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Environmental policy and innovation: a decade of research

Abstract

Encouraging innovation is an important part of environmental policy. A large literature in environmental economics examines the links between environmental policy and innovation. This paper reviews recent literature on green innovation. I highlight major trends in the literature, including an increased number of cross-country studies and a focus on the effect of different policy instruments on innovation. I include a discussion of the justifications and evidence for technology-specific policy incentives and present evidence on the effectiveness of government R&D spending. My review concludes with a discussion of three promising areas for new research on environmental innovation.

JEL-Codes: O310, O380, Q550.

Keywords: green innovation, induced innovation, pollution, climate change, renewable energy, energy efficiency, research and development, technology policy.

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1. Introduction

Innovation is an important part of environmental policy. Regulatory pressures spur firms to develop new and better ways to improve environmental performance. As a result, forecasted costs of new environmental regulations often exceed actual costs (Harrington *et al*. 2000, Morgenstern 2015). Moreover, promoting technological change is often a specific goal of environmental policy, such as through support mechanisms like feed-in tariffs for solar energy or by devoting a portion of funds from carbon taxes to energy research and development (R&D) programs. For example, meeting climate policy goals currently under consideration, such as European Union discussions to reduce emissions by 40 percent below 1990 levels by 2030 or California's target of relying solely on zero-emission energy sources by 2045, requires replacing vast amounts of fossil fuel energy sources with alternative, carbon-free energy sources. While innovation over the past decades has helped reduce the cost of wind and solar energy, many technical challenges remains, including low-cost battery storage, both for intermittent energy sources and to bring down the cost of electric vehicles.

There is a large literature in environmental economics examining the links between environmental policy and innovation. Popp *et al*. (2010) provides an extensive review of the literature on environmental innovation. But much has changed since that paper first appeared. Researchers have extended the study of environmental innovation by looking at the effects of different policies, by looking at a wide variety of new technologies, and by incorporating more micro-based data in their analyses. This review highlights the major advances in the literature on environmental innovation in the decade since Popp *et al*. (2010) first appeared in print.[1] While I include some references to key papers in the field, my focus is on papers published since that earlier review. Moreover, given the large number of studies, my focus is narrower than in Popp *et al*. (2010). That paper reviewed both theoretical and empirical literature, and included papers studying either innovation or diffusion. Here, my main focus is on empirical papers focused specifically on different aspects of environmentally friendly innovation. During the past decade, there has also been a growing literature on environmental technology diffusion and the effectiveness of policies for encouraging their use, particularly pertaining to renewable energy and energy efficiency. Allan *et al*. (2013) provides a review of this literature.

Studies on the effect of policy or prices on environmental innovation draw their motivation from the notion of induced innovation (Hicks 1932, Binswanger and Ruttan 1978), which recognizes that R&D is a profit-motivated investment activity and that the direction of innovation likely responds positively in the direction of increased relative prices. Responding to criticisms that this early literature lacked micro-economic foundations, Acemoglu (2002) developed a model of directed technical change, which incorporates, among other things, the importance of market size along with prices as factors biasing the equilibrium direction of technical change. Acemoglu's work spurred both new modeling efforts (e.g. Acemoglu *et al*. 2012, Lemoine, 2017, Hart forthcoming) and empirical analyses (e.g. Aghion *et al*. 2016) of directed technical change in an environmental setting.

Important to the micro-economic foundations of environmental innovation is the role of market failures. Market forces provide insufficient incentives for investment in either the development or diffusion of environmentally-friendly technologies. Two types of market failures

[1] The NBER Working Paper version of Popp *et al*. (2010) was published in April 2009 (NBER Working Paper #14832), almost exactly a decade prior to the first publication of this review.

provide the motivation for policy intervention. One market failure is the traditional problem of environmental externalities. Because pollution is not priced by the market, firms and consumers have no incentive to reduce emissions without policy intervention. Thus, without appropriate policy interventions, the market for technologies that reduce emissions will be limited, reducing incentives to develop such technologies. Policies addressing environmental externalities increase the potential market size for environmental innovation, and are often referred to as *demand-pull* policies in the literature.

The second set of market failures pertaining to environmental R&D are knowledge market failures. Primary among these is the public goods nature of knowledge (see, for example, Geroski 1995). In most cases, new technologies must be made available to the public for the inventor to reap the rewards of invention. By making new inventions public, some (if not all) of the knowledge embodied in the invention becomes public knowledge. This public knowledge may lead to additional innovations, or even to copies of the current innovations. These knowledge *spillovers* provide benefit to the public as a whole, but not to the innovator. As a result, private firms do not have incentives to provide the socially optimal level of research activity. More recently, the literature on environmental innovation has focused on additional knowledge market failures, such as path dependency (e.g. Aghion *et al*. 2016) and capital market imperfections (e.g. Howell, 2017). Policies addressing knowledge market failures are often referred to as *technology-push* policies.

I begin this review of empirical work on policy-induced environmental innovation discussing the issues relevant to measuring innovation and environmental policy. Section 3 presents general advances in the literature on environmental innovation over the past decade. In sections 4 and 5 I focus on two key advances over the past decade: cross–country studies of policy induced innovation and studies focusing on the effect of different policy instruments. I then dive deeper into research on policy instruments, discussing the justifications and evidence for technology-specific policy incentives (section 6) and presenting evidence on the effectiveness of government R&D spending (section 7). Section 8 presents three promising areas for new research on environmental innovation. Section 9 concludes.

2. Measurement issues

Scholars studying environmentally friendly (or "green") induced innovation face two measurement challenges. First, the knowledge that makes any technology a valuable improvement is an abstract concept. We do not observe knowledge directly. Rather, we observe inputs that create knowledge or outputs that contain knowledge. Second, because environmental policy is a main driver of green innovation, capturing the array of policy instruments used to create demand for green innovation remains a challenge. While economists often focus on "getting prices right" through policies such as emissions taxes, in practice policymakers use a range of environmental policies, including technology mandates, subsidies, preferential tax treatment, and cap-and-trade policies. Not only does the choice of policy instrument differ across jurisdiction, but so does the stringency of the policies chosen. Representing the multiple dimensions of policy options remains a challenge.

2.1. Measuring innovation

Research and development (R&D) data offer a straightforward measure of innovative activity. R&D is an input into the innovation process. Variations in environmentally friendly R&D spending tell us the relative importance placed on such innovation. However, as R&D is an input, measures of R&D effort do not reveal information about outcomes of the innovation process. Moreover, detailed information on specific types of R&D is often unavailable. For instance, in a survey of energy R&D activity, Gallagher *et al*. (2011) note that while government spending on energy R&D is widely available for International Energy Agency (IEA) member nations, data on energy R&D efforts from private firms are scarce. Increased availability of firm level data has improved access to private sector R&D information, particularly in Europe where innovation surveys (described below) include questions on green R&D efforts.

