Volume Title: The Role of Innovation and Entrepreneurship in Economic Growth

Volume Authors/Editors: Michael J. Andrews, Aaron Chatterji, Josh Lerner, and Scott Stern, editors

Volume Publisher: University of Chicago Press

Volume ISBNs: 978-0-226-81078-2 (cloth), 978-0-226-81064-5 (electronic)

Volume URL: https://www.nber.org/books-and-chapters/role-innovation-and-entrepreneurship-economic-growth

Conference Date: January 7-8, 2020

Publication Date: Februrary 2022

Chapter Title: Innovation and Entrepreneurship in the Energy Sector

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Chapter URL: https://www.nber.org/books-and-chapters/role-innovation-and-entrepreneurship-economic-growth/innovation-and-entrepreneurship-energy-sector

Chapter pages in book: p. 175 – 248

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Innovation and Entrepreneurship in the Energy Sector

David Popp, Jacquelyn Pless, Ivan Haščič, and Nick Johnstone

4.1 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 past 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 also create 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 puts downward pressure on fossil

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We thank Julie Lassébie 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. Hunt Allcott and participants at the NBER Conference on The Role of Innovation and Entrepreneurship in Economic Growth provided helpful comments on an earlier draft. A special thank you to Aaron Chatterji, Josh Lerner, Scott Stern, and Mike Andrews for their efforts organizing this project and for helpful comments throughout. Funding from the National Bureau of Economic Research project on The Role of Innovation and Entrepreneurship in Economic Growth was used to purchase data for this research. The views expressed in this chapter are the authors' own and do not necessarily reflect those of the OECD, the IEA, nor their member countries. For acknowledgments, sources of research support, and disclosure of the authors' material financial relationships, if any, please see https://www.nber.org/books-and-chapters/role-innovation-and-entrepreneurship-economic-growth/innovation-and-entrepreneurship-energy-sector.

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, which would reduce (but not eliminate) projected climate change impacts, is only possible by achieving zero net carbon emissions 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 Energy Agency 2019a; 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 has historically proceeded slowly. Energy firms invest less in R&D than almost all other sectors of the economy. There are also several unique features of the energy sector that make innovation in the energy context particularly challenging. Energy production is capital intensive, and especially long-time horizons between initial idea and commercialization create a "Valley of Death" for energy innovation (e.g., Mowrey, Nelson, and Martin 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 startups are frequently the vehicle through which innovation reaches the market in many sectors, they have historically played a smaller role in the energy sector (Gaddy et al. 2017; Nanda, Younge, and Fleming 2015).

Could this be changing, given the evolving nature of energy markets? 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 in which fast-moving startups are more prominent players. For instance, new smart grid technologies depend on software and information technology (IT)—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 IT component? Do energy startups with a high-tech component perform better than other energy startups?

We explore these questions in three parts. We begin by providing an overview of the energy industry and energy innovation literature, exploring how both unconventional natural gas and oil and increasingly affordable renewable energy technologies are changing the industry. We focus on the electricity sector, considering the generation of electricity and the supply of fuel (e.g., coal and natural gas) to power plants. While we do not directly address energy in the transportation sector, there are technological needs that overlap both sectors, such as innovation in batteries for energy storage on the power grid and for powering electric vehicles.

We then provide two new descriptive data analyses on the changing nature of innovation in energy, with a particular focus on the increasing role of digitalization. First, we examine patenting activity and document that, despite rapid growth in the late 2000s, energy patenting activity overall has fallen since about 2010 or 2011. We consider possible explanations for this decline, such as the rise of hydraulic fracturing, changing regulations, diminishing returns to research, and the existence of a cleantech bubble. The share of power sector patents that can also be considered "high-tech," though, began to increase in the past couple of years of our sample (2013–2014). This increase suggests that digitalization may be an increasingly important aspect of energy innovation moving forward.

Second, we present data on startup activity in the energy sector, with a similar focus on entrepreneurial energy firms that operate in high-tech fields. The findings are consistent with what we observe in the patenting data. We document a similar decline in energy startups since about 2010, but again, an increasing share of these energy startups are also "high-tech" firms. We also show that high-tech energy startups are more likely to attract venture capital (VC) investments, but they do not necessarily perform better than non-high-tech energy startups. Furthermore, conditional on receiving funding, energy startups generally do not perform better than the average funded firm, although there is some evidence of overinvestment in clean energy, corresponding with growth and a subsequent fall in both patenting and VC funding during the 2006–2012 period.

The rest of this chapter proceeds as follows. In section 4.2, we provide industry background and a review of the energy innovation literature so far. Sections 4.3 and 4.4 present our patenting and startup analyses, respectively. We conclude with a discussion of emerging trends in the energy sector and suggestions for future research in section 4.5.

4.2 Industry Background

Fossil fuel combustion generated nearly 5 billion metric tons of greenhouse gases in 2016, accounting for 76 percent of all US emissions (US Environmental Protection Agency 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 Environmental Protection Agency 2019). Nonetheless, significant innovation and progress is still needed to mitigate the potential impacts of climate change and to meet future energy policy goals in a cost-effective manner, and innovation in the energy sector has historically moved relatively slowly.

Examining historical R&D investment trends can begin to shed light on this phenomenon. Consider the data provided in table 4.1, for instance, which shows domestic R&D paid for and performed by US companies in select industries, as a percentage of net sales. Over the past 10 years, the industrial sector as a whole spent between 2.5 to 3.5 percent of sales on R&D. For manufacturing industries, the share ranges from 3.1 to 3.9 percent, with shares approaching 10 percent in R&D-intensive industries, such as pharmaceuticals and computers. In contrast, mining and extraction industries, which include the oil and gas sector, were spending less than 1 percent of sales on R&D until 2015. Utilities spend just 0.1 percent of sales on R&D. Only the engine and turbine manufacturing component of the energy industry has R&D spending levels comparable to the rest of the manufacturing sector.

Fostering and accelerating innovation, though, is not simply a matter of increasing R&D expenditures. Such spending must effectively translate into the commercialization and diffusion of new technologies, processes, business models, and management practices that improve performance, such as the financial and environmental performance of the power sector. Beyond the lessons from innovation economics, strategy, and management that apply broadly to many sectors, there are several unique features of the energy industry that make the process of technological change different in this sector:

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 and are unwilling to pay a premium for clean energy. As a result, 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 sector. As a result, uncertainty over future policy can dampen incentives for R&D.

3. Energy generation is capital intensive. Economies of scale are pervasive

Table 4.1 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	11.0	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

Source: National Science Foundation *Business Research and Development and Innovation*, various years.

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). Data for 2006 and 2007 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 US.

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 startup firms (Nanda, Younge, and Fleming 2015).

4. Long time horizons between initial idea and commercialization in the energy sector also make it more difficult for small startup firms to raise capital (e.g., Howell 2017; Popp 2016). Venture capital investors expect returns within 3 to 5 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 twenty-first 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 that make them competitive with fossil fuels. Below we describe the impact of each of these technological advances on the energy industry.

4.2.1 The Rise of Shale Gas and Oil

Access to natural gas and oil reserves in shale deposits on competitive terms 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, O'Sullivan, and Palstev 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 4.1), allowing the US to play a larger role in global oil markets. In September 2019, the US exported 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 4.2), 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 4.3). Since 2010, US power plant emissions of sulfur dioxide (SO_2) fell by 75 percent, and carbon dioxide emissions fell by over 25 percent. 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).

The rise in hydraulic fracturing began in the early 2000s, stimulated by

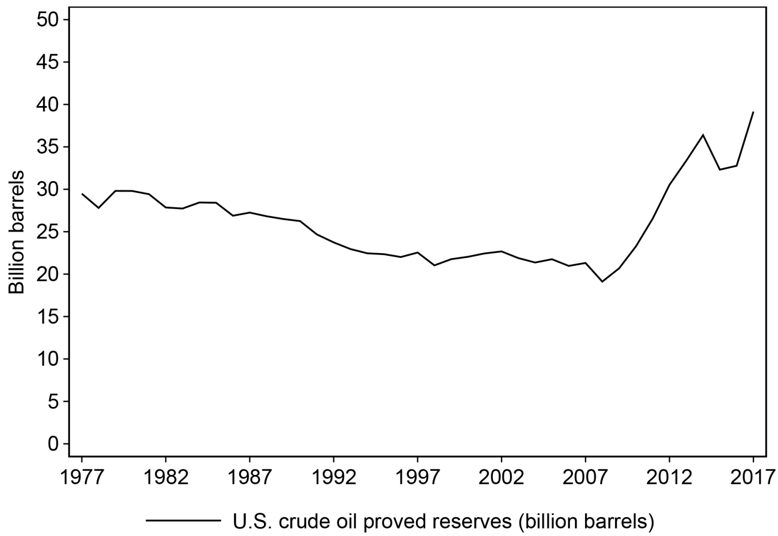


Fig. 4.1 US crude oil proved reserves

Source: US Energy Information Administration (2018).

Note: US crude oil proved reserves, in billions of barrels.

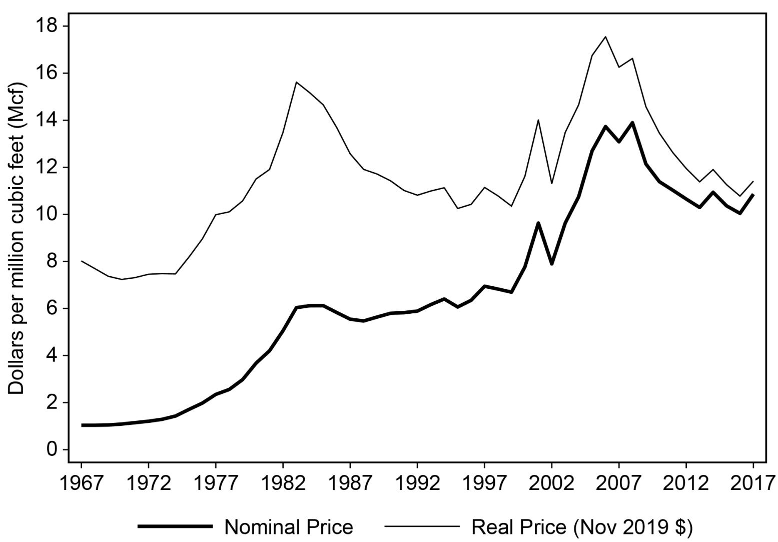


Fig. 4.2 Annual residential natural gas price

Source: US EIA Short-Term Energy Outlook, November 2019.

Note: Average annual price of residential natural gas in the United States, in 2019 US dollars.

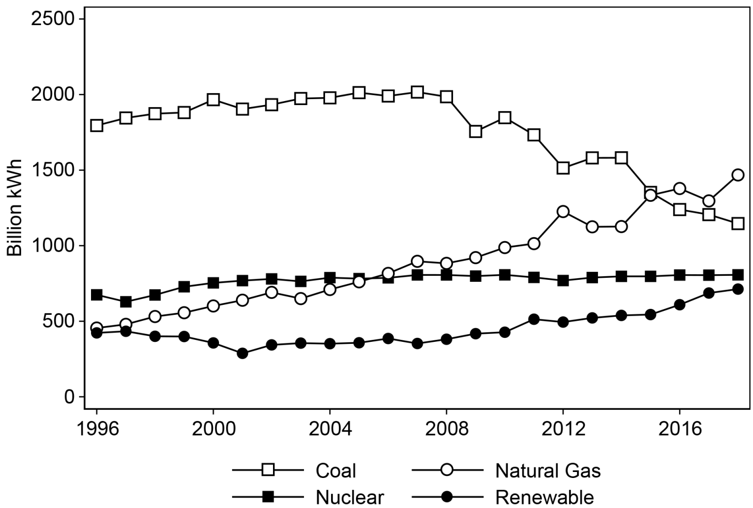


Fig. 4.3 US electricity generation, by fuel source

Source: US Energy Information Administration (2019).

Note: "Renewable" includes conventional hydropower, wind, wood biomass, waste biomass, geothermal, and solar.

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 US 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, Gehman, and Lei 2013). In 2001, Devon Energy, with expertise 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, Gehman, and Lei 2013).

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 4.2). Communities in the top quartile of

Table 4.2 **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

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

potential hydraulic fracturing productivity experienced a 4.8 percent growth in employment and a 5.8 percent increase in household income (Bartik et al. 2019). Taking into account indirect impacts, Maniloff and Mastromonaco (2017) estimate that the shale boom created about 550,000 local jobs. Feyrer, Mansur, and Sacerdote (2017) find that every million dollars of new oil and gas extracted creates 0.85 jobs in 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 4.2).
- 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 does conventional drilling. Moreover, there are concerns that leaks and spills from hydraulic fracturing activity may contaminate groundwater. As a result, several countries and some US states have banned hydraulic fracturing while further study is conducted (Krupnick and Wang 2017).

4.2.2 Increased Penetration of Renewable Energy Sources

Increasing electricity generation from wind and solar energy provides a second opportunity for the energy sector, but it also comes with its own set of challenges. The costs of electricity generated from solar photovoltaic (PV) and onshore wind turbines has fallen dramatically since 2010, making both competitive with electricity generated from fossil fuels (figure 4.4). While renewable energy sources are still a small share of electricity generation in the US (17 percent), their use is growing rapidly (figure 4.3). Solar and energy generation typically occurs at a smaller scale than for fossil fuels. Figure 4.5 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. 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 4.2).

Wind and solar energy are examples of *intermittent* sources of power, as

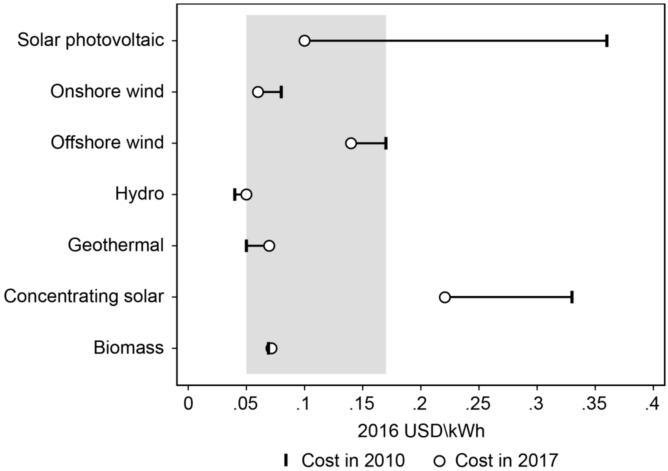


Fig. 4.4 Costs of electricity from selected sources

Note: 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 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.

