, T. and M. Woerter. 2017. "Green Inventions: Is Wait-and-see a Reasonable Option?" *The Energy Journal*. 38(4): 43-71.

Tang, T. 2018. "Explaining Technological Change in the US Wind Industry: Energy Policies, Technological Learning, and Collaboration." *Energy Policy*. 120: 197-212.

Trajtenberg, M, Jaffe, A., and R. Henderson (1997). "University versus Corporate Patents: A Window on the Basicness of Inventions", *Economics of Innovation and New Technology*, 5(1): 19-50.

U.S. Department of Energy. nd. "What is the Smart Grid?" https://www.smartgrid.gov/the_smart_grid/smart_grid.html, last accessed November 22, 2019.

U.S. Energy Information Administration (EIA). 2019. "Monthly Energy Review: Table 7.2a: Electricity Net Generation (Total, All Sectors)." U.S. Energy Information Administration, Washington, DC.

U.S. Energy Information Administration. 2018. *U.S. Crude Oil and Natural Gas Proved Reserves, Year End 2017.* U.S. Dept. of Energy, Washington, DC.

United States Environmental Protection Agency. 2019. *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2017* EPA 430-R-19-001.

Veefkind, V., F.J. Hurtado-Albir, S. Angelucci, K. Karachalios, and N. Thurman. 2012. "A New EPO Classification Scheme for Climate Change Mitigation." *World Patent Information*. 34: 106-111.

Verdolini, E. and M. Galeotti. 2011. "At Home and Abroad: An Empirical Analysis of Innovation and Diffusion in Energy Technologies." *Journal of Environmental Economics and Management*. 61: 119–134.

Weyant, J. 2011. "Accelerating the Development and Diffusion of New Energy Technologies: Beyond the 'Valley of Death.'" *Energy Economics*. 33: 674-682.

Table 1: Domestic R&D as a Percentage of Net Sales, selected industries

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Energy Industry											
NAICS 21: Mining, extraction and support activities	0.7%	0.9%	0.4%	0.7%	0.5%	0.4%	0.9%	0.8%	0.8%	1.2%	1.4%
NAICS 22: Utilities	0.1%	0.1%	0.1%	0.1%	N/A	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
NAICS 3336: Engines, turbines, & power trans. equip.	N/A	N/A	4.1%	3.3%	5.1%	3.0%	3.3%	2.7%	N/A	5.1%	6.0%
Comparison Industries											
NAICS 21-23, 31-33, 42-81: All industries	3.4%	3.5%	3.0%	3.0%	2.5%	2.6%	2.7%	2.7%	2.9%	3.3%	3.5%
NAICS 31-33: All manufacturing industries	3.6%	3.7%	3.5%	3.7%	3.3%	3.2%	3.1%	3.1%	3.3%	3.7%	3.9%
NAICS 3361-63: Automobiles, bodies, trailers, & parts	2.4%	2.4%	2.5%	2.4%	1.8%	2.1%	2.2%	2.0%	2.2%	2.1%	2.2%
NAICS 3254: Pharmaceuticals and medicines	13.5%	12.7%	12.2%	12.3%	11.7%	10.6%	11.2%	9.0%	11.3%	11%	9.7%
NAICS 334: Computer and electronic products	9.2%	8.4%	10.1%	9.2%	8.2%	8.5%	8.6%	9.0%	8.9%	8.7%	8.7%

Notes: Table shows domestic R&D paid for and performed by the company as a percentage of domestic net sales (percent of domestic sales of R&D performers or funders). 2006 & 2007 data are not comparable to other years due to changes in data availability. Data in those years represent company and other nonfederal funds for industrial R&D as a percent of net sales of companies performing industrial R&D in the United States. Source: National Science Foundation *Business Research and Development and Innovation*, various years.