Patents offer an alternative measure of inventive activity. Patents themselves are indicators of the output of innovative activity. However, patents, sorted by their date of application, also provide a good indicator of R&D activity, as patent applications are usually filed early in the research process (Griliches 1990). As a result, patent counts not only serve as a measure of innovative output, but are indicative of the level of innovative activity itself.

Patents provide a detailed record of each invention. From the bibliographic data on a patent, the researcher can learn the identity and home country of the inventor, read a description of the invention, and see references to earlier patents. Using patent data, it is possible for researchers to collect data in highly disaggregated forms. Patent classifications can be used to distinguish between different types of R&D at great detail, such as air pollution control devices designed to reduce NO_X emissions versus devices designed to control SO_2 emissions. Of particular use to researchers are recent efforts of the European Patent Office to classify sustainable technology patents using the "Y scheme", which provides separate classifications for technologies pertaining to climate change mitigation and adaptation, as well as for smart grids. These classifications complement standard patent classification schemes such as the Cooperative Patent Classification (CPC) scheme, grouping together relevant technologies that may appear in a wide range of traditional patent classes (Veefkind *et al*. 2012, Angelucci *et al*. 2018).

However, patent data also have drawbacks. While patent counts should be expected to increase as R&D activity increases, the correlation need not be exact. Variations in patent law, both across countries and across time, must be controlled for to properly interpret patent data. Furthermore, the existence of a patent does not mean that the technology has been adopted. Indeed, studies of the economic value of patents find that most patents have little commercial value, suggesting that adoption of most patented inventions is not widespread (e.g. Lanjouw *et al*. 1998). Moreover, firms are more likely to use patents to protect new products than new processes (Levin *et* al. 1987). As such, patent data may understate changes in the nature of innovation as countries shift their environmental policy focus from end-of-the-pipe to integrated solutions leading to modified production process. Because the patentability of innovations varies across technologies, patent data should be interpreted carefully, with the primary focus being on changing trends over time, rather than comparing levels of innovation across different technologies.

Important for this caveat is that any search strategy to identify relevant patents faces a tradeoff between using broad searches that identify as many relevant patents as possible but also include some irrelevant patents or using narrower searches that filter out irrelevant articles but may miss some relevant ones. Narrower search strategies are preferable, so as to avoid irrelevant patents that would respond differently to policy trends and thus bias results downward. A working paper by Bruns and Kalthaus (2017) provides interesting evidence on this. Using search strategies from 51 different papers and looking at six different commonly used methods for counting patents, they develop 306 different counts of solar patents. The level of patent activity varies widely, with the maximum count 243 times larger than the minimum. They then replicate the results of two papers (Johnstone *et al*. 2010 and Peters *et al*. 2012) using these various counts. While findings about the signs of policy effects are robust, there is variance in the magnitude of effects. Uncertainty is reduced if they exclude search results yielding the 10% smallest and largest patent counts, which may reaffirm the need to avoid overly broad search strategies. Their results caution against unconscious *p*-hacking by researchers choosing search strategies more likely to produce statistically significant results, and serve as a reminder that careful theoretical justification of the chosen search strategy is needed.

Other options for measuring knowledge creation are also available to researchers. Some studies focus on the effects of innovation. For instance, Knittel (2011) infers technological progress from changes in fuel efficiency relative to other vehicle characteristics. The use of survey data has become more prominent in studies of green innovation. Many of these papers use the Community Innovation Survey (CIS) as their starting point. CIS is a bi-annual survey of innovative European firms. Beginning in 2008, the CIS survey has included a block of questions on eco-innovation, following suggestions by Kemp and Pearson (2007) (Rogge and Schleich, 2018). The survey allows for more nuanced observation of eco-innovation. While patent data are more suited to studying product innovations, such as end-of-pipe pollution control or new energy technologies, survey respondents are asked about both product and process innovation. Moreover, unlike most studies using patent data, environmental benefits do not need to be the *primary* goal of a new product or process. The definition of eco-innovation used in the survey focuses on results. Thus, eco-innovations could be the unexpected result of other innovative activity (Hornbach *et al*. 2012).

2.2. Measuring environmental policy

To estimate the effect of environmental policy on innovation, measures of environmental policy are needed. Early empirical studies used pollution abatement control expenditures (PACE) to proxy for environmental regulatory stringency (e.g. Jaffe and Palmer, 1997; Brunnermeier and Cohen, 2003). Other studies focus on the relationship between prices and innovation, with the implicit link that more stringent environmental policy raises prices (e.g. Newell *et al*. 1999, Popp 2002).

A major advance in the environmental technology literature over the past decade has been a better understanding of the impact of different types of policy instruments. Studies have considered a wider range of policy instruments. Several studies use survey data to attain information on the types of policies faced (e.g. Hornbach *et al*. 2012, Veugelers 2012), policy relevance (Stucki *et al*., 2018), or policy consistency (Rogge and Schleich 2018). I review these studies in section 3.3. Aggregate policy effects can be assessed using outcome measures, such as emissions (Carrión-Flores and Ines, 2010; Carrión-Flores *et al*., 2013) or renewable energy investment (Peters *et al*. 2012, Dechezleprêtre and Glachant, 2014). For example, Carrión-Flores and Innes (2010) use simultaneous equations to link environmental innovation and pollution. They use industry-level panel data for 127 US manufacturing industries from 1989-2004. Because environmental policy is not directly observed across such a diverse range of industries, they model emissions as a function of unobserved environmental standards, which are themselves a function of technology (measured using patents), lagged policy, and a set of control variables. Patents are a function of unobserved environmental R&D and the control variables, while environmental R&D is a function of expected and current environmental standards. Substitution provides structural equations for both emissions and patents. Using dynamic General Methods of Moments estimation, they jointly estimate both equations. They find bi-directional flows between innovation and emissions: innovation leads to stricter environmental standards, and that anticipated increases in standards increase patenting.

Finally, new databases enable more researchers to directly include both the presence and level of specific policy instruments in their analysis, allowing for comparison of the impact of different instruments on innovation. Common data sources include the OECD Environmental Policy Stringency index (Botta and Koźluk 2014) and the International Energy Agency Renewable Energy Policy Database (IEA 2004). In some cases, continuous measures of stringency are available. For example, Johnstone *et al*. (2010) create continuous measures of the stringency of renewable portfolio standards and feed-in tariffs that have since been updated and made publicly available (OECD 2013). In other cases researchers use 0/1 dummies to indicate the presence of various policy options. Nesta *et al*. (2014) create a renewable energy policy index that counts the availability of eight different policies, arguing that a count of policies places additional weight on countries with diversified policy portfolios. Fabrizio *et al*. (2017) search the IEA Renewable Energy Policy database to find policies pertaining to energy storage, batteries, or electric vehicles. Using policy descriptions, they separate policies into those designed to increase demand (e.g. tax credits or financing incentives) and policies to support R&D efforts (e.g. research grants), creating 0/1 dummies for the presence of each type of policy.