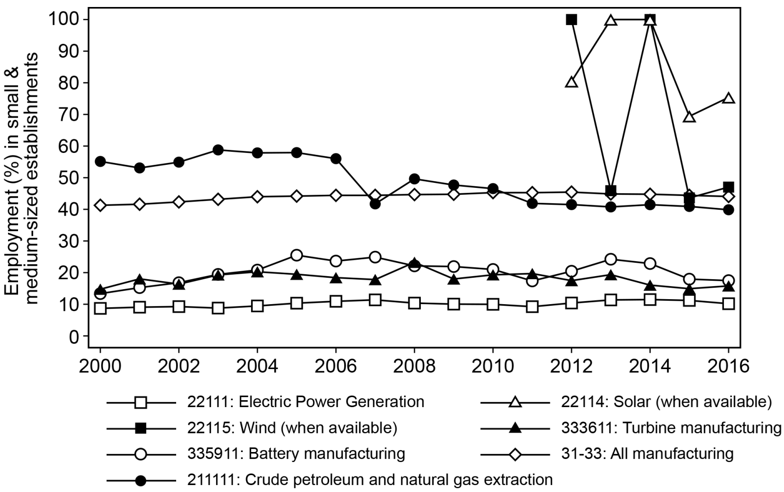


Fig. 4.5 Percentage of employment in small and medium enterprises, select industries

Source: US Census Bureau: Statistics of US Businesses, various years.

Note: Figure shows the percentage of employees working in small and medium enterprises, which include establishments of 500 workers or fewer. Separate breakdowns for solar and wind are unavailable until 2011.

the electricity generated depends on factors beyond the operator's control, such as wind speeds. Intermittent sources create challenges for managing the electricity grid (Borenstein 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; International Energy Agency 2019a). To illustrate, consider the structure of the US electricity grid. The continental US 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 nonprofit organizations, such as the Midwest Independent System Operator or the New York Independent System Operator (EIA Today in Energy 2011).

The increased penetration of intermittent renewable sources poses two additional challenges. First, because the marginal cost of renewables is close to 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 has 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 (International Energy Agency 2019b). 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 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 Department of Energy n.d.).

4.2.3 Innovation in the Energy Sector

The increased use of both hydraulic fracturing and renewable energy creates new technological challenges, but it 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 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. Several distinct features of energy innovation make it particularly important to study today. First and foremost, addressing climate change and mitigating its 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 innovation 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 (e.g., 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 US 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 (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 for 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. In contrast, 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. The Johnstone, Haščič, and Popp (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 that 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, Preonas, and Newell 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., Fischer, Preonas, and Newell 2017; Nemet 2012; 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 is 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 they 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., Branstetter 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, Younge, and Fleming (2015) provide descriptive data comparing clean energy innovations supported by venture capital to other clean energy innovations, showing that patents from firms receiving 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, in which 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, Leboeuf, and Schwienbacher (2017) consider crowdfunding as an alternative to venture capital. They collect data on crowdfunded projects from Indiegogo, with 7.4 percent 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 they 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 also 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 consist of 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 makes 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, Poczter, and Zelner (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.

4.3 Patenting in the Energy Sector

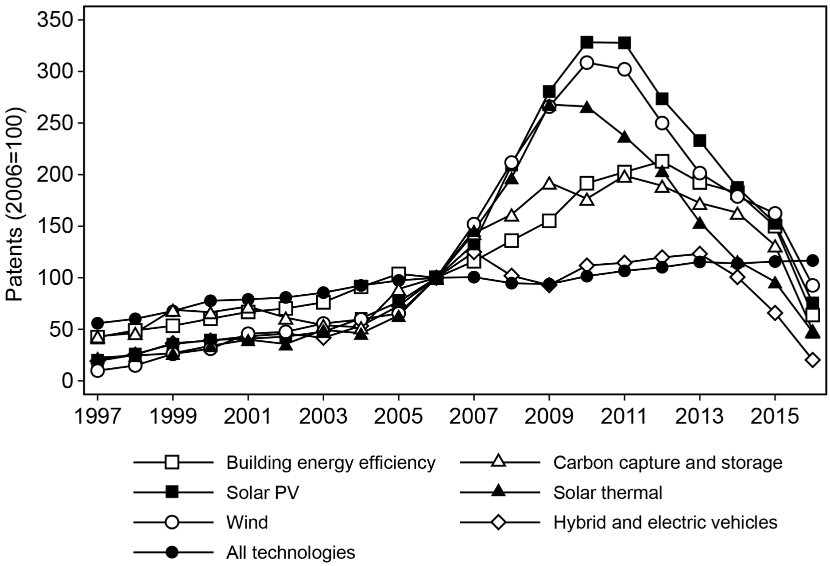
In this section, we present patenting trends for a range of energy technologies, focusing on technologies related to the changing nature of energy: clean energy technologies and hydraulic fracturing. A large literature on energy innovation has shown that clean energy patenting is responsive to both higher energy prices (e.g., Aghion et al. 2016; Newell, Jaffe, and Stavins 1999; Popp 2002; Verdolini and Gaelotti 2011) and policy (e.g., Dechezleprêtre and Glachant 2014; Fabrizio, Poczter, and Zelner 2017; Johnstone, Haščič, and Popp 2010; Nesta, Vona, and Nicolli 2014; Peters et al. 2012). 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 (EPO) 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., Harhoff, Scherer, and Vopel 2003; Lanjouw, Pakes, and Putnam 1998). We use the EPO'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 (Angelucci, Hurtado-Albir, and Volpe 2018; Veefkind et al. 2012).

We first present data for 11 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 4.A1 lists the patent classes used to identify each technology below. In the following three figures, the trend for all technologies is included for comparison.

Figures 4.6 through 4.8 present our patent data. Panels A and B of figure 4.6 show global trends for clean energy and enabling energy technologies, respectively. Our data include patents applied for between 1997 and 2015, so that our focus is on innovation since the Kyoto Protocol. Because the

A. Clean Energy Technologies



B. Enabling Energy Technologies

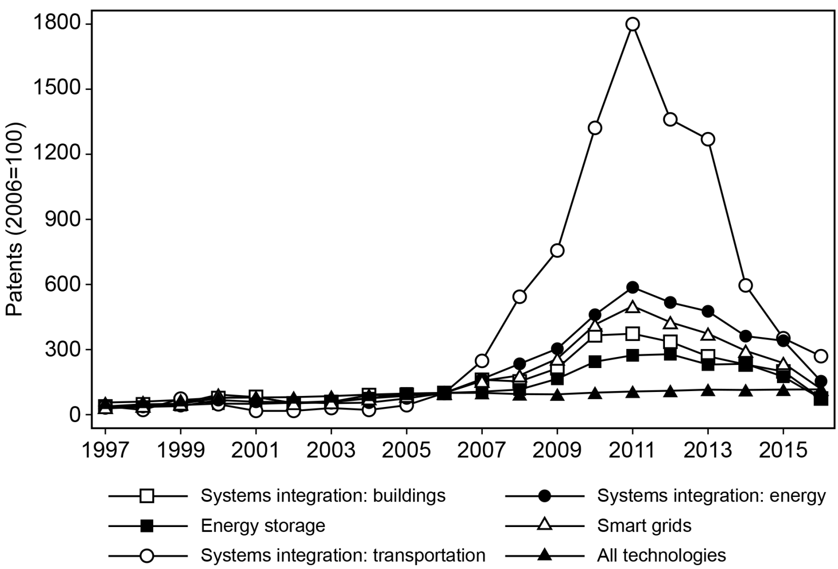


Fig. 4.6 Global energy patents

Note: 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).

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 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 twenty-first 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 had been at the 2010–2011 peak. This stands in contrast to the small, steady increases in patenting for all technologies.

Figures 4.7 and 4.8 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 US, the European Union (EU), 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 US and EU, similar peaks and declines are observed for clean energy technologies in the US, EU, and Japan.

4.3.1 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.

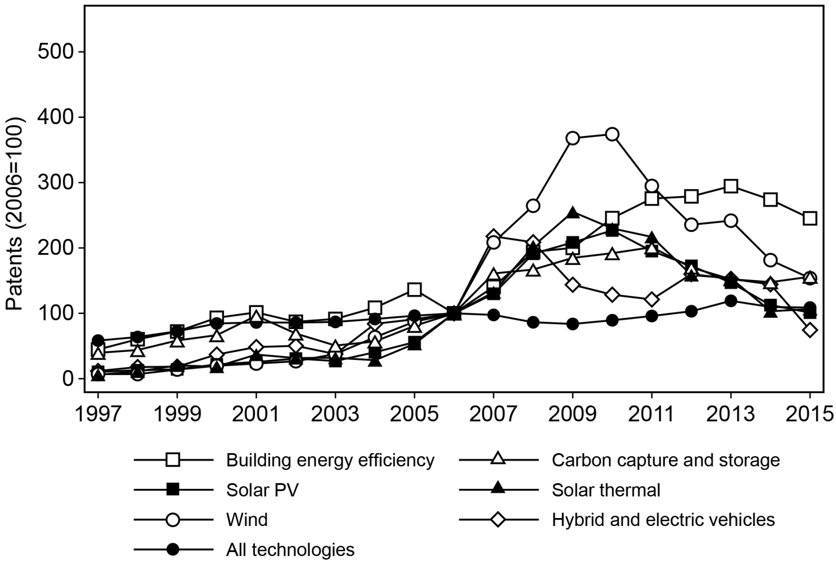
4.3.1.1 Innovation Follows Energy Prices

As previously noted, energy prices are an important driver of energy innovation (e.g., Aghion et al. 2016; Popp 2002; Verdolini and Galeotti 2011). Both the recent increase and decrease in patenting coincide with trends in energy prices, particularly in the fuel sector (figure 4.9). Similar spikes in patenting also occurred during the period of high energy prices in the late 1970s and early 1980s. Figure 4.10 provides a longer-term look at patenting for selected technologies.[2] To control for overall growth in patenting, we

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.

2. Because our search terms use the EPO's Y-scheme, which uses internal EPO classifications, we cannot extend the data prior to 1978. The EPO was founded in late 1977.

A. United States



B. European Union

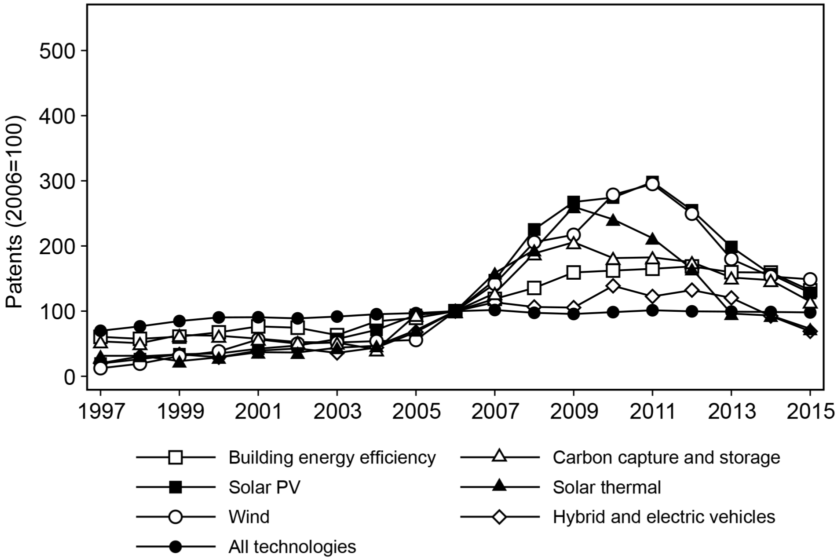
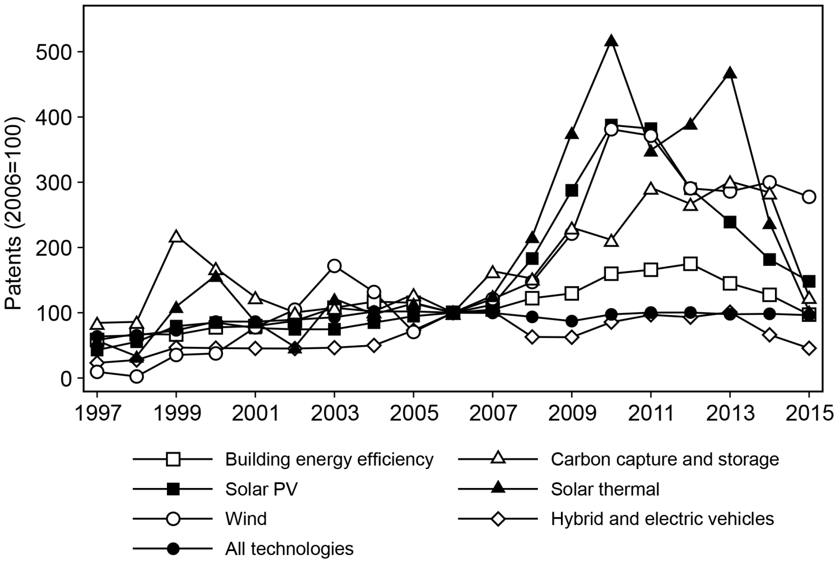


Fig. 4.7 Clean energy patents by country

Note: 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).