Table 2: Total employment (thousands): Select Industries

	2000	2005	2010	2011	2012	2013	2014	2015	2016
211111: Crude petroleum and natural gas extraction	73.7	72.4	99.5	109.0	114.5	120.1	126.7	124.8	113.4
2121: Coal mining	70.7	74.3	81.4	86.2	89.4	84.0	76.6	69.9	55.0
23712: Pipeline construction		86.3	126.9	127.9	143.4	163.1	167.7	178.3	163.7
22111: Electric Power Generation	143.9	120.8	132.8	135.7	134.5	135.4	137.5	134.9	135.2
22114: Solar					0.8	0.9	1.2	1.4	1.6
22115: Wind					2.4	2.9	2.8	3.1	3.2
335911: Battery manufacturing	22.8	17.1	17.8	18.9	19.3	18.9	19.2	19.7	20.8
3361-3: Automobiles	1198.1	1033.2	627.6	667.3	727.1	769.7	811.1	865.6	901.9
31-33: All manufacturing	16474.0	13667.3	10862.8	10984.4	11192.0	11276.4	11424.3	11605.5	11590.4

Note: Table shows total employment, in thousands, for select industries. . Source: US Census Bureau: Statistics of US Businesses, various years.

Table 3: Percentage of patents with inventors from selected countries and regions

	2000	2005	2010	2015
United States				
Fracking	52.0	53.4	53.3	54.8
Solar PV	17.2	22.7	21.5	20.6
Wind	10.5	21.9	19.9	15.6
Hybrid and Electric Vehicles	15.7	20.7	19.0	18.7
Carbon capture and storage	35.3	31.9	38.3	41.8
Energy Storage	17.8	9.9	14.4	19.4
Smart Grids	33.8	41.7	33.4	33.3
All technologies	27.0	24.6	21.9	23.4
European Union				
Fracking	31.2	25.8	24.4	20.8
Solar PV	18.8	26.2	17.8	17.8
Wind	69.0	47.8	50.7	51.5
Hybrid and Electric Vehicles	18.7	23.2	30.9	26.1
Carbon capture and storage	27.4	30.9	30.1	25.6
Energy Storage	16.8	13.8	19.1	17.9
Smart Grids	34.2	22.6	20.3	26.2
All technologies	31.1	26.7	25.9	22.7
China				
Fracking	0.7	1.6	2.7	3.8
Solar PV	0.4	2.1	3.4	7.6
Wind	0.0	3.8	5.0	6.5
Hybrid and Electric Vehicles	0.5	0.5	2.9	3.9
Carbon capture and storage	0.8	2.0	1.2	1.1
Energy Storage	1.0	3.4	4.4	4.8
Smart Grids	0.0	1.1	2.7	5.3
All technologies	1.0	2.8	6.1	10.7
Japan				
Fracking	1.7	2.3	0.9	1.5
Solar PV	57.2	33.0	31.4	25.8
Wind	8.5	7.6	8.7	12.0
Hybrid and Electric Vehicles	60.2	51.5	39.3	35.6
Carbon capture and storage	27.7	15.7	13.1	10.3
Energy Storage	52.6	49.4	38.2	36.0
Smart Grids	18.2	13.1	21.9	16.6
All technologies	28.4	26.7	24.5	21.2

Notes: Table shows the percentage of inventors coming from each country for selected technologies. Fractional counts used for patents with inventors from multiple countries. Source: Authors' calculations using data from the EPO World Patent Statistical Database (PATSTAT).

Table 4: Firm Classifications and Descriptions

Firm Type (1)	Crunchbase Categories (2)	Number of Firms (3)
A. High-Level Sectoral Groupings		
All firms	Total sample of firms across sectors	604,884
Energy	All energy types	13,515
Financial Services	Financial services, lending, and payments	48,923
Science	Science and engineering	40,464
Health/Biotech	Healthcare and biotechnology	62,414
Manufacturing	Manufacturing	32,116
Transport	Transportation	22,300
High-tech	Apps, AI, data, hardware, IT, internet services, telecommunications, mobile, platforms, and software	300,251
B. Energy Types		
Clean	Clean energy, renewable energy, storage, solar, wind	6,276
Dirty	Fossil fuels, fuel cells, and oil and gas	2,265
Grid Management	Electricity distribution, energy management, and power grid	887
Energy Efficiency	Energy efficiency	466
Other Energy	All other energy types, including biomass and biofuel	3,621
C. Energy and High-Tech Firms		
Energy only	Energy firms not in high-tech	10,129
High-tech only	High-tech firms not in energy	296,865
Energy and high-tech	Energy firms that are also high-tech	3,386
Clean and high-tech	Clean energy firms that are also high-tech	1,414
Dirty and high-tech	Dirty energy firms that are also high-tech	341
Grid and high-tech	Grid management and high-tech	386
Energy efficiency & high-tech	Energy effiency firms that are also high-tech	238
Other energy and high-tech	Other energy firms that are also high-tech	1,007