3. General advances on innovation and environmental policy

Early studies of environmental induced innovation either used pollution abatement control expenditures (PACE) to proxy for environmental regulatory stringency or examined the effect of changing energy prices on innovation, providing evidence on how innovation will react to higher energy prices resulting from regulation. Examples of studies using PACE include Lanjouw and Mody (1996), Jaffe and Palmer (1997), and Brunnermeier and Cohen (2003). These studies typically found a correlation between PACE and innovation. Among the early studies on induced innovation and energy prices are Newell *et al*. (1999) and Popp (2002), both of whom document increased innovation following periods of higher energy prices.

During the past decade, researchers have extended this work in several directions. Several studies confirm the existence of induced innovation in different technological areas. Multiple studies look at innovation in the automobile sector. In the US, transportation was responsible for 28.5% percent of greenhouse gas emissions in 2016, exceeding the share from the electric power sector for the first time (US EPA, 2018). Transportation accounts for over 55% of nitrogen oxide (NO_X) emissions.[2] As such, innovation in this sector can play a significant role reducing several environmental problems.

[2] https://www.epa.gov/transportation-air-pollution-and-climate-change/smog-soot-and-local-air-pollution, accessed February 12, 2019.

Crabb and Johnson (2010) amend the model of Popp (2002) to consider variables appropriate for the automobile sector. They consider both the effects of expected oil prices and fuel economy regulations on US energy efficient automotive patents from 1980-1999. Unlike much of the existing literature, they use monthly, rather than annual, data. Knowledge decays more quickly but diffuses more slowly in the automotive sector than in the sectors included in Popp (2002). Higher prices spur innovation, with an estimated elasticity of 0.238 between oil prices and patents in their primary specification, but fuel economy standards themselves do not spur innovation.

Aghion *et al*. (2016) use firm-level patent data to explore innovation in the global auto industry. Their regressions run from 1986-2005, although they use data as far back as 1965 to construct pre-sample variables. They consider both clean and dirty patents pertaining to automobiles. Examples of clean technologies include electric and hybrid vehicles. Dirty patents pertain to internal combustion. Patents that improve the fuel efficiency of internal combustion engines are categorized as "gray", allowing for sensitivity checks on the coding of such patents. Higher fuel prices incentivize more innovation in clean technologies, with an estimated elasticity around 0.98 for just "clean" technologies (e.g. electric and hybrid vehicles), and an elasticity between 0.4 and 0.6 if including "gray" technologies (e.g. energy efficiency). Thus, their estimated elasticity for purely clean technologies is higher than Popp (2002) or Crabb and Johnson (2010), but similar in magnitude if they include energy efficiency patents, as those previous papers did. Once again, other policies (emissions regulation and R&D subsidies) have little effect on innovation.

Like Popp (2002), they consider both demand and supply side influences. Because they use firm-level data, they consider the effect of both a firm's own previous knowledge stock as well as spillovers from other firms. As most automobile firms are multinational, they include inventors from multiple countries. Spillovers are weighted by the geographic location of a firm's inventors – e.g. inventors in the US are more likely to be exposed to spillovers from other US inventors than from inventors in Japan. Unlike previous work, they interpret the effects of previous knowledge stocks as evidence of path dependency. Firms with previous clean technology innovation experience are more likely to continue to produce clean innovations, as are firms exposed to more clean technology spillovers. In contrast, access to more dirty spillovers both increases dirty innovation and reduces clean innovation. While these results are consistent with an interpretation of path dependency, it is also notable that a firm's own stock of dirty knowledge increases clean innovation (although with a magnitude less than half of that of the firm's clean knowledge stock). Thus, other interpretations of a firm's own knowledge, such as overall adaptive capacity of the firm (e.g. Cohen and Levinthal 1989), may also be consistent with the knowledge stock results in this paper.

While each of these papers use patents as a measure of technological progress, Knittel (2011) uses the relationship between fuel efficiency and vehicle characteristics to infer rates of technological progress. He models a vehicle's fuel economy as a function of weight, horsepower, and torque. Technological process is neutral in Knittel's main model. He observes that the average fuel economy of new US automobile passenger vehicles increased by less than 6.5 percent, while average horsepower increased by 80 percent from 1980-2004. Had weight, horsepower, and torque been held constant at their 1980 levels, fuel efficiency could have increased by nearly 60 percent. Consistent with induced innovation, the estimated effect of technological progress is largest in years with high gasoline prices. Whereas Crabb and Johnson (2010) find no effect of fuel efficiency standards on patenting, Knittel finds they have a positive effect on observed technological progress for cars, but not for trucks.

Turning from fuel efficiency to emissions control, Lee *et al*. (2011) consider how different types of regulation affect innovation for automobile emissions control technology. Using data for the US auto industry from 1970-2008, they ask whether performance-based technology-forcing regulations spur innovation. While command-and-control regulations are typically criticized for inducing less innovation, they note that regulations focused on performance standards allow flexibility as to how the performance targets are met. Moreover, designing targets that exceed current technological capabilities may encourage firms to innovate to meet new policy goals. Thus, stringency of regulation is important. Similar to studies using PACE, they measure stringency based on EPA cost estimates for automobile emission control devices, which they interact with several time period dummies to capture the effect of different policy regimes. Patenting is highest under the technology-forcing regulations of the 1970 and 1990 Clean Air Acts. Policy affects both auto assemblers and part manufacturers. Interestingly, the 1970 regulations spurred more innovation from US firms than foreign ones, but there is no such difference after the 1990 Clean Air Act. While their paper offers no welfare analysis of whether technology-forcing regulations are a better option than other policies, it does provide evidence that such regulations can inspire innovation for firms to comply with more ambitious targets.

Also pertaining to the transportation sector, Kim (2014) uses a panel of 12 countries from 1990 to 2012 to ask how a country's energy resource endowments affect innovation. She contrasts innovation on technologies designed to reduce fuel consumption in vehicles (such as fuel cells, hybrid and electric vehicles and energy efficiency) with innovation designed to enhance fuel supply (e.g. oil extraction and petroleum refining). As in other studies, higher gasoline prices promote innovation on automotive technologies. Higher gasoline prices also discourage innovation on oil extraction. However, countries with larger oil endowments perform less innovation on automotive technologies designed to reduce energy consumption. Interestingly, they also perform less innovation on petroleum refining technologies, primarily because much of the innovation on refining aims to improve the environmental performance of refineries. Thus, the energy endowments of countries may work against attempts to promote clean energy innovation through environmental policy.