C. Japan



D. China

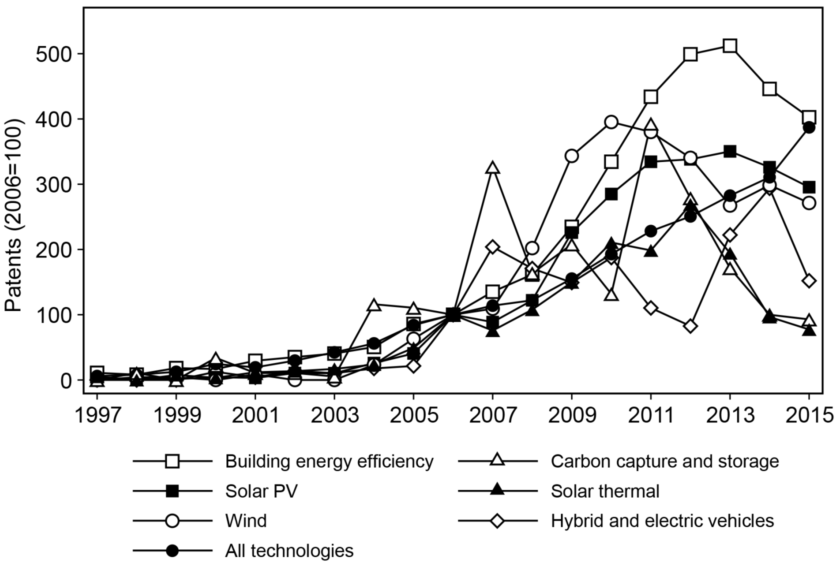
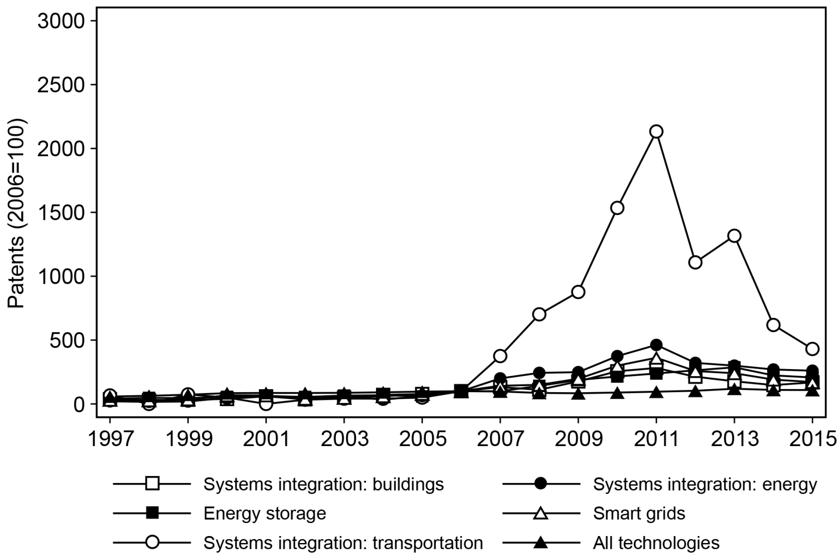


Fig. 4.7 (cont.)

A. United States



B. European Union

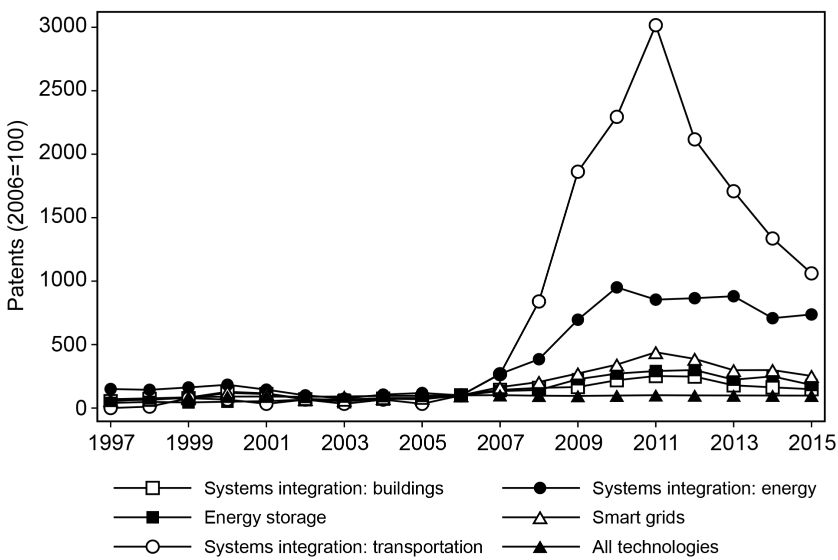
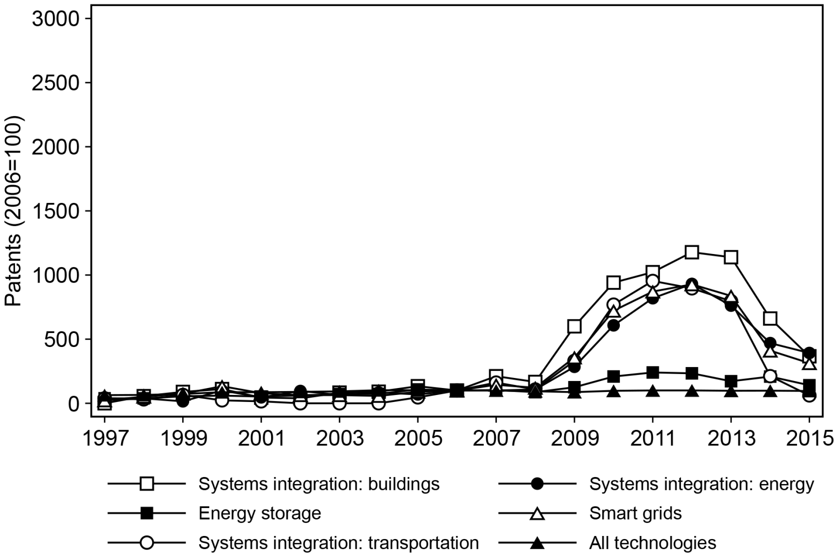


Fig. 4.8 Enabling energy technology patents, by country

Note: Figure shows 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).

C. Japan



D. China

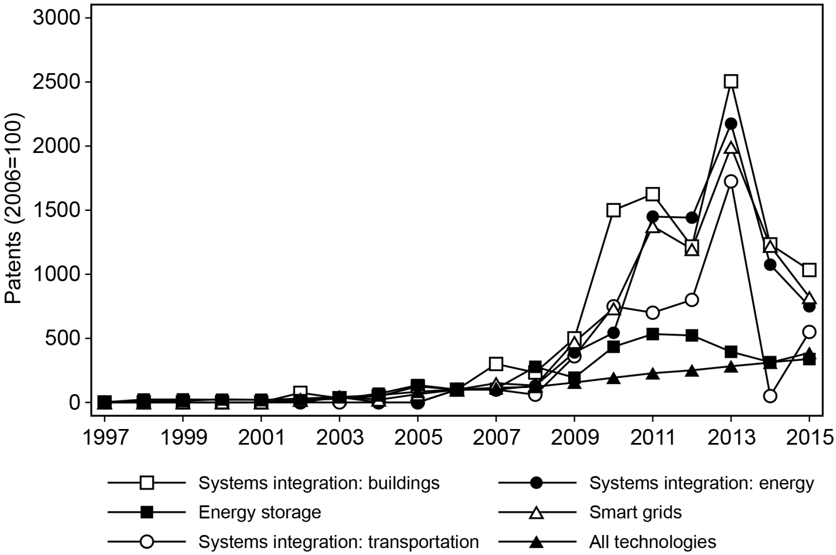
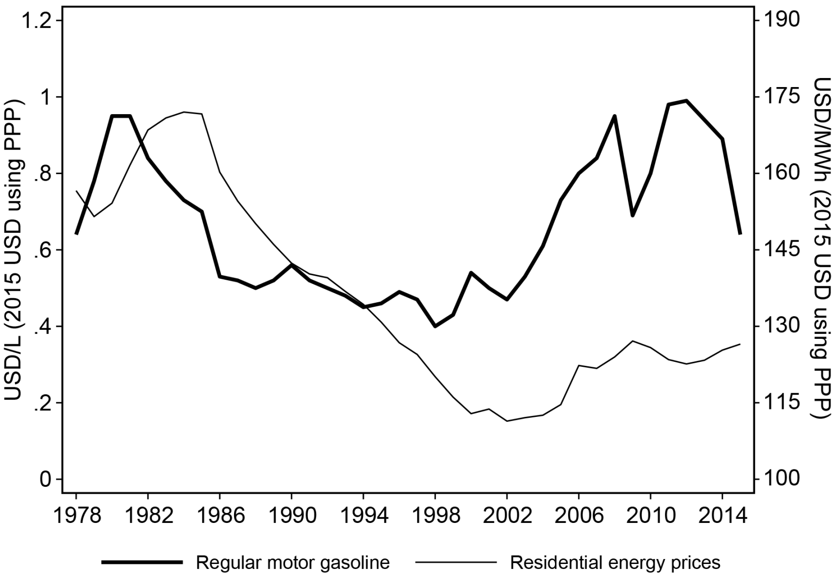


Fig. 4.8 (cont.)

A. United States



B. European Union

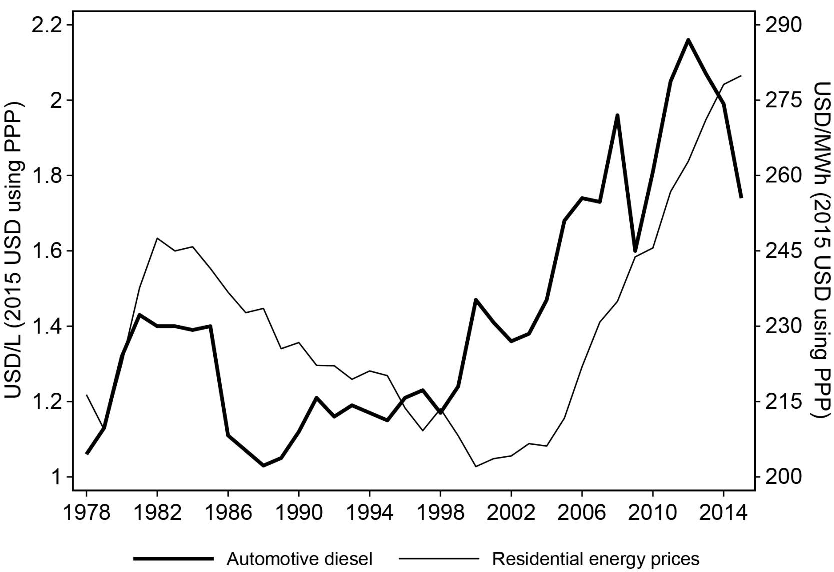


Fig. 4.9 Energy prices, selected countries

Source: IEA (2019c).

Note: Figures show gasoline and residential electricity prices for select countries, in 2015 US dollars.

C. Japan

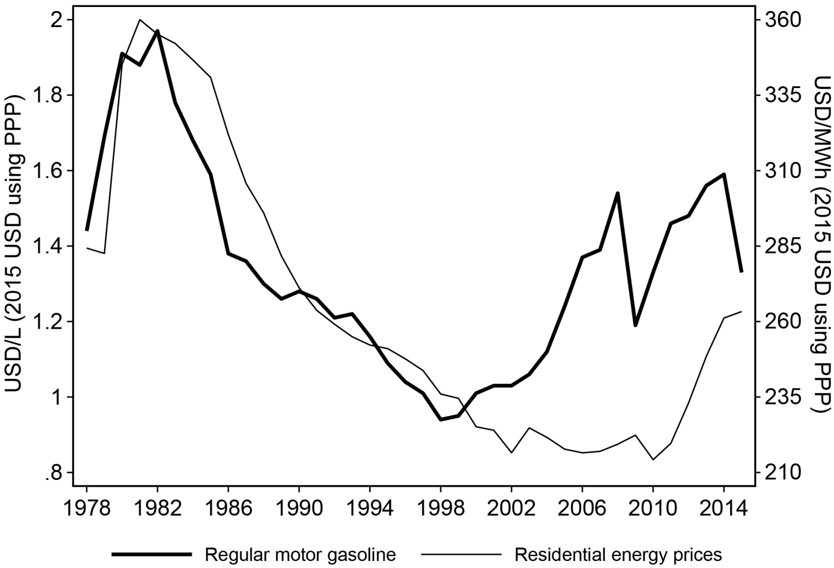


Fig. 4.9 (cont.)

present these data as the share of all global patents pertaining to a given technology. The trends clearly suggest that clean energy patenting fell as energy prices declined in the mid-1980s.

While it is tempting to conclude that history is simply repeating itself, the most striking take-away from figure 4.10 is the unprecedented growth in patenting through the late 2000s. The share of patents devoted to such technologies as wind, energy efficiency, and energy storage is three to five times higher in the late 2000s and very early 2010s than during the first energy crisis. Only solar thermal technology experienced a peak in the late 1970s comparable to its peak just after 2010. Presumably this is a result of changing emphasis in solar energy, where modular solar photovoltaic panels, rather than large-scale solar thermal installations, have become the cost-effective technology. Recall from figure 4.4 that concentrated solar power was cheaper than solar PV in 2010, but by 2017, solar PV was three times less expensive than concentrated solar power. As figure 4.10 shows, these cost reductions followed a remarkable growth in solar PV innovation.

The observation that "peak" patenting is so much higher at the turn of the last decade emphasizes how other energy policies complemented the incentives provided by energy prices. During the energy crisis of the 1970s, government R&D investments for clean energy were the main targeted clean energy policy. By the 2000s, direct subsidies (such as feed-in tariffs guaranteeing a minimum price for clean energy or government mandates for renew-

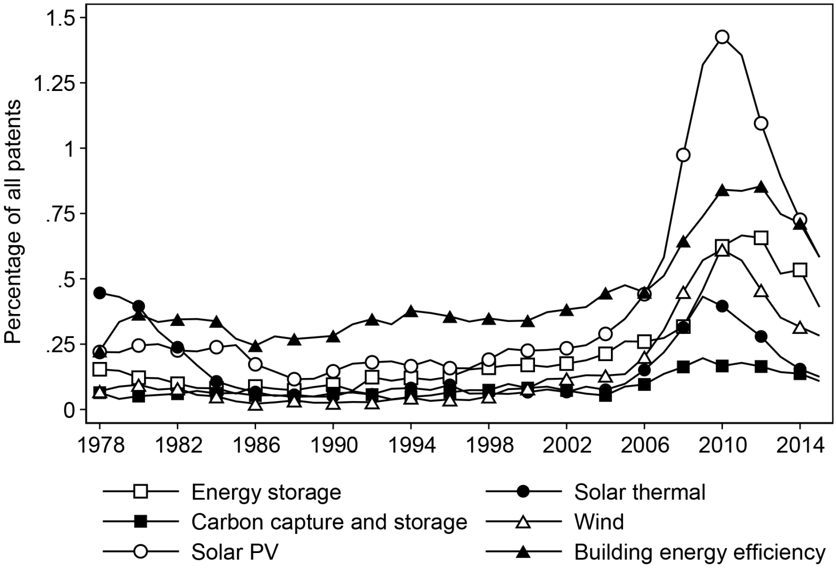


Fig. 4.10 Historical patent counts, selected technologies

Note: Figure shows the share of all patents in selected 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. Patent extractions from the EPO World Patent Statistical Database (PATSTAT).

able energy sources) became more prevalent, as did broad-based carbon pricing following the introduction of the EU Emissions Trading Scheme in 2005 (e.g., Ang, Röttgers, and Pralhad 2017; EIA 2004). The importance of both targeted and broad-based energy policy for promoting innovation is further supported by recent evidence that consumers are more responsive to energy price changes driven by carbon taxes than to other market dynamics, as tax changes may be more salient and are perceived as being more persistent (Davis and Kilian 2011; Li, Linn, and Muehlegger 2014; Rivers and Schaufele 2015). Furthermore, targeted subsidies are particularly important for fostering innovation in technologies that had not yet become cost-effective, such as solar PV in the early 2000s (Johnstone, Haščič, and Popp 2010). While increases in the price of fossil fuels, either due to market forces or carbon-pricing policies, may affect which energy technology is cheapest at the margin, price increases tend to not spur producers or consumers to choose technologies that remain relatively costlier, even with higher fossil fuel prices. Given the important supporting role of policy, the drop in energy prices alone is not sufficient to explain the recent decline in patenting.