Table 5: Energy Firms Relative to the Average Firm

Dep. Variable:	Acquired	IPO	Raised Funds	Amount Raised	Time to Exit
	(1)	(2)	(3)	(4)	(5)
Energy	0.042***	0.063***	0.145***	23.609***	-0.845***
	(0.006)	(0.009)	(0.009)	(4.300)	(0.132)
Sample mean for dep. var.	0.086	0.011	0.283	13.81	7.141
No. of Observations	398,473	398,473	398,473	112,618	36,414

Notes: Regression results for various dependent variables to assess energy firms relative to the average firm. The dependent variable is a dummy equal to 1 if the firm is acquired or has an IPO in Columns 1 and 2, respectively. In Column 3, the dependent variable is a dummy indicating whether the firm raised VC funding. In Column 4, the dependent variable is the amount of funding raised conditional on raising funds. In Column 5, the dependent variable is the time to exit conditional on having a successful exit. Controls include founded year fixed effects and a dummy for being located in the US. Standard errors are clustered by founded year. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Energy + High-Tech Firms Relative to the Average Firm

Dep. Variable:	Acquired	IPO	Raised Funds	Amount Raised	Time to Exit
	(1)	(2)	(3)	(4)	(5)
Energy + High-Tech	0.005	0.003	0.292***	-3.251**	-0.382
	(0.006)	(0.004)	(0.011)	(1.298)	(0.261)
Energy Only	0.043***	0.058***	0.182***	22.928***	-1.011***
	(0.006)	(0.008)	(0.010)	(4.368)	(0.150)
High-Tech Only	0.002	-0.009***	0.062***	-1.028	-0.305***
	(0.002)	(0.002)	(0.005)	(0.742)	(0.069)
Sample mean for dep. var.	0.086	0.011	0.283	13.81	7.141
No. of Observations	398,473	398,473	398,473	112,618	36,414

Notes: Regression results for various dependent variables to assess energy firms relative to the average firm. The dependent variable is a dummy equal to 1 if the firm is acquired or has an IPO in Columns 1 and 2, respectively. In Column 3, the dependent variable is a dummy indicating whether the firm raised VC funding. In Column 4, the dependent variable is the amount of funding raised conditional on raising funds. In Column 5, the dependent variable is the time to exit conditional on having a successful exit. Controls include founded year fixed effects and a dummy for being located in the US. Standard errors are clustered by founded year. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Different Types of Energy Firms Relative to the Average Firm

Dep. Variable:	Acquired	IPO	Raised Funds	Amount Raised	Time to Exit
	(1)	(2)	(3)	(4)	(5)
Clean Energy	-0.016***	0.025***	0.164***	15.784***	-0.718***
	(0.005)	(0.007)	(0.010)	(4.602)	(0.239)
Dirty Energy	0.147***	0.133***	0.111***	29.873**	-0.923***
	(0.019)	(0.016)	(0.017)	(14.079)	(0.175)
Grid Management	0.085***	0.014***	0.203***	-5.266**	0.245
	(0.016)	(0.005)	(0.014)	(2.076)	(0.316)
Energy Efficiency	0.003	0.007	0.340***	-1.571	0.506
	(0.015)	(0.007)	(0.028)	(2.785)	(0.440)
Other Energy Firms	0.020***	0.040***	0.214***	12.236**	-0.906***
	(0.006)	(0.008)	(0.014)	(4.377)	(0.177)
Sample mean for dep. var.	0.086	0.011	0.283	13.81	7.141
No. of Observations	398,473	398,473	398,473	112,618	36,414