Two papers, Noailly (2012) and Costantini *et al*. (2017), examine innovation for energy efficiency in the residential sector such as insulation, energy-efficient boilers, lighting, and building materials. In Europe, national building codes set energy requirements for new buildings.[3] Noailly (2012) studies the effect of these policies on innovation to improve energy efficiency in buildings. To control for energy prices, she constructs a weighted average of energy prices relevant for the residential sector – including electricity, natural gas, and petroleum –with weights corresponding to usage rates in each country. Whereas studies on the auto industry and on renewable energy find prices play an important role, here it is changes to the stringency of building codes that induce innovation. Energy prices are insignificant in all model specifications. This is consistent with the notion that market failures such as principal-agent problems reduce the impact of energy prices on residential energy consumption. Confirming this, Noailly notes that prices do have an effect on innovation for visible and portable technologies, such as boilers and lighting, but not for less-visible technologies such as insulation that are installed by builders and are not easily

[3] This differs from the US, where most building code regulations are at the state or local level.

modified. Her results provide support for continued use of building code regulations to address concerns about energy consumption in residential buildings.

Costantini *et al*. (2017) compare the effect of demand-pull policies, such as energy prices, technology-push policies, such as R&D subsidies, and "soft" instruments such as information provision and voluntary tools designed to increase consumer awareness of energy efficiency. Capturing soft instruments accurately illustrates the measurement challenges highlighted in section 2.2. Here, the authors collect data from the EIA data base on Energy Efficiency Policy and Measures (IEA, 2013). They use 0/1 indicators for the presence of three different types of policies (informational, institutional support, and voluntary approaches such as labeling). They aggregate these to get a single count of relevant "soft" policies in place for a given country and year. Because energy efficiency innovations may occur in a wide range of fields, they use a combination of keywords and IPC classes to identify relevant patents. While Costantini *et al.* find that demand-pull policies have a greater impact on innovation, unlike Noailly (2012), they do not include energy efficiency standards in their set of controls. Thus, their results cannot address the relative effectiveness of prices over building codes for residential energy efficiency. Soft and systemic policies have a smaller and less robust positive effect on innovation.

Lazkano *et al*. (2017) apply Aghion *et al*.'s (2016) empirical strategy to energy storage innovation, including its interaction with renewable and efficiency-improving fossil fuel innovation. Energy storage projects to be an important complement to intermittent renewable energy sources such as wind and solar. Compared to wind and solar energy, energy storage technologies are at an earlier stage of the technology life cycle, and this paper is one of the first to examine these technologies. Using firm-level data on internal and external knowledge for energy storage, renewable, and conventional energy storage, they ask how firm experience with energy storage innovation affects innovation across each of the three aforementioned energy types. Previous renewable energy innovation spurs additional energy storage innovation. Similarly, because it complements intermittent renewables, advances in energy storage help promote additional innovation on renewable energy sources such as wind and solar. Interestingly, energy storage also increases innovation that improves energy efficiency for fossil fuels, and the effect seems to be largest for what are known as "baseload" fossil fuels such as coal. These fuels are less likely to be replaced by renewable energy, which seems to explain this novel result.

Finally, a recent working paper by Gerarden (2018) emphasizes the importance of considering induced innovation when evaluating policy effectiveness. Gerarden analyzes the effect of consumer subsidies for solar panels. Such subsidies both increase demand for solar panels and encourage producers to innovate to reduce costs. By permanently reducing future costs, the benefits of induced innovation may extend be yond the life of a subsidy. Simulating the external benefits of German solar subsidies, he finds that accounting for induced innovation increases the benefits of these subsidies by at least 22%.

3.1. Where Does Green R&D Come From?

Another recently emerging area of empirical research on green innovation addresses the source of these innovations. Previous climate policy modeling work highlight the importance of this question. Using the ENTICE model, Popp (2004) begins with a base case that assumes one-half of new energy R&D crowds out other R&D. In this case, induced innovation increases welfare by 9%. Assuming no crowding out increases the welfare gains from induced innovation to as much as 45%, while assuming full crowding of R&D reduces welfare gains to as little as 2%. Gerlagh (2008) extends this work by separately modeling the choice of carbon-energy producing R&D, carbon-energy saving R&D, and neutral R&D. In such a case, it is carbon-producing R&D, rather than neutral R&D, that is crowded out by induced carbon-energy saving R&D. As a result, the impact of induced technological change is larger, with optimal carbon taxes falling by a factor of 2.

Given the range of possible outcomes depending on assumptions about crowding out, understanding the sources of green R&D is important. Gray and Shadbegian (1998) find that more stringent air and water regulations had a positive impact on paper mills' technological choice in the US, but that the increased investment on abatement technologies came at the cost of other types of productivity-improving innovation. Hottenrott and Rexhaüser (2015) find that regulation-induced environmental innovation crowds out R&D in other technologies, especially for small firms that are credit constrained. Because their data include both clean and dirty patents, Aghion *et al*. (2016) also contribute to the recent literature on where green energy innovation comes from. A 10 percent increase in fuel prices not only increases clean innovation by nearly 10 percent, but also reduces innovation on dirty technologies by about 6 percent.

Popp and Newell (2012) use patent and R&D data to examine both the private and social opportunity costs of climate R&D. Looking first at R&D spending across industries, they find that funds for energy R&D do not come from other sectors, but may come from a redistribution of research funds in sectors that are likely to perform energy R&D. Given this, they link firm-level patent and financial data to take a detailed look at climate R&D in two sectors – alternative energy and automotive manufacturing – asking whether an increase in alternative energy patents leads to a decrease in other types of patenting activity. They find evidence of crowding out. Interestingly, the patents most likely to be crowded out by alternative energy research are innovations enhancing the productivity of fossil fuels, such as energy refining and exploration. This is consistent with the notion that any apparent crowding out reacts to market incentives – as opportunities for alternative energy research become more profitable, research opportunities for traditional fossil fuels appear less appealing to firms.

Noailly and Smeets (2015) use patent data on both fossil fuel and renewable energy technologies for over 5000 European firms from 1978-2006. While Popp and Newell compare rates of patenting for different types of technologies, they do not consider how policy affects these rates. In contrast, Noailly and Smeets ask whether policy shifts innovation away from fossil fuels towards renewable energy – a test more directly in line with the modeling efforts of Gerlagh (2008). Following the directed technological change literature, they consider the role of energy prices, market size, and the existing knowledge stock. For renewable energy, market-size captures the effect of demand-pull policies. They make a distinction between "mixed" firms that have both types of patents and firms that specialize in one technology or the other. Using zero-inflated count data models allows them to study patenting behavior at both the intensive (rate of innovation) and extensive (decision to patent) margin. They find that increases in the share of renewable energy patents come primarily from entry of specialized renewable firms and exit of specialized fossil fuel firms. Both higher fossil fuel prices and increased renewable market size encourage renewable energy innovation. Among mixed firms, innovation remain largely concentrated in fossil fuel technologies.