4.3.1.2 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

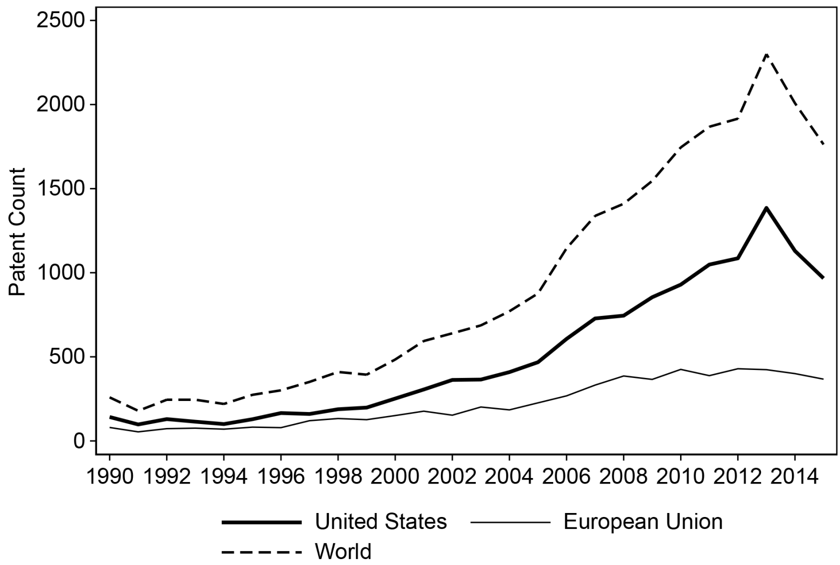


Fig. 4.11 Hydrofracturing patents, 1990–2015

Note: 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).

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 4.9). Acemoglu et al. (2019) posit that the shale boom caused energy innovation to shift from clean energy to fossil fuels.

Data on hydraulic fracturing patents provide some support for this argument. Figure 4.11 shows patent counts related to hydrofracturing for the world, the US, and the EU.[3] Together the US and EU account for 79 percent of these patents. Two trends emerge. First, after a period of relatively flat innovation, hydrofracturing innovation took off during the first decade of the twenty-first century. Between 1990 and 1999, fracking patents grew by just over 50 percent. From 2000 to 2009, they grew by more than a factor

3. As in other figures, data include 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 unrelated technologies. For this reason, they are combined with a keyword search on patent titles and abstracts using the terms "hydraulic fracturing," "horizontal drilling," and "well completion" (following Cahoy, Gehman, and Lei 2013). These counts are not directly comparable to our other patent trends, as the keyword searches are only possible for patents applications registered at 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 US inventors. Search terms for both search strategies are listed in Appendix A.

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 US, as nearly all 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 percent of most energy inventions (table 4.3), it is responsible for over 50 percent 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, 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 (see figure 4.9). Electricity prices were relatively stable in the US, thanks in part to lower natural gas prices, but they were steadily increasing in the EU and began to rise in Japan after bottoming out in 2010. Thus the rise of hydrofracking offers at best a partial explanation for the decline in clean energy patents.

4.3.1.3 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 US increased expectations that the US 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 US 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 EU'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, Marcantonini, and Zaklan 2016). Allowance prices would not reach pre-crisis levels again until phase IV began in 2018.[4]
- As the cost of renewable energy technology fell, government support

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

Table 4.3 **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

Source: Authors' calculations using data from the EPO World Patent Statistical Database (PATSTAT).

Notes: Table shows the percentage of inventors coming from each country for selected technologies. Fractional counts used for patents with inventors from multiple countries.

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 (2020) 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 70 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 such studies Dechezleprêtre and Glachant (2014) and Peters et al. (2012), who demonstrated the importance of global markets for wind and solar innovation, respectively.

4.3.1.4 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 2010–2011 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.

4.3.1.5 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 have 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 (that is, citations made by a given patent to the prior art):

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

$$Radicalness_p = \sum_{j}^{n_p} \frac{CT_j}{n_p} \text{ for } IPC_{pj} \neq IPC_p,$$

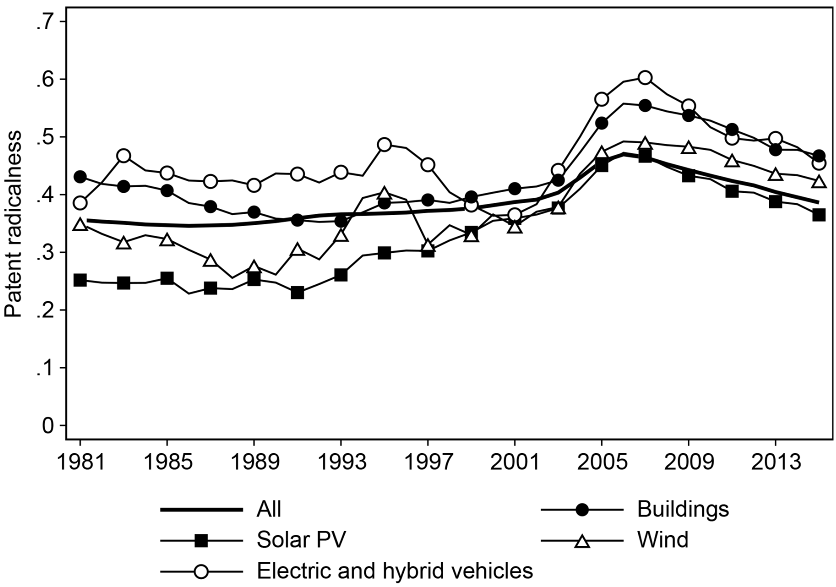
  where CT_j is the count of IPC 4-digit classifications IPC_{pj} cited by patent p that are not assigned to patent p, and n_p represents the total number of IPC classes in the prior art cited by patent p (Squicciarini, Dernis, and Criscuolo 2013).
- *Originality*, first proposed by Trajtenberg, Jaffe, and Henderson (1997), measures the breadth of technology fields on which a patent relies. It also relies on backward 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, Dernis, and Criscuolo 2013).

Figures 4.12 and 4.13 present radicalness and originality for a select set of our energy patent technologies, as well as for all patents (bold lines) for comparison. Because the annual averages for small technological fields are noisy, we present the data as 3-year moving averages. In each figure, panel A 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 except for vehicles and wind in the mid-1990s, these peaks appear to coincide with a similar peak for all technologies. Pertaining to the recent drop in clean energy pat-

A. Clean Energy Technologies



B. Enabling Energy Technologies

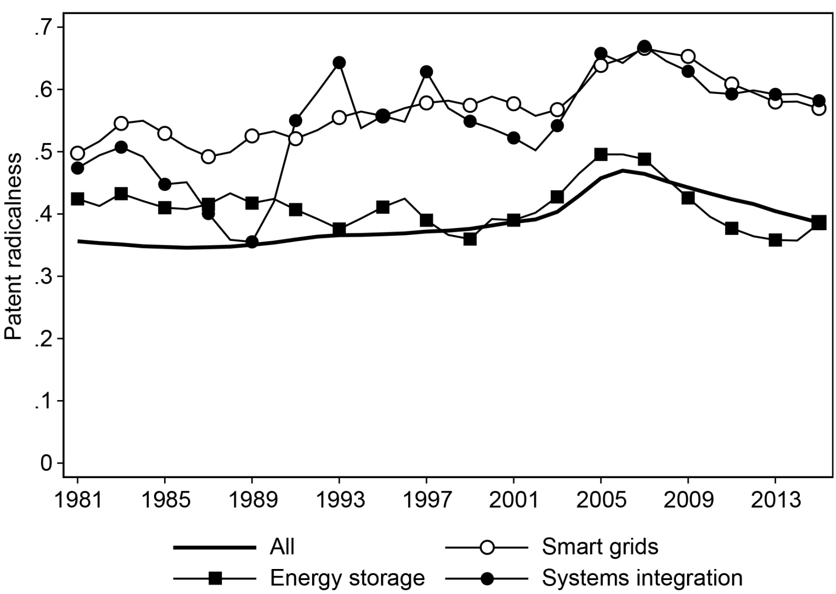
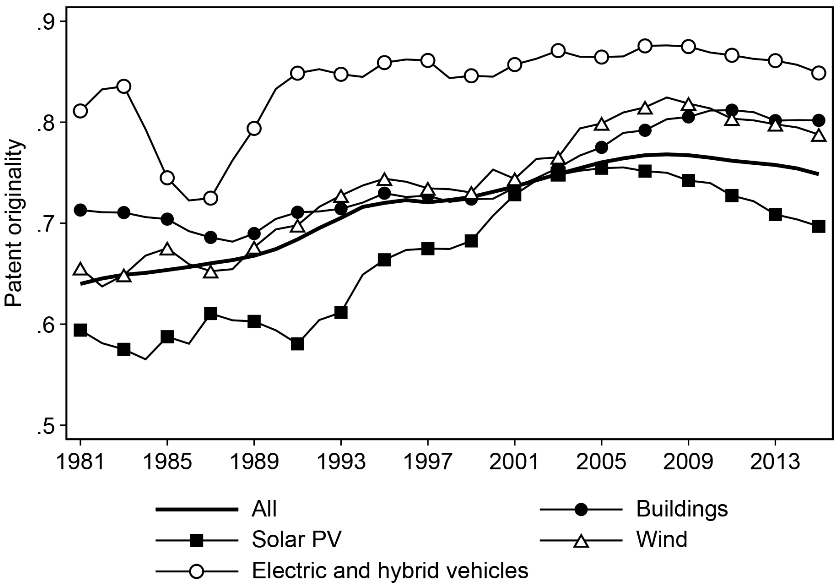


Fig. 4.12 Radicalness

Source: Authors' calculations using data from the EPO World Patent Statistical Database (PATSTAT).

Note: Figure shows the 3-year moving average of radicalness for selected energy technologies.

A. Clean Energy Technologies



B. Enabling Energy Technologies

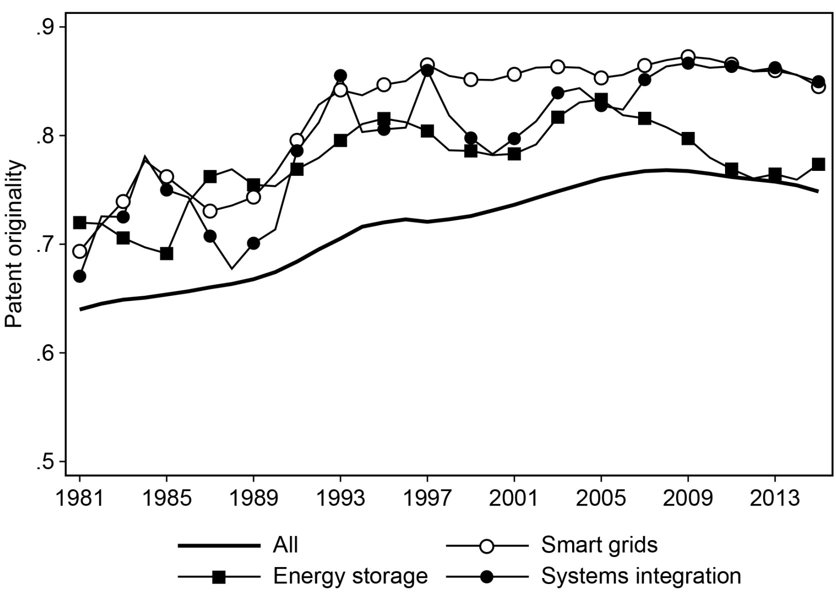


Fig. 4.13 Originality

Source: Authors' calculations using data from the EPO World Patent Statistical Database (PATSTAT).

Note: Figure shows the 3-year moving average of originality for selected energy technologies.

enting, radicalness for patents for solar, wind, and energy efficiency buildings all peak right before the spike in patenting. That radicalness begins to fall along with patenting provides some suggestive evidence of diminishing returns. However, the radicalness of these technologies remains higher than the radicalness of technology as a whole. The originality of both wind and solar patents appear to peak slightly before the spike in patenting, although the drop-offs in recent years are not large. Electric and hybrid vehicles are both more radical and more original than other clean energy technologies or all technologies in general (in bold). Nonetheless, while their originality has been fairly constant since the early 1990s, the radicalness of electric and hybrid vehicles peaks in 2007, which is when patenting peaks for these vehicles. In contrast, the radicalness of building energy efficiency technology peaks in 2006, although patenting doesn't peak until 2012. Solar PV is nearly always less radical and less original than the average technology. This result also suggests that the era of "peak patenting" for 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 off technological classes outside 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 patent 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 appear to be only a partial explanation at best for decreased clean energy patenting.

4.3.1.6 Innovation Has Worked

Concerns about diminishing returns pertain to the supply-side of innovation. Related to the possibility that research has hit diminishing returns is the possibility that clean energy research in existing technologies has been a success. In such a case, there will be less demand for continued research and relatively more resources devoted to incremental innovations that cannot be patented. Recall from section 4.2 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 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. The decrease in innovation, at least as measured by patent counts, may suggest a challenge for business and policymakers 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.

4.3.2 The Challenges of New Energy Technologies

For many reasons, relative to past trends, the remaining technological needs for a clean energy transition are more challenging and are likely to grow more so in the future. Overcoming these challenges will 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, Martin, and Mohnen (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, Mueller, and Trancik 2016). This interdependency raises uncertainty about the future profits from innovation.