Notes: Regression results for various dependent variables to assess energy firms relative to the average firm. The dependent variable is a dummy equal to 1 if the firm is acquired or has an IPO in Columns 1 and 2, respectively. In Column 3, the dependent variable is a dummy indicating whether the firm raised VC funding. In Column 4, the dependent variable is the amount of funding raised conditional on raising funds. In Column 5, the dependent variable is the time to exit conditional on having a successful exit. Controls include founded year fixed effects and a dummy for being located in the US. Standard errors are clustered by founded year. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Impact of Being High-Tech for Different Types of Energy Firms

Dep. Variable:	Acquired	IPO	Raised Funds	Amount Raised	Time to Exit
	(1)	(2)	(3)	(4)	(5)
Clean + High-Tech	-0.007	-0.020***	0.050**	-24.806***	0.090
	(0.008)	(0.006)	(0.018)	(5.659)	(0.318)
Dirty + High-Tech	-0.135***	-0.140***	0.250***	-38.789***	1.498***
	(0.018)	(0.017)	(0.039)	(11.158)	(0.465)
Grid Mgmnt. + High-Tech	-0.119***	0.002	0.218***	6.456*	1.048*
	(0.028)	(0.017)	(0.039)	(3.571)	(0.593)
Energy Efficiency + High-Tech	0.084**	-0.001	0.045	0.987	1.800*
	(0.035)	(0.017)	(0.037)	(5.678)	(0.865)
General Energy + High-Tech	-0.018	-0.042***	0.093***	-28.626***	-0.336
	(0.013)	(0.010)	(0.023)	(6.414)	(0.526)
Clean Energy	-0.041***	-0.021**	-0.029	0.792	0.047
	(0.012)	(0.008)	(0.019)	(9.992)	(0.332)
Dirty Energy	0.146***	0.100***	-0.111***	17.219	-0.196
	(0.020)	(0.020)	(0.022)	(19.833)	(0.306)
Grid Management Energy	0.120***	-0.043***	-0.088***	-34.000***	0.738
	(0.021)	(0.015)	(0.023)	(7.040)	(0.471)
Energy Efficiency Energy	-0.069***	-0.041**	0.144***	-25.193***	0.053
	(0.020)	(0.016)	(0.041)	(8.269)	(0.759)
Sample mean for dep. var.	0.137	0.059	0.456	30.16	6.826
No. of Observations	8,689	8,689	8,689	3,965	1,512

Notes: Regression results for various dependent variables to assess energy firms relative to the average firm. The dependent variable is a dummy equal to 1 if the firm is acquired or has an IPO in Columns 1 and 2, respectively. In Column 3, the dependent variable is a dummy indicating whether the firm raised VC funding. In Column 4, the dependent variable is the amount of funding raised conditional on raising funds. In Column 5, the dependent variable is the time to exit conditional on having a successful exit. Controls include founded year fixed effects and a dummy for being located in the US. Standard errors are clustered by founded year. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Exit of Energy Firms Relative to the Average Funded Firm

Dep. Variable:	*Any Exit*			
	Overall	2000-2005	2006-2012	2013-2018
	(1)	(1)	(2)	(3)
Clean Energy	-0.026***	-0.025	-0.038**	-0.011
	(0.008)	(0.016)	(0.014)	(0.007)
Dirty Energy	0.018	0.069	0.023	-0.004
	(0.013)	(0.037)	(0.018)	(0.018)
Grid Management	-0.012	-0.045	-0.011	0.007
	(0.017)	(0.047)	(0.027)	(0.022)
Energy Efficiency	-0.009	0.098	-0.047*	-0.007
	(0.017)	(0.053)	(0.023)	(0.017)
Other Energy Firms	-0.025**	0.018	-0.040*	-0.023**
	(0.012)	(0.039)	(0.018)	(0.008)
Sample mean for dep. var.	0.116	0.328	0.152	0.04
No. of Observations	112,618	13,605	41,836	57,177

Notes: Regressions include funded firms only. The dependent variable is a dummy equal to 1 if the firm is either acquired or has an IPO. Controls include founded year fixed effects and a dummy for being located in the US. Standard errors are clustered by founded year. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.