Marin (2014) looks at a different aspect of crowding out, asking whether the returns to firms for environmental R&D are different than the returns from other types of R&D. Combining balance sheet and patent data for Italian manufacturing firms, Marin considers both the decision to do R&D and the effect of R&D on firm productivity. Environmental innovation leads to smaller productivity gains for firms, suggesting an indirect crowding out effect. However, Marin does not directly test whether greater investment in environmental R&D leads to less investment in other types of R&D.

Another important question pertaining to the source of clean R&D is who performs such R&D. Studying innovation in the US electricity market, Sanyal and Ghosh (2013) make a distinction between upstream technology suppliers and downstream buyers of technology. After deregulation of electricity markets in the 1990s, utilities reduced investment in equipment. Overall, innovation at equipment suppliers fell as a result. However, equipment suppliers who produce pollution abatement equipment increased innovation due to new Clean Air Act regulations.

Franco and Marin (2017) examine innovation in 13 manufacturing sectors across 8 European countries, making a similar distinction between upstream and downstream firms. The investigate both the weak and strong versions of the Porter Hypothesis, where the weak version hypothesizes that environmental regulation spurs new innovation, and the strong version hypothesizes that new innovation is sufficient to offset the costs of environmental regulation, so that overall productivity of regulated firms may increase after regulations are in place.[4] To address potential endogeneity between regulations, innovation, and productivity, Franco and Marin use patents in other sectors in the same country and patents in the same sector in other countries as instruments. They find evidence for both the weak and strong versions of the Porter Hypothesis, as stringency of environmental regulations not only increases innovation, but innovation also mediates the potential negative effects of environmental regulation on productivity. The effect is strongest for regulations affecting downstream firms. In contrast, regulations on upstream sectors constrain innovation and thus have a negative impact on productivity. This work highlights that both direct and indirect effects of environmental regulation are important.

3.2. Identification of policy effects on innovation

Increased availability of firm-level data allows researchers to identify the effects of policy using quasi-experimental methods, comparing firms above and below regulatory thresholds. However, as the discussion on who performs clean R&D suggests, careful interpretation of such studies is warranted, as environmental policy need not only induce innovation at regulated firms

For example, Calel and Dechezleprêtre (2016) take advantages of criteria for inclusion in EU-ETS to develop a matched set of regulated and unregulated firms. Inclusion is based on individual plant characteristics, not firm characteristics. Using firm-level data on innovation, they compare low-carbon innovation in firms that have at least one plant covered by EU-ETS to a matched control group of firms with no such plants. They find matches for 3,428 of the 5,568 regulated firms in their data set. Regulated firms have 36.2% more low-carbon patents than unregulated firms. However, because these firms are a small subset of all firms, this results in just a 0.38% increase in low-carbon patents for the EU as a whole.

[4] While the induced innovation studies reviewed here provide evidence related to the weak Porter Hypothesis, evaluating the strong Porter hypothesis requires data linking environmental regulation to firm performance. Such studies are beyond the scope of this review. Cohen and Tubb (2018) provide a recent review and meta-analysis.

Because innovation in response to environmental regulation also occurs at upstream equipment manufacturers (e.g Sanyal and Ghosh 2013) and at new entrants to the market (e.g. Noailly and Smeets 2015), economy-wide studies of innovation, such as those using country-level patent data, will capture these innovations, while firm-level studies may not. Calel and Dechezleprêtre acknowledge this possibility and address it indirectly by studying jointly filed patents that include regulated and unregulated firms. Low-carbon patents at the unregulated co-inventors experienced no increase after EU-ETS. However, they do not look at downstream suppliers specifically.

Two recent working papers provide preliminary evidence on the potential magnitude of these additional patents. Miller (2014) notes that innovation could occur both at upstream suppliers and at downstream users of technologies. For example, if EU-ETS leads to higher electricity prices, users of electricity may innovate to improve energy efficiency and reduce electricity consumption. Miller estimates that simply focusing on the direct effect of innovation by regulated firms underestimates induced innovation from EU-ETS by 71%. Calel (2018) argues that imperfect appropriability makes the returns to innovation greater for treated firms than non-treated firms, so that the induced innovation should be larger for treated firms. However, his theoretical model does not distinguish equipment users from suppliers. In his empirical work, Calel compare patent counts from EU-ETS regulated firms and the top 100 non-ETS innovators. Both types of firms see an increase in patenting after EU-ETS. However, only if all of the increase in patenting from top innovators was attributable to the EU-ETS would the aggregate effect on innovation be as large as found by Miller (2014). These studies suggest there is still much work to be done to understand the drivers through which policy induces innovation. While quasi-experimental studies of treated effects offer valuable evidence on the effects of environmental regulation on firm performance, for studies of innovation it is important to remember that directly treated firms aren't necessarily those who innovate in response to new regulation. Complimentary studies, such as surveys of innovative firms, can help identify process innovations that may benefit treated firms but that firms may not choose to patent, as well as offer a better understanding of how regulations faced by downstream consumers affect innovation. I turn to studies using survey data next.

3.3. Survey data

Given the challenges measuring research efforts and output, several papers use surveys of innovative firms to assess green innovation. Many of these papers use the eco-innovation questions in the Community Innovation Survey (CIS), described in section 2.1, as their starting point. Hornbach *et al*. (2012) and Veugelers (2012) are among the first papers to make use of the eco-innovation survey in CIS. Hornbach *et al*. (2012) uses data from the 2009 German CIS. They ask whether different types of eco-innovations, such as process innovations or end-of-pipe pollution control, arise from similar or different motivations. Not surprisingly, regulation is a more important driver of eco-innovations than for other types of innovation. The marginal effects of regulation on eco-innovation are highest for end-of-pipe emissions reduction. Within eco-innovations, cost savings, rather than regulation, are the main motivation for energy saving innovations. Subsidies are important for reducing CO_2 emissions. The authors note that reducing CO_2 emissions was still a relatively young innovation area at that time, so that public research subsidies were important. Customer demand is an additional motivation for eco-innovation, particularly for products. Looking at how eco-innovations affect firm results, innovations that reduce material consumption lead to higher turnover, whereas energy savings increase short run costs, and thus reduce short run turnover.