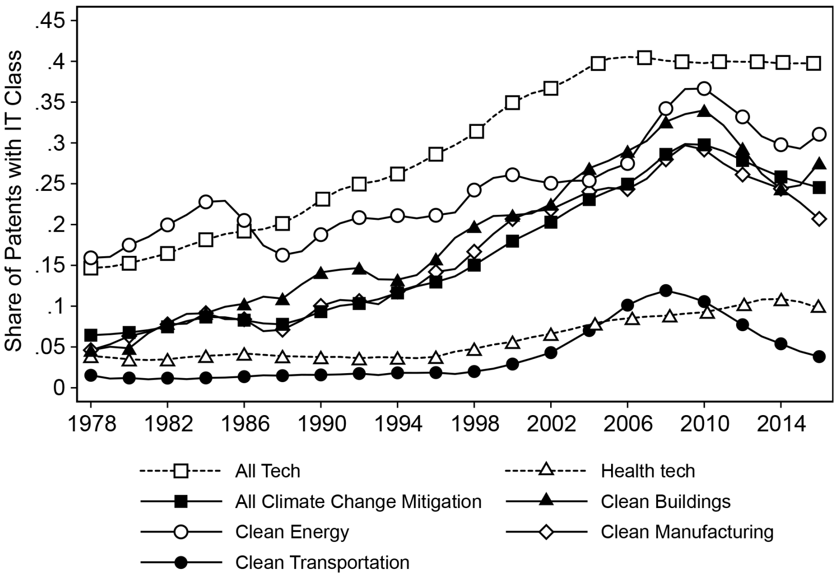
Finally, grid integration and energy storage innovations also provide examples of how the building blocks of energy innovation are changing. The high degree of radicalness and originality of both smart grids and system integration technologies suggests that technologies will require more innovation across 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 technology (ICT) has permeated both energy and other sectors.

Figure 4.14 illustrates the penetration of digital technology in different technological domains, measured as the 3-year moving average of the percentage of patents in different fields that also have an ICT patent classification. Appendix table 4.A.1 lists the patent classes used to identify each technology discussed here. Overall, the share of patents also having an ICT class rose through the end of the twentieth century, plateauing at around 40 percent by 2006. Trends in ICT penetration among climate mitigation technologies is similar (figure 4.14, 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 it follows similar trends. ICT penetration is a bit lower for climate mitigation technologies in the manufacturing sector, and much lower in the transportation sector. For comparison, we also include the health sector, which has a lower ICT penetration of just 10 percent.

Panel B of figure 4.14 provides evidence from other energy and engineering technologies. Compared to these technologies, ICT penetration appears more important for climate mitigation. ICT penetration for power technologies plateaus at around 25 percent. Patents related to general engineering, engines, or combustion have ICT penetration rates below 10 percent.

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, Drev, and Kwon 2019). ICT improvements are also modular. Software components can be developed remotely and inte-

A. Climate change mitigation technologies



B. Broad energy technologies

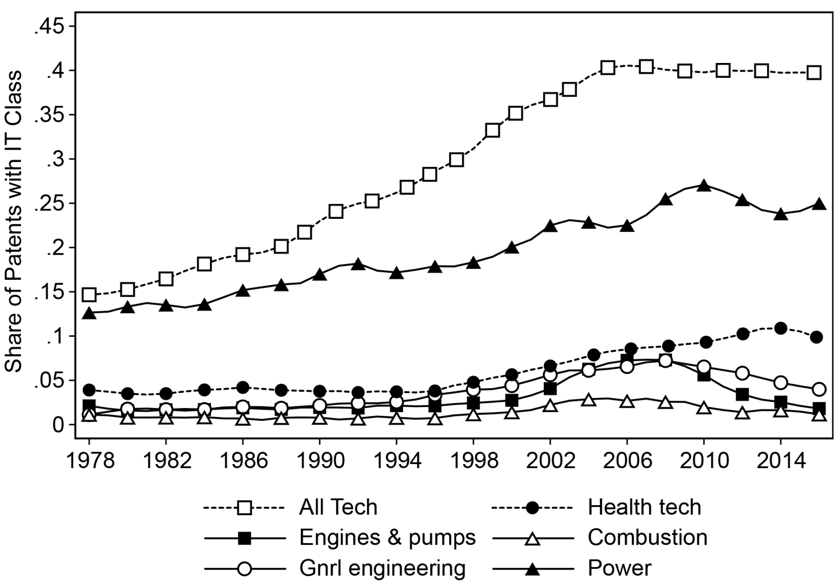


Fig. 4.14 Penetration of digital technologies in various technologies

Note: Three-year moving average of percentage 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).

grated into larger systems, allowing R&D to be done in more locations, both domestically and abroad (Branstetter, Glennon, and Jensen 2019). 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.

4.4 Early-Stage Financing for Startups in the Energy Sector

Startups historically played a minor role in the energy sector (Gaddy et al. 2017; Nanda, Younge, and Fleming 2015). 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 toward a more decentralized energy system characterized by increasing levels of renewable energy and storage technologies may change the role of energy startups. 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, IT and blockchain technology are further helping to facilitate this transition to a more decentralized energy system and are becoming increasingly abundant. Blockchain energy startups are multiplying, raising more than 265 million euros for applications in the energy sector in 2017 (European Commission 2018).

At the same time, startups 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 observers 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: firms may have achieved the desired returns but on a time scale that is typically not attractive to VCs. This suggests that 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 startups as they become increasingly complex and perhaps difficult to evaluate ex ante. While Nanda, Younge, and Fleming (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 startups 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 startups. 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.

4.4.1 Data Overview

We gather firm-level data on startup companies and VC activity from Crunchbase, a commercial database of innovative companies.[5] 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 US, and it has been embraced by the investor community as a leading platform for discovering and connecting with innovative companies.

That said, the data come with 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-checked against traditional sectoral classifications. Finally, the coverage for firms in some countries, such as China, is very low, which may be particularly important in 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 in the energy sector, our analyses still provide some meaningful insight about energy startups that is new to the literature.

We link several Crunchbase datasets to compile our dataset for analysis. First, we start with the full cross-section of 733,133 organizations.[6] We keep only those that were founded in 2000 or later and those that indicated their

5. 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. See Dalle, den Besten, and Menon (2017) for a discussion of the use of Crunchbase data in economic and managerial research.

6. We accessed the data in summer 2019.

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 US dollars) to real 2010 dollars using the consumer price index from the World Bank. The funding deal dataset includes 268,774 observations with about 71,000 missing actual funding amount information, so the totals used throughout the analysis are lower bounds for this sample of firms.[7] 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 IPOs). After dropping duplicate observations, the datasets include information on about 87,000 acquisitions and 17,000 IPOs.

Perhaps most interestingly for our analysis, Crunchbase sector classifications allow us to identify startups that operate in multiple (and possibly complementary) fields, such as IT. We classify firms based on whether they indicate that they are in the energy sector, and separately firms also indicating that they operate in a high-tech sector. Table 4.4 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 on high-level sectors. We classify different types of energy firms in Panel B, and in Panel C, we further break down the energy firms based on 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.

4.4.2 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.[8] Figure 4.15 illustrates these trends from 2000 through 2018 in four panels. 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 2012, which is a little later than when it peaks when measured as a share of founded firms. This suggests

7. 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.

8. Note that because some firms may participate in multiple sectors, some firms and their associated funding are double counted.

Table 4.4 **Firm classifications and descriptions**

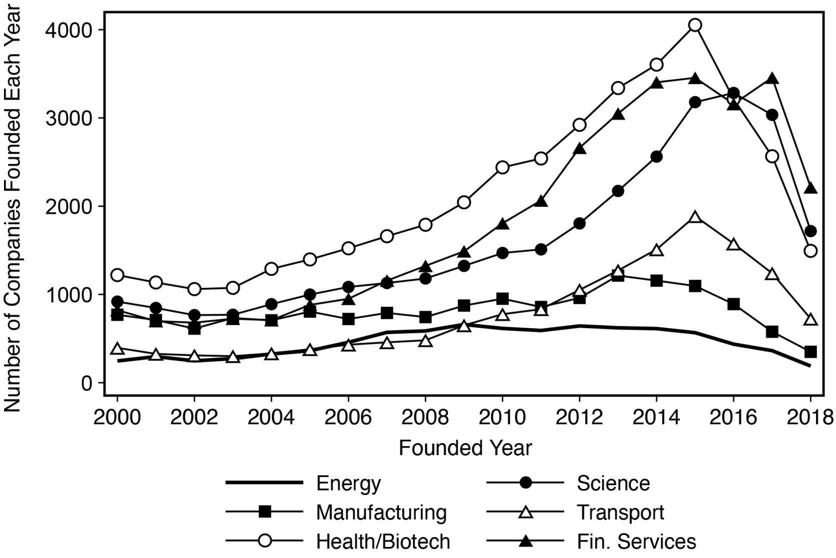
Firm type (1)	Crunchbase categories (2)	Number of firms (3)
	A. High-level sectoral groupings	
All firms	Total sample of firms across sectors	604,884
Energy	All energy types	13,515
Financial services	Financial services, lending, and payments	48,923
Science	Science and engineering	40,464
Health/biotech	Health care 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
Fossil fuel	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
Fossil fuel and high-tech	Fossil fuel energy firms that are also high-tech	341
Grid and high-tech	Grid management and high-tech	386
Energy efficiency and high-tech	Energy efficiency firms that are also high-tech	238
Other energy and high-tech	Other energy firms that are also high-tech	1,007

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 startups in financial services, science, and engineering all increase more quickly than energy startups following the recession, with the share of firms founded that are energy-related falling from about 2007 onward.

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).[9] 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 of funding deals for energy firms in 2008. This aligns with energy

9. 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.

A. Number of Companies Founded Each Year



B. Share of Companies Founded Each Year

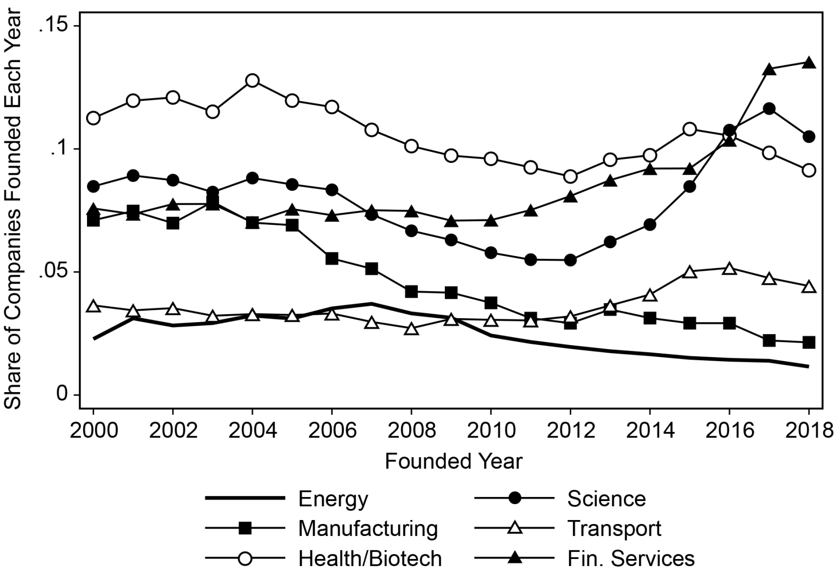
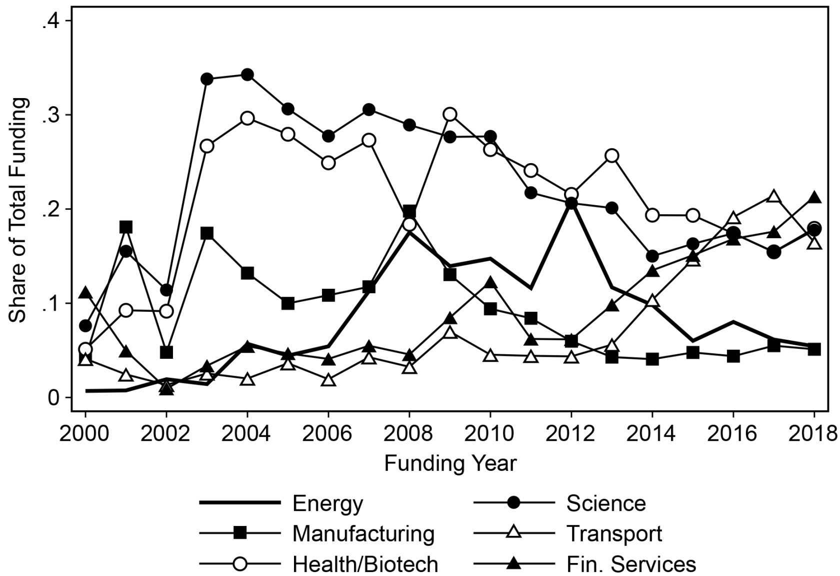


Fig. 4.15 Comparison of energy firms to other sectors

Note: 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.

C. Share of Total Funding by VCs Each Year



D. Share of Total Funding Deals by VCs

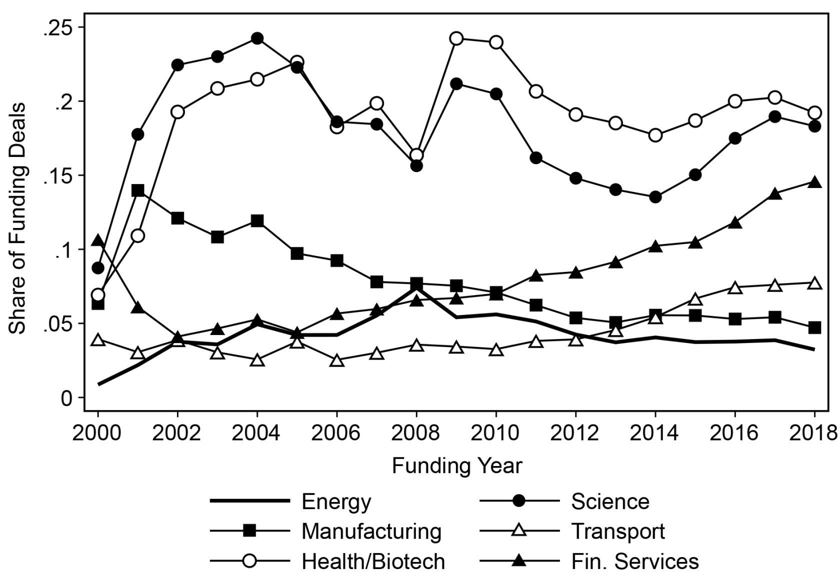


Fig. 4.15 (cont.)

firm founding year peaks, descriptively suggesting that such funding may be correlated with the successful startup 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 startup performance in section 4.4.3.