Demirel and Kesidou (2011) also address the distinction between product and process innovation. They use a 2005-06 survey of 289 United Kingdom firms carried out by the Department for Environment, Food and Rural Affairs. The survey distinguishes between end-of-pipe eco-innovation, integrated process innovation, and environmental research and development. Note that positive firm responses to the first two may be evidence of technology adoption, rather than invention. Their results suggest a U-shaped relationship between regulation and innovation. In response to regulation, firms are more likely to choose either low cost adoption of existing technology or innovation to find a better solution, but are not more likely to invest in integrated process innovations. As in other studies, cost savings are the main driver of process innovations. Environmental taxes have no effect on any category of eco-innovation, which they argue may be because of the low tax levels used in the UK.

Veugelers (2012) examines data from the 2006-2008 Flemish CIS eco-innovation module. She uses the data to compare the influence of environmental regulation and taxes to R&D subsidies. Interestingly, voluntary sectoral codes of practice agreed upon between regulators and polluters and existing or expected demand from consumers are the most important drivers of eco-innovations. Regulations and taxes are more important for promoting adoption, rather than innovation, of clean technology. While government subsidies are generally less important, like in Hornbach *et al.*, they appear more important for reducing CO_2 emissions, supporting the finding that subsidies are more important for emerging technologies. Veugelers concludes that her results remind policymakers of the importance of the "private innovation machine," which governments must leverage to successfully promote eco-innovation.

Costa-Campi *et al*. (2015) use survey data spanning 2008-2011 from the Technological Innovation Panel (PITEC), which provides data on Spanish firms to determine factors encouraging these firms to pursue energy efficient innovation. Because energy efficiency improvements may involve process innovation, and because energy efficiency spans a range of technological areas (e.g. more efficient lighting, better building design), survey data can provide information not likely identified by simply using patent data. Energy efficient innovation appears to be connected to broader technological improvements embodied in capital, as capital spending predicts energy innovation, but neither internal nor external spending on R&D does. Larger firms are more likely to consider energy efficiency innovation important, as are firms that consider environmental impacts to be an important innovative goal. Firms perform energy efficient innovation t meet legal requirements, but public R&D subsidies have no impact.

Survey data allow a better understanding of the decision-making process of firms. Moreover, by asking about the *perception* of environmental regulation, such surveys allow a more nuanced look at the effects of regulation on innovation than simple measures of policy stringency. Rogge and Schleich (2018) exemplify how survey data provides information on policy nuances not available otherwise. They designed their own survey instrument, using the German Community Innovation Survey as a starting point. They consider not only the mix of policy instruments used, but also the credibility, consistency, comprehensiveness, and coherence of policy instruments. In their work, consistency considers how well different elements of the policy mix align; credibility addresses the extent to which the policy mix is believable; comprehensiveness considers how extensive and exhaustive the mix of policies is; and coherence considers whether policy making and implementation are synergistic. Their data include responses from 390 German energy companies, all received in 2014. Both the consistency and credibility of policy is important, suggesting that innovators need strong political signals. Regarding the types of policy instruments used, both technology push (via public R&D support) and demand pull (represented by expected increases in green sales) encourage more green innovation.

Cecere *et al*. (2019) use survey data to understand how technological opportunities affect green innovation. They construct a firm-level panel data set that combines survey data from the Mannheim Innovation Panel (MIP) with patent data from the European Patent Office. MIP is based on the Community Innovation Survey for Germany. Unlike Community Innovation Surveys in other countries, it is conducted annually. Cecere *et al.* include firms with at least one information and communications technology (ICT) patent from 1992-2009. They use patent data to identify fields with high and low innovation potential, based on whether patents in the field are still growing. Separating ICT innovation into "Green" ICT and "Pure" ICT, firms with at least one patent in high opportunity fields the previous year are more likely to have a Pure ICT patent the following year. Thus, high-opportunity firms stay in their technological domain, making them less likely to switch to green innovation. In contrast, firms in low-opportunity areas are less likely to innovate, but more likely to change direction towards green innovation. This raises an interesting policy conundrum that is not explored by Cecere *et al*. Policy efforts to encourage green innovation are more likely to affect the research direction of firms currently working in low-opportunity areas. But, does the fact that these firms were in low-opportunity areas suggest they are less likely to produce high-impact research?

In sum, increased use of survey data to study green innovation has allowed a more nuanced look at the effects of policy on green innovation. Direct regulation appears more likely to stimulate end-of-pipe innovation than process innovation. This may suggest new policy instruments are needed to encourage firms to think more about reducing the creation of pollution, rather than end-of-pipe treatment. By providing evidence on firm perceptions, these surveys also illustrate the importance of policy consistency. In turbulent political times, providing signals of such consistency will be an important challenge for governments to address. More research on *what features* of policy make it consistent and credible will be important for this effort.

4. Cross-country studies of green innovation

Two topics on green innovation in particular have received significant attention over the past decade. One is an increasing number of studies with an international dimension. In this section I summarize the contributions of this work. A second is the effectiveness and choice of various policy instruments. I discuss research on policy instruments in sections 5 and 6.

Many early studies of green innovation focused on a single country, often the United States. Expanding data to include multiple countries helps verify the applicability of results across a range of economic conditions. For example, Ley *et al*. (2016) compares the effect of energy prices on "green" and "non-green" innovations.[5] Their study includes both multiple technologies and multiple countries. Because they calculate industry-specific energy prices, they can include country-specific time fixed effects to control for country-specific shocks that may be correlated with both innovation and energy prices. They show that omitting such effects biases the effect of

[5] They use the OECD Indicator of Environmental Technologies (OECD 2012) to identify green technologies in seven different environmental areas.

energy prices downward. A 10 percent increase in average energy prices over the previous five years leads to a 3.4% increase in green inventions, and a 4.8% increase in the ratio of green to non-green inventions.

By providing more variation in the types of policy instruments used, studying multiple countries allows researchers to compare the effectiveness of different policy instruments, as explained in greater detail in section 5 (e.g. Johnstone *et al*. 2010). Cross-country studies also raise questions specific to an international context. In this section I discuss two such questions: the relative influence of domestic and foreign environmental policies on innovation and the role of knowledge spillovers and technology transfer across international borders.

4.1. Domestic vs. foreign environmental policies

Most early work on environmental innovation focused on the effect of domestic environmental policies – e.g. policies enacted where innovation takes place. One early exception is Popp (2006), which examined the effect of SO_2 and nitrogen oxide (NO_X) regulations in the US, Japan, and Germany. While innovation responds to domestic, rather than foreign policy changes across these three countries, the study focuses on just three countries, each of which are leaders in the pollution control field. More recent work considers a larger range of countries and provides evidence for when foreign policies matter.

Dekker *et al*. (2012) study the effect of international agreements on innovation. Using a difference-in-differences specification, they ask whether innovation for sulfur dioxide (SO_2) abatement technologies increases in countries that sign the Helsinki and Oslo protocols. Acknowledging the cross-border nature of SO_2 pollution, both protocols committed signatories to significant SO_2 emission reductions. However, not all major polluters signed the protocols, with Japan, Poland, the UK and US being notable exceptions. Innovation does increase in signatory countries just prior to and in the year of signing the protocol. As in Popp (2006), the increase in innovation does not appear to be permanent, however. Such a result is consistent with the notion that command and control regulations setting specific targets temporarily increase innovation to meet new targets, but do not incentivize continued improvement. Local regulations in Germany also encourage innovation, but the advent of the 1990 Clean Air Act in the US did not spur innovation in the US. The authors argue that is because the largest innovator in SO_2 control technologies at that time was Japan.

Two recent studies compare the effect of domestic and foreign environmental policy for renewable energy. In a study of 15 OECD countries using patent data form 1978 to 2005, Peters *et al*. (2012) 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, but that technology-push policies such as R&D subsidies only affect domestic innovation. To address potential endogeneity for solar PV R&D subsidies, they use public R&D funding for other renewable technologies as instruments. In contrast, Dechezleprêtre and Glachant (2014) compare wind energy patents across OECD countries, using data from 1991-2008. Their observations are country pairs, as they look at both the source (e.g. where patents are filed from) and destination (e.g. where patents are granted) of invention. While both domestic and foreign demand-pull renewable policies positively affect renewable technology innovation, the marginal effect of policies implemented at home is 12 times higher. However, since the foreign market is much larger than the domestic market across the sampled countries, the overall impact of foreign policies is on average twice as large as the overall impact of domestic policies on innovation. They note that both trade barriers and weak intellectual property rights dampen the influence of foreign policies on wind energy patenting in a given country.

A working paper by Fu *et al*. (2018) find similar results comparing wind innovation across US states. Their work includes indicators for different policy types, such as tax incentives and renewable portfolio standards. They consider both the effect of own-state policies and a spatially weighted average of policies in other states. Policy type matters. For renewable portfolio standards, the overall level of policy in the US induces innovation. However, for financial incentives such as tax incentives and subsidies, it is own state policy that increases innovation. The authors argue that this is because suppliers must live in the state to take advantage of state-level tax incentives. However, because of the relative market sizes, the marginal effect of own-state financial incentives on innovation is smaller than the marginal effect on other-state renewable portfolio standards. Thus, market size appears most important for spurring innovation.

Fabrizio *et al.* (2017) compare the effect of policy on domestic and foreign innovation for energy storage. Combining data on energy storage policies in 11 OECD countries from 1990-2011 with data on energy storage patents from 61 countries during the same time frame, they show that demand-pull polices both promote domestic innovation and increase technology transfer coming into the country, measured as domestic patent applications filed for technologies that originally filed for patent protection elsewhere. Unlike the aforementioned papers, their sample includes patents from countries not directly regulating energy storage, showing that increased innovation from environmental policy may come from abroad. In contrast, technology-push policies promote domestic innovation, but do not increase technology transfer.

Using data on green patents from a set of 1200 multinational corporations (MNCs), Noailly and Ryfisch (2015) consider the globalization of green R&D. For the MNCs in their sample, about 17% of green patents result from R&D investments outside of the MNCs home country. In most cases, green R&D not performed at home occurs in other OECD countries, although China is also an important destination, particularly for lighting and solar technologies. Stringent environmental regulation attracts green R&D to a country, but so do lower wages for scientists and engineers and strong intellectual property protection.

Finally, a working paper by Brunel (2018) asks whether environmental regulation stimulates domestic economies, using innovation as a driving mechanism. She first estimates the effect of environmental policy on innovation, and then considers how the resulting innovation affects manufacturing production. She distinguishes between new inventions (those never filed anywhere else before) from transfers of existing technology (e.g. patents previously filed abroad). While environmental policy increases patent filings by about 30 percent, these patent filings are mostly transfer of existing foreign technology. The exception is in the leading innovative countries of the US, Japan, and Germany. These results suggest that early innovators have a first mover advantage, and that the innovative capacity of a country is just as important as policy support. Brunel then asks how technology adoption affects renewable energy imports and exports. Using gravity equations for each, she shows that a one percent increased stock of renewable energy patents leads to a 0.146 percent increase in exports, with no effect on imports. Patents coming from abroad appear to be filed to protect local production, rather than imports. Thus, for most countries, renewable energy policies stimulate the economy through manufacturing, rather than through innovation.

In sum, these studies comparing the influences of domestic and foreign policy illustrate that demand is important, but also global in nature. Market size matters, so that while demand-side policies promote innovation, the resulting innovation need not occur at home. In contrast, supply-side policies, such as R&D support, tend to favor local inventors. These distinctions are important for policy makers who often promote clean technology policies as a way to create new, high paying jobs for the local economy.

4.2. Knowledge spillovers across countries

Knowledge spillovers across countries are another important issue for cross-country studies to address. Such spillovers are a form of technology transfer. However, unlike direct production (as in the aforementioned paper by Brunel) or imports of technology into a country (e.g. embodied technology transfer), flows of knowledge across countries represent disembodied technology transfer. These knowledge flows help recipient countries gain the know-how or experience needed to improve productivity and innovate on their own. For countries that are not first-movers in green technology, they can be an important entry point into green innovation.[6]

The aforementioned Dekker *et al*. (2012) study on international agreements also provides evidence of technology transfer. Dekker *et al*. distinguish between “mother” patents and patent families. Patent protection is country-specific. Inventors must file for protection in each country where they wish to enforce their patent rights. Mother patents (often referred to as priority patents) represent the first filing to protect an idea in any country. Family patents represent related filings of the same idea in other countries. Dekker *et al*. observe increases in both mother patents (e.g. local innovation) and patent families in countries signing the Helsinki and Oslo protocols. The increase in patent family filings show that inventors from other countries are more likely to file patent applications in a given country when regulation provides a market for their technologies. Thus, regulation leads to both new innovation and technology transfer of new innovations from other countries.

Verdolini and Galeotti (2011) extend Popp’s (2002) induced innovation framework to a panel of 17 countries. Adopting methods from Peri (2005), they create external and internal knowledge stocks for each country. Internal knowledge stocks are a function of previous patents in the country. External stocks represent knowledge produced abroad that cross into the country. For a set of energy efficient and environmentally friendly technologies similar to those first studied in Popp (2002), they use patent citation data to model the probability that a patent from country *j* receives a citation (and thus crosses into) country *i*. Interestingly, and in contrast to studies in other technological domains, once knowledge crosses a country border, increased physical distance does not reduce the probability of citation. However, increased technological distance does, where technological distance measures similarities in the types of patents granted in each country pair.