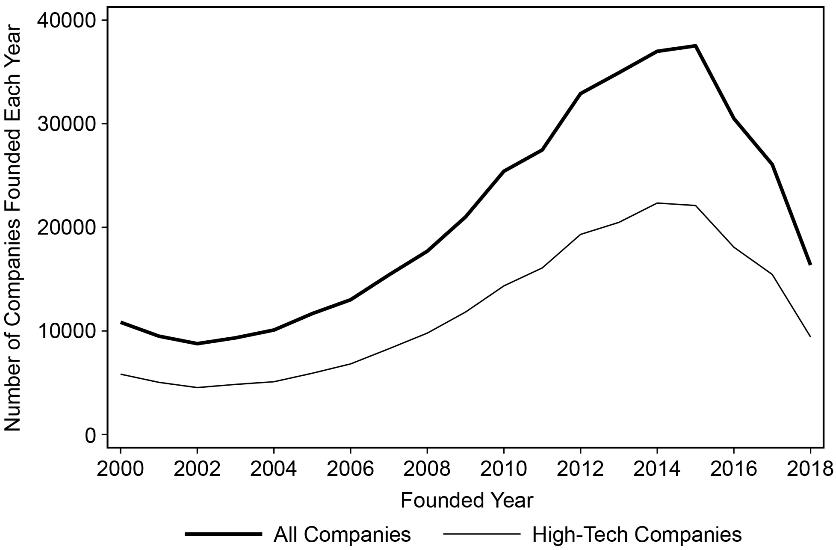
The rise and fall of the share of VC funding going to energy firms also closely mirrors the trends in patenting presented in section 4.3. In both cases, rapid growth begins in the mid-2000s. While the peak in venture capital funding comes slightly later than the peak in many clean energy patents, both drop significantly after 2012, and both remain above the levels achieved prior to the initial increase in 2006. These data are only suggestive, but 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.

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 4.16. 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 onward. Panels C and D explore VC funding allocated, revealing that most 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 recession and through 2010, but then rose again quickly from 2010 onward, suggesting that VCs may be particularly drawn to firms reporting to operate in high-tech sectors.

We explore this further to see whether a similar relationship holds in the energy sector specifically (figure 4.17). Panel A of figure 4.17 plots the share of all companies founded that are energy firms also categorized as high-tech vs. 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 startups 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 onward (but then leveling off from about 2012 onward). The proportion of energy startups that are also high-tech have therefore been rising quickly. Comparing these findings with funding for these types of firms in panels C and D, we can see that the spike in the number of high-tech energy startups around the year 2008 also aligns with a spike in funding (both in totals and in shares) at the same time.

We explore this distinction between energy-only and high-tech energy firms by energy type as well (see figure 4.18). Panel A plots the number of

A. Number of Companies Founded Each Year



B. Share of Companies that are High-Tech

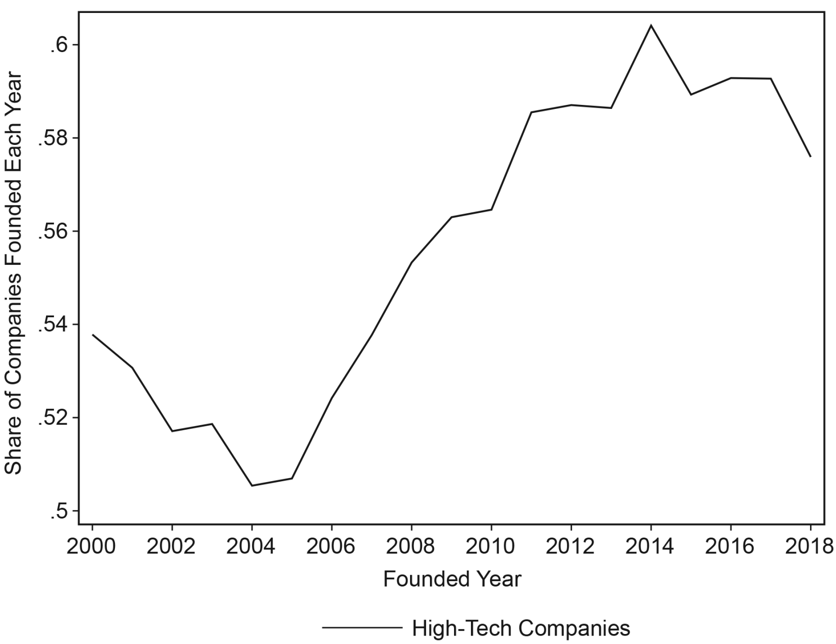
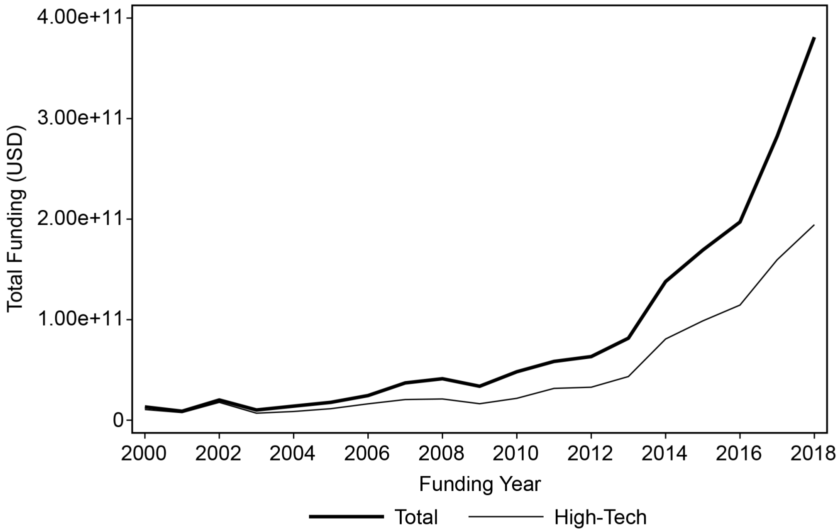


Fig. 4.16 Growing share of companies founded are high-tech, 2005–2014

C. Total Funding for All Companies vs. High-Tech



D. Proportion of Funding to High-Tech

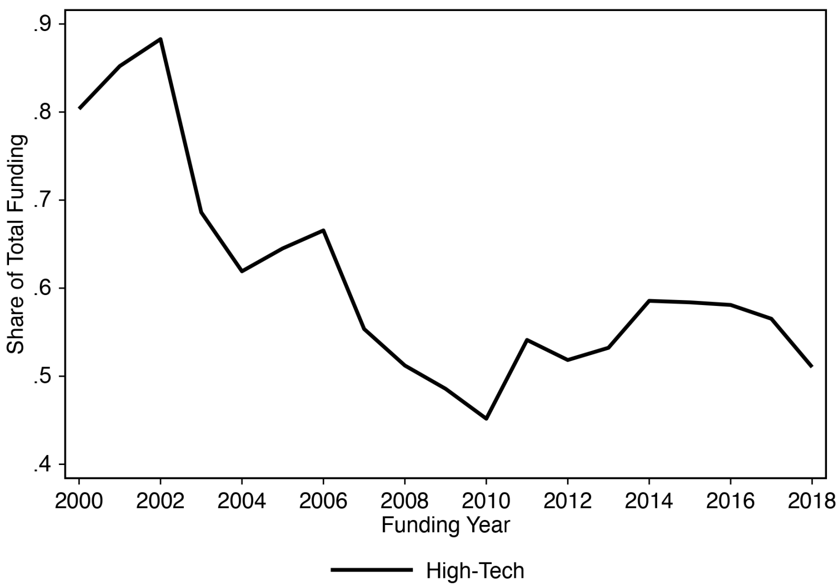
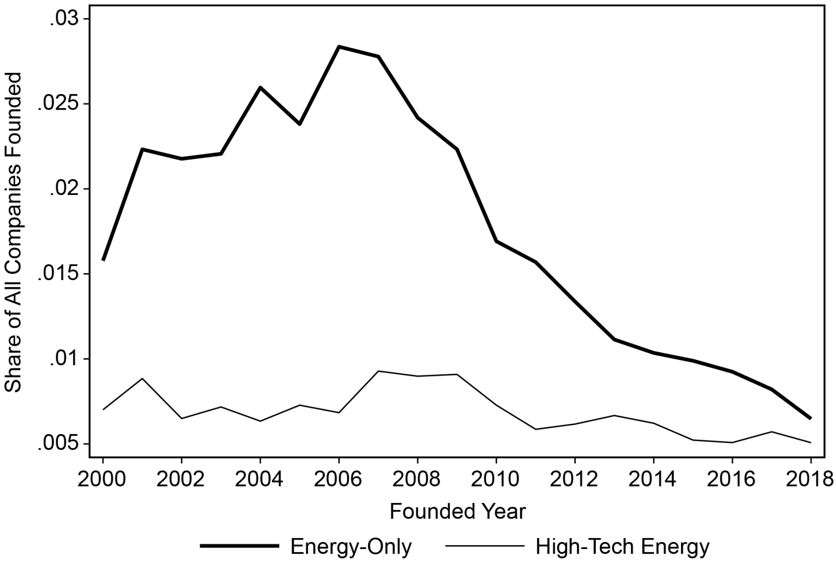


Fig. 4.16 (cont.)

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



B. Increasing share of high-tech energy cos.

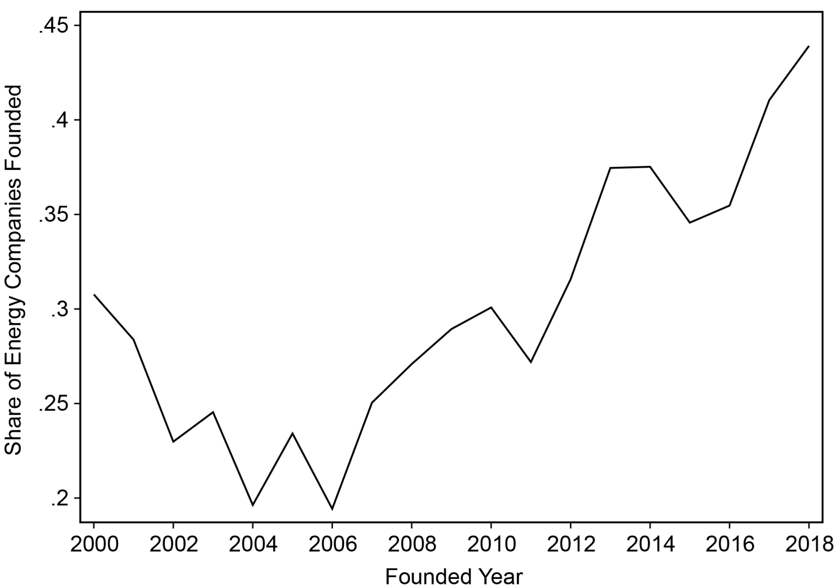
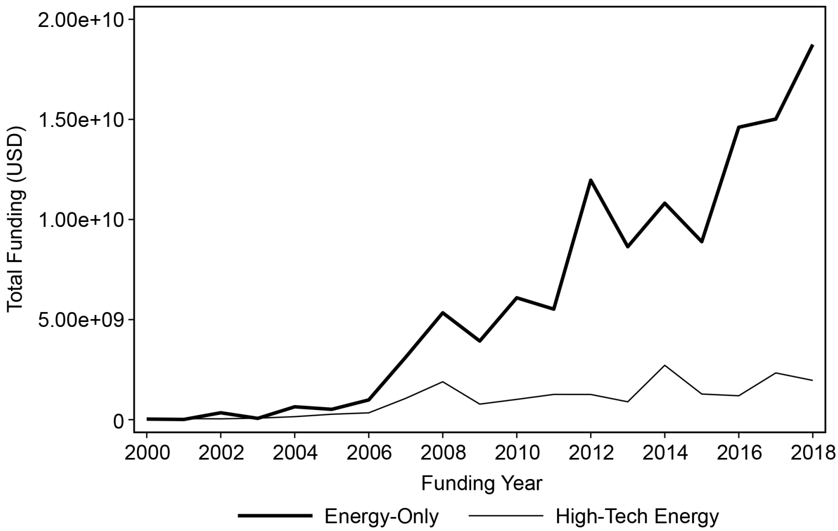


Fig. 4.17 Energy-only and high-tech energy companies

C. Total Funding: Energy & Energy High-Tech



D. Share of Funding: Energy & Energy HT

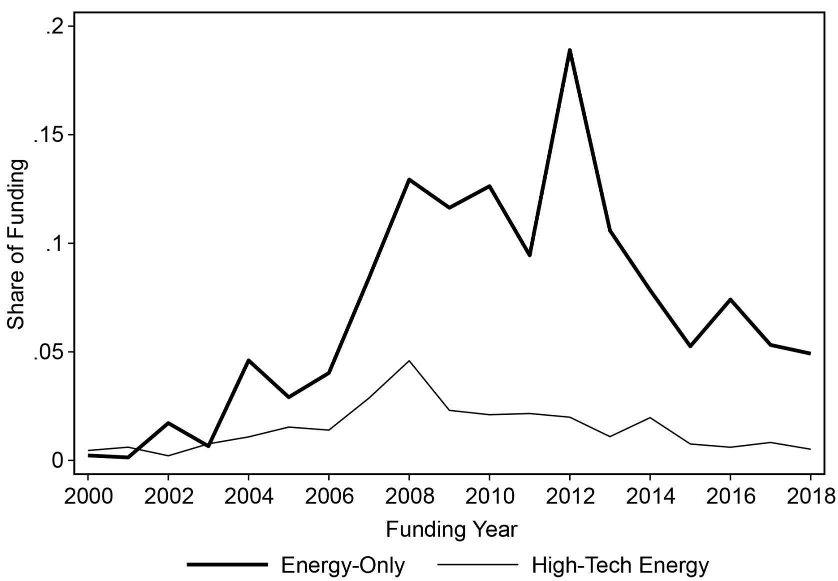
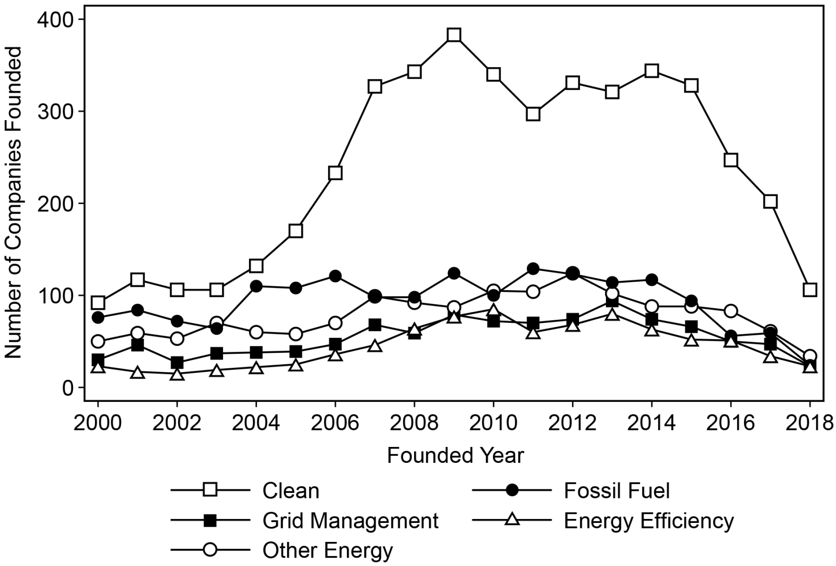


Fig. 4.17 (cont.)

A. Number of Companies by Energy Type



B. Share of All Companies by Energy Type

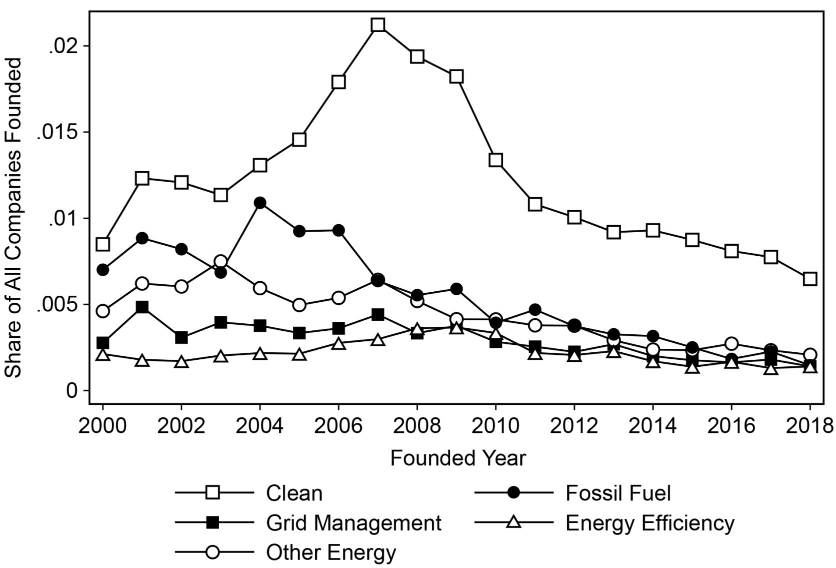
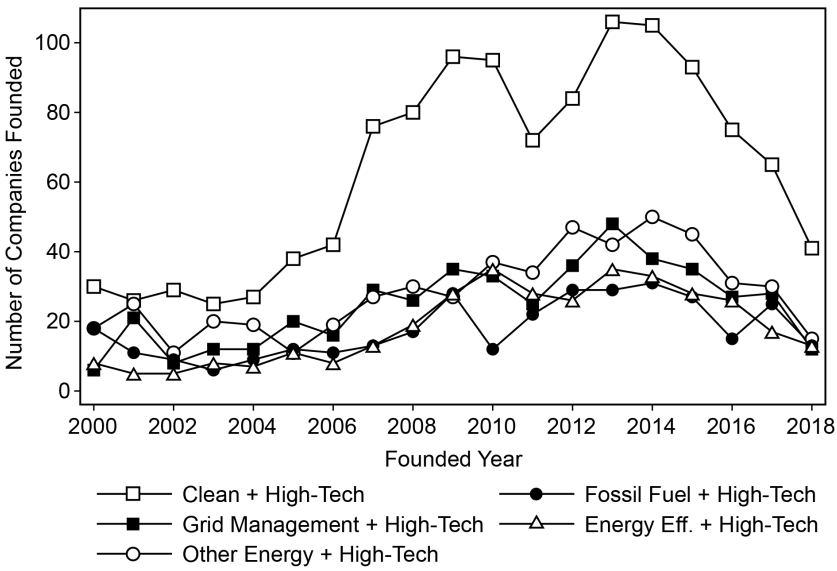


Fig. 4.18 Energy companies founded each year, by energy type

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

C. Number of Companies by Energy Type



D. Share of All Companies by Energy Type

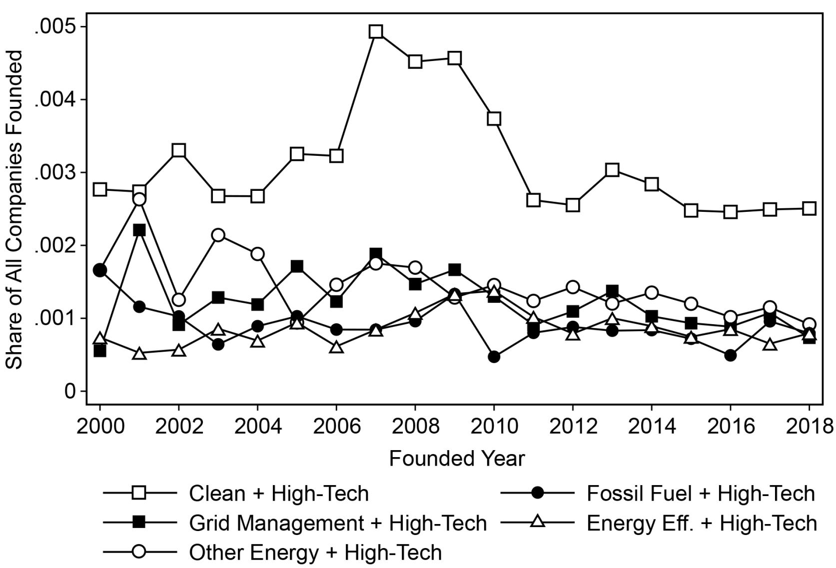


Fig. 4.18 (cont.)

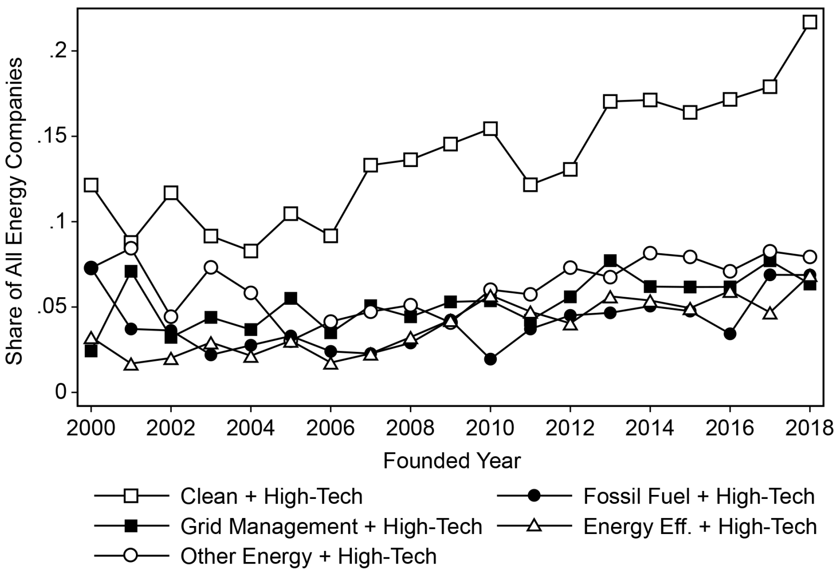
companies by energy type (clean, fossil fuel, grid management, energy efficiency, and other), and panel B plots the share of all firms that fall into each category. These figures very clearly show the "bubble" of clean energy firms that emerged through the Great Recession: while the number of firms in fossil fuel, grid management, and so forth 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 onward. When examining firms that specifically are also high-tech in these energy subcategories 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 in 2008 before leveling off in 2011.

As one final exploration of whether energy startups 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 4.19 plots energy firms that are also high-tech by energy subgroup as shares of all energy companies founded each year, and panel B of figure 4.19 plots firms that are also high-tech as shares of their own subgroup. 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 subgroups, startups are increasingly either claiming to be high-tech or actually are high-tech. This growth is similar to that observed in the share of energy patents also classified as high-tech, as well as supporting the anecdotal evidence presented in section 4.2 that IT is also of growing importance in the search for new energy resources.

Last, 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 of attracting VC—a hypothesis that's been posed in light of Crunchbase being used as a platform by VCs. This could mean that VCs overvalue 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 4.20 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 subcategory (panels A and B) and then by energy subcategory for firms that are also high-tech. Panels A and B illustrate the clean energy funding

A. Share of All Energy Companies Founded



B. Share of Each Energy Sub-Group Also HT

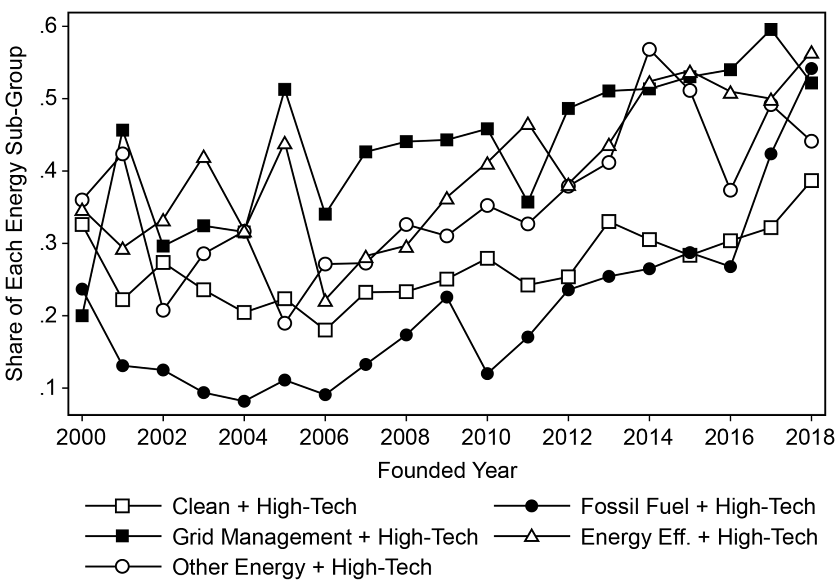


Fig. 4.19 Increasing trends in energy firms that are also high-tech

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

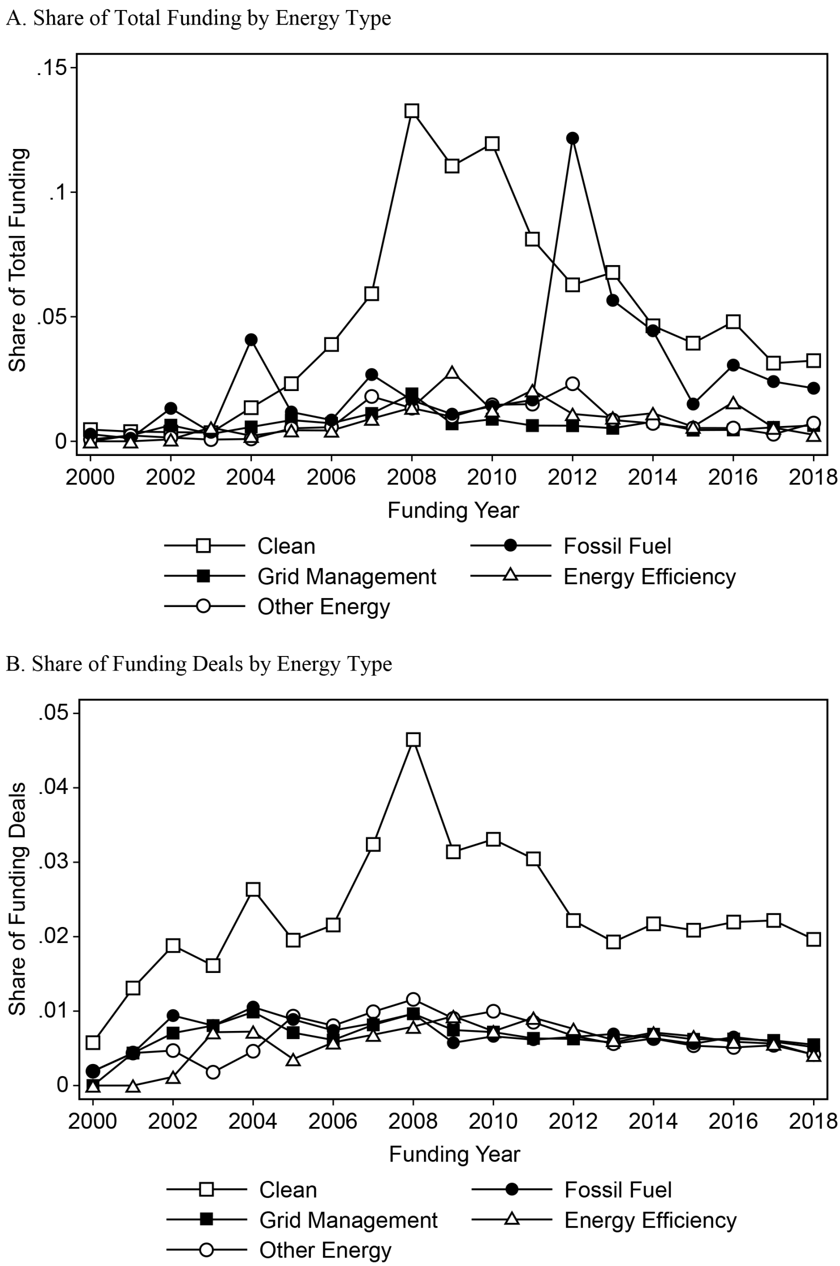
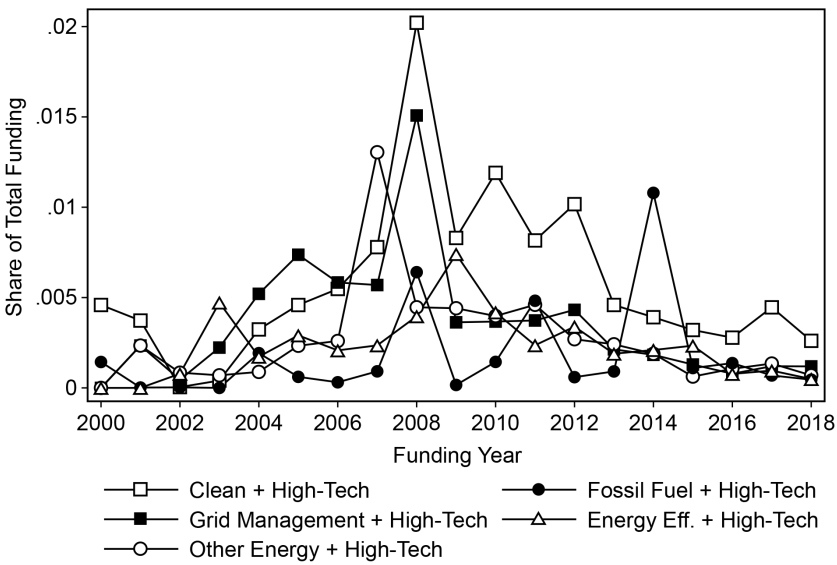


Fig. 4.20 Share of funding going to energy firms

Note: 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.

C. Share of Total Funding by Energy Type



D. Share of Funding Deals by Energy Type

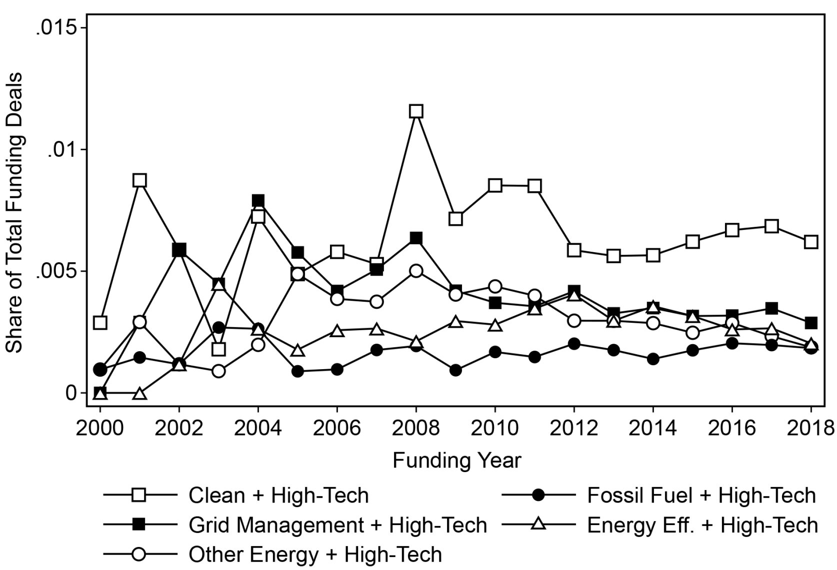


Fig. 4.20 (cont.)

"bubble" that occurred around the year 2008, where a large spike occurs 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 fossil fuel energy around 2012–2013, which is likely driven by the fracking revolution. Panels C and D specifically look at high-tech energy firms by subcategory. Despite there only being a spike in funding for clean energy firms in general around 2008, it appears as though a spike occurs 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 artificial intelligence 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 the unexpectedly low returns to investments in the clean energy sector so far.

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 underestimate innovation and startup 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.

4.4.3 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 overvalue such firms. To explore these potential explanations, we examine 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

Table 4.5 Energy firms relative to the average firm

Dependent variable	Acquired (1)	IPO (2)	Raised funds (3)	Amount raised (4)	Time to exit (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 dependent variable	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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

between the founding and exit years. In each case, we regress these outcomes on indicator variables that capture firm type (energy only, high-tech only, high-tech energy, etc.), along with founding-year fixed effects and a dummy variable indicating whether the firm is located in the US. We cluster our standard errors by founding year. We focus on two broad sets of questions:

1. Are energy startups more or less likely to raise funds and/or successfully exit via acquisition or IPO? Does this vary by the type of energy firm (see tables 4.5–4.8)?
2. Conditional on having received funds, are energy startups 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 (see table 4.9).

Since the firms listed in Crunchbase are not a random sample of startups, 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 4.5 presents the correlations between being an energy firm and the five measures of firm performance. Across all metrics, energy firms perform better than the average firm in our sample. They are 4.2 percent, 6.3 percent, and 14.5 percent more likely to be acquired, go public, or raise funds over their lifetimes, respectively. They also raise more money conditional on raising funds (column 4), and they take 0.85 fewer years on average to exit conditional on either being acquired or going public.

Given that VC has been considered a "failed" financing model for the

Table 4.6 **Energy + high-tech firms relative to the average firm**

Dependent variable	Acquired (1)	IPO (2)	Raised funds (3)	Amount raised (4)	Time to exit (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 dependent variable	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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

energy sector after some investments did not provide the expected returns, it is interesting that the energy startups listed in Crunchbase perform relatively *better* than the average startup. One potential explanation is that investors may place an unwarranted premium on energy firms that are also high-tech—or claim to be high-tech—relative to energy firms that are not high-tech. This might occur if there is a perception that high-tech firms are more likely to perform better, or perhaps generate returns in a shorter timeframe relative to energy-only firms. To test this hypothesis, we explore whether firms operating in both the energy and high-tech spaces raise more VC funding than their energy-only counterparts, and then also whether they perform better. We do this by regressing the performance outcomes on indicator variables for firm type (energy only, high-tech only, or both) and provide the correlations in table 4.6.[10] While firms that operate only in the energy space appear to 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 they are 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 they take longer to exit relative to energy-only firms (column 5). Yet high-tech energy firms are 11 percent *more* likely to

10. 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 percent level in column 1, at the 5 percent level in columns 2 and 5, and at the 1 percent level in columns 3 and 4).

Table 4.7 **Different types of energy firms relative to the average firm**

Dependent variable	Acquired (1)	IPO (2)	Raised funds (3)	Amount raised (4)	Time to exit (5)
Clean energy	−0.016***	0.025***	0.164***	15.784***	−0.718***
	(0.005)	(0.007)	(0.010)	(4.602)	(0.239)
Fossil fuel 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 dependent variable	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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

raise funds relative to energy-only firms (column 3).[11] This suggests that VC firms possibly were placing a premium on high-tech energy firms relative to energy-only firms but without reaping the expected rewards.

We also consider whether the performance of energy startups 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 energy? The evidence presented in table 4.7 suggests that this is not the case.[12] Clean energy firms are less likely to be acquired relative to the average firm as well as to 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 fossil fuel firms and

11. This is significant at the 1 percent 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, which is also when the number of energy plus high-tech firms is increasing.

12. Each of these categories is mutually exclusive.

Table 4.8 Impact of being high-tech for different types of energy firms

Dependent variable	Acquired (1)	IPO (2)	Raised funds (3)	Amount raised (4)	Time to exit (5)
Clean + high-tech	−0.007	−0.020***	0.050**	−24.806***	0.090
	(0.008)	(0.006)	(0.018)	(5.659)	(0.318)
Fossil fuel + 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)
Fossil fuel 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	−0.069***	−0.041**	0.144***	−25.193***	0.053
	(0.020)	(0.016)	(0.041)	(8.269)	(0.759)
Sample mean for dependent variable	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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 is the same as fossil fuel energy firms, they would have (just slightly) underestimated 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.

Finally, in table 4.8, we examine the same correlations for energy-only firms and high-tech energy firms conditional on energy type, with the omitted category being 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, high-tech energy firms raise more funds than their energy-only counterparts. The chances of raising funds are negative for fossil fuel 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 fossil fuel high-tech energy firms are less likely to go public, and high-tech fossil fuel energy firms are also less likely to be acquired. Being high-tech also increases the time to exit for fossil fuel, grid management, and energy efficiency firms.

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 of energy startups) 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 these correlations across the full sample, as well as for subsamples based on the firm's founding year (2000–2005, 2006–2012, and 2013–2018) 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.[13] 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 4.9 presents the results. Column 1 uses the full sample. We see that

13. We do not include separate categories for high-tech energy firms in table 4.9, 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.

Table 4.9 **Exit of energy firms relative to the average funded firm**

	Any exit			
Dependent variable	Overall (1)	2000–2005 (1)	2006–2012 (2)	2013–2018 (3)
Clean energy	−0.026***	−0.025	−0.038**	−0.011
	(0.008)	(0.016)	(0.014)	(0.007)
Fossil fuel 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 dependent variable	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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 difference is substantial. Unlike the estimates for the full sample in table 4.7 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 (see table 4.7), so that overall, they exit more frequently than do 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 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. Since both factors may be different for the different subsets of energy startups, this may also help explain the differences we see in the sector.

Why do some funded energy firms fare worse than nonenergy 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 nonenergy 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 (see figure 4.19). 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 not statistically significant, with a p-value of 0.12. Fossil fuel energy funded firms are still just as likely to exit as nonenergy 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 are consistent with the possibility of a clean-tech bubble, although we cannot rule out other potential explanations. If investors were overly exuberant about clean energy during the boom period and invested too much in 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, for instance, 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.

4.4.4 Summary of Findings on Startups

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 are 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 overinvestment in clean energy during 2006–2012, 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.

4.5 Conclusions

Because energy is a commodity, measuring the returns to R&D in the energy sector requires different metrics than those used in other sectors. Reducing costs and environmental impacts matter more than increasing productivity. As our chapter has documented, the nature of innovation in the energy sector is changing in ways that both reduced costs and environmental impacts. In the past decade, the use of hydrofracturing technology in the US 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 gas 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 4.3 highlight the role of innovation promoting these trends. Patents for wind, solar, and hydrofracturing 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. To compound this challenge, not only has patenting in clean energy technologies (such as wind and solar energy) fallen from its 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 4.3, 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 relatively slowly compared to firms in other sectors. 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 observation up. Energy startups 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 conditioned 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 set of research questions considers the relative importance of different policy instruments for promoting clean energy innovation. First, what role can marketwide increases in energy prices (such as through carbon taxation) play relative to targeted energy policies, such as renewable energy mandates for promoting clean energy innovation? While recent studies on the drivers of clean energy innovation consistently find that policies to increase clean energy demand promote innovation, those studies that also control for energy prices find mixed results. Some find that higher prices on their own have little effect on innovation once controlling for policy (e.g., Johnstone, Haščič, and Popp 2010; Nesta, Vona, and Nicolli 2014), while others find both policy and prices matter (e.g., Verdolini and Galeotti 2011; Peters et al. 2012). One important distinction is the difference between higher prices following the imposition of new taxes versus higher prices in response to market shocks. Studies of gasoline consumption suggest that consumers are more responsive to changes in taxes than market-generated fluctuations in price, as tax increases are perceived as more persistent (Davis and Kilian 2011; Li, Linn, and Muehlegger 2014; Rivers and Schaufele 2015). Similar studies comparing the effect of taxes versus market-generated price changes on innovation would help uncover the potential of broad-based policies, such as carbon taxes for promoting clean energy innovation.

Getting policies right is important. While energy prices remain a key driver of innovation in the sector, market prices do not capture the full social costs of energy use, absent a carbon tax. Public policy thus shapes both demand for green energy and the innovation necessary to meet this demand. Worldwide, policy goals are becoming more ambitions. The EU's Green Deal aims to reduce European greenhouse gas emissions to net zero by 2050. In the US, California plans to rely solely on zero-emission energy sources by 2045, and advocates of the Green New Deal propose using 100 percent zero emission power sources in just 10 years' time.

These ambitious goals raise new challenges for energy storage and smart grid technologies to integrate unprecedently large quantities of intermittent energy sources into the grid. Thus, a second set of questions considers 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? As noted in International Energy Agency (2020), "low-carbon electricity systems are characterized by increasingly complex interactions of different technologies with different functions in order to ensure reliable supply at all times," placing a premium on collaborative research among different partners, stretching well beyond partners in the energy field. Distributed energy generation provides an example where such collaborative research is likely to yield significant benefits. With the costs of solar power generation now being extremely competitive and likely to become more so (International Energy Agency 2020), the potential for households to become significant producers of electricity presents technical challenges from the microscale to the grid infrastructure.

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., Conti et al. 2018; Haščič, Johnstone, and Kahrobaie 2012) or across institutions. For alternative energy technologies, both scientific articles and patents with authors from multiple types of institutions (e.g., universities and corporations) are cited more frequently, suggesting that collaborations may have positive impacts on research quality (Popp 2017). In the EU, 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, Guarini, and Meliciani 2018). Less research has been done on promoting collaborations across fields.

Do patents combining energy and high-tech come from incumbent firms or new entrants to the field? Are they more likely to be collaborative? While the growth in energy startups that are also high-tech observed in section 4.4 shows cross-fertilization of innovation across fields within the firm, are such firms more likely to have collaborative research strategies across firms and other institutions as they grow? The lines between sectors are blurring. Electricity is a general-purpose technology. As electricity costs fall and more stringent environmental regulation increases the costs of or even prohibits the use of fossil fuel energy, sectors such as transportation will increasingly depend on electricity. Efficient interaction between different technologies and firms from different sectors is essential for a smooth transition to an increasingly electric future.

Because of the potential growth in high-tech energy solutions, smaller firms, particularly those operating in the high-tech space, will play a larger role in driving energy innovation moving forward. Developing a better understanding of how policy interventions have heterogeneous effects on innovation outcomes depending on firm size—and whether firms focus on high-tech solutions as opposed to hardware—is therefore also important. For instance, 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 to what extent financial constraints hinder clean energy investment relative to a lack of demand, given how clean energy technologies 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 is it 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 with the 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 startup firms in the energy patenting boom of the early 2010s? Were their patents heavily cited? That is, did startups provide new insights to the evolving energy sector and even beyond?

Finally, it is important to note that 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. While startups may play a larger role for modular technologies, like solar PV or the emerging needs for innovation with a high-tech component, such as grid integration, they remain just part of an industry where high capital costs play an important role. Moving forward, both policymakers and industry leaders will need to identify when smaller, modular technologies are likely to be successful and when large-scale, capital-intensive technologies are needed (e.g., Nemet 2019, chapter 11) to devise policy solutions that recognize the different needs of each type of technology and the different implications of policy for small and larger firms. The climate problem is too expansive and complex for a one-size-fits-all solution, and so is the energy system on which solving the climate problem depends.

Appendix

Table 4.A.1 **CPC classifications for energy technologies**

Clean energy technologies	
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
Enabling technologies	
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

(*continued*)

Table 4.A.1 (cont.)

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 3 includes the above CPC codes and additional CPC codes in combination with keyword searches:[a]	
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

CPC and IPC codes used in Figure 14:	
Climate change mitigation technologies	
All Climate Change Mitigation	
Y02	Technologies for mitigation or adaptation against climate change
Clean energy	
Y02E	Reduction of greenhouse gas emissions, related to energy generation, transmission, or distribution
Clean transportation	
Y02T	Climate change mitigation technologies related to transportation
Clean buildings	
Y02B	Climate change mitigation technologies related to buildings, and related end-user applications
Clean manufacturing	
Y02P	Climate change mitigation technologies in the production or processing of goods
Broad energy technologies	
Engines and pumps	
F02	Combustion engines; hot-gas or combustion-product engine plants
General engineering	
F15	Fluid-pressure actuators; hydraulics or pneumatics in general
F16	Engineering elements and units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general
F17	Storing or distributing gases or liquids
Health technology	
A61	Medical or veterinary science; hygiene
Combustion	
F23	Combustion apparatus; combustion processes
Power	
H02	Generation; Conversion or distribution of electric power
ICT technologies	
The patent search strategy follows the J-tags from Inaba and Squicciarini (2017)	

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

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