Verdolini and Galeotti then include these knowledge stocks in an induced innovation regression that also considers the role of energy prices, environmental policy, and public R&D spending on green innovation. Knowledge stocks play an important role. A 10% increase in domestic knowledge increases patenting by 3%, and a 10/% increase in foreign knowledge increases patenting by 9.6%. Thus, foreign knowledge spillovers are particularly important. In

[6] Popp (2011) provides a more complete review of international technology transfer as it relates to green technology.

contrast, a 10% increase in the energy price index increases patenting by just 6%. Interestingly, when splitting the sample into top five innovators and other countries, the effect of domestic and foreign knowledge is similar for the top five innovators, whereas the impact of foreign technologies is even larger for other countries.

Building on this work, Stucki and Woerter (2017) ask whether technological followers might benefit from a "wait-and-see" strategy whereby they wait for knowledge spillovers to close the gap between themselves and technology leaders. If possible, countries could avoid locking in higher cost green technology inventions. They distinguish between two impacts of available knowledge. Knowledge spillovers stimulate current innovation. At the same time, accumulating knowledge in a specific technological domain may reduce a firm's flexibility, leading to path dependency. For instance, firms with substantial non-green knowledge bases may find it difficult to switch to green innovation when market conditions change. Their data span 22 manufacturing industries for 13 countries from 1980-2009. Their dependent variable is the green technology gap between industry *i* in country *j* and the technology leader in industry *i*. The technology gap is measured as the log of the ratio of green patents in the leader country over green patents in country *j*. Increases in both an industry's internal stock of green patents the overall stock of green patents in the country reduce the technology gap, suggesting that positive spillover effects are important. However, an increase in foreign green knowledge increases the technology gap. Thus, Stucki and Woerter's results suggest that while foreign spillovers may enhance innovation, they do not enable late movers to catch up to technology leaders. A wait-and-see strategy does not appear beneficial.

Given the importance of international spillovers, Conti *et al*. (2018) ask whether policy can provide coordination among countries. Using patent citations to track knowledge spillovers, they show that renewable energy innovation in the European Union has become more integrated over time. The probability of citations between EU countries increase over time, while domestic patent citations fall. This pattern is not observed for fossil-fuel based energy sources, nor is it observed for other emerging technologies such as IT or biotechology. Thus, their findings provide suggestive evidence that EU policy support for renewables helped reduce fragmentation in renewable energy innovation in individual member states. However, they caution that the EU renewable energy innovation system remains more geographically localized than the US or Japan, so that more work remains to be done.

Knowledge spillovers may also come from related industries. Grafström (2018) considers both spillovers within the wind power industry itself and from related machinery fields. Using patents from 8 European countries from 1978-2008, he finds evidence of international spillovers from both other country's wind inventions and inventions in related fields (e.g. machines with rotors or pumps). However, Grafström does not present results with both wind and related machinery knowledge included in the same regression, likely due to collinearity concerns. Thus, the results for each knowledge stock do not control for any potential relationships in innovation in these two related fields.

5. Policy instruments

Policymakers have a range of instruments available to regulate environmental quality. Command-and-control regulations direct a specific level of performance. For instance, performance standard sets a uniform control target for firms (such as pounds of sulfur dioxide emissions per million BTUs of fuel burned), but do not dictate how this target is met. Technology-based standards specify the method, and sometimes the actual equipment, that firms must use to comply with a particular regulation, such as requiring that a percentage of electricity be generated using renewable sources. Market-based policies establish a price for emissions, either directly through the use of fees, such as a carbon tax, or indirectly through the use of permits that can be bought and sold among firms, such as in the US SO_2 market or the European Union's Emission Trading System for carbon.

Historically, economists have argued that market-based policies provide greater incentives for innovation. Market-based policies provide rewards for continuous improvement in environmental quality, whereas command-and-control policies penalize polluters who do not meet the standard, but do not reward those who do better than mandated (Magat 1978, Milliman and Prince 1989, Fischer *et al*. 2003). However, more recent research suggests that the effects are more nuanced. Simply getting the prices right by accounting for environmental externalities is not sufficient to promote green innovation. Looking at renewable energy policy, recent theoretical models by Fischer *et al*. (2017) and Lehmann and Söderholm (2018) explore the role of other market failures justifying targeted renewable energy support policies as part of a menu of policy solutions. For example, to promote the development of electric vehicles, charging stations must be in place. However, the private sector has little incentive to provide charging stations without existing demand from electric vehicles. In the case of such network externalities, clear technology standards provide guidance to firms as to the expected future direction of technology (Vollebergh and van der Werf, 2014). I discuss evidence on potential market failures supporting targeted policy support in section 6. Here I focus on studies comparing the effectiveness of different policy instruments.

Given the ambiguous predictions of theoretical models, empirical evidence on the effects of various market instruments on innovation is important. Early studies suggest differences between policies matter, even among market-based policy options. Johnstone *et al*. (2010) compare price-based policies such as tax credits and feed-in tariffs to quantity-based policies such as renewable energy mandates and find important differences across technologies. Quantity-based policies, such as renewable energy certificates, favor development of wind energy. Of the various alternative energy technologies, wind has the lowest cost and was closest to being competitive with traditional energy sources during their study period. As such, when faced with a mandate to provide alternative energy, firms focus their innovative efforts on the technology that is closest to market. In contrast, direct investment incentives are effective in supporting innovation in solar and waste-to-energy technologies, which are further from being competitive with traditional energy technologies. This result suggests that even policies purporting to be technology neutral, such as renewable energy mandates, can favor one technology over another.

Building on the work of Johnstone *et al*. (2010), several studies use data on specific policies to explore the effectiveness of different policy types. Fabrizi *et al.* (2018) use a country-level panel of green patents in 23 European countries from 2003-2012. Using the OECD Environmental Policy Stringency index, they create separate indicators for market-based and non-market-based policies. While market-based policies consistently induce greater innovation, the effect of non-market-based policies is generally insignificant. Using a panel of Norwegian firm-level data on patents and environmental regulations faced by each firm, Klemetsen *et al*. (2018) show that direct command-and-control innovation can spur innovation if the costs of non-compliance are meaningful. They create a measure of the implicit costs of regulation based on firm-level data on annual emission permits, inspections, and violations. Firms with more serious violations – and thus in greater danger of being sanctioned – create more green innovations. Kim *et al*. (2017) use data from 16 OECD countries from 1991-2007 to estimate a system of equations identifying the effectiveness of demand-pull and technology-push policies on wind and solar innovation. They estimate equations for patenting activity, per-unit installed system cost, and cumulative installed capacity, which allows them to simulate the effect of policies on both innovation and diffusion. Technology-push policies both encourage short-run invention and lead to long-run cost reductions. Price-based policies such as feed-in tariffs perform better than quantity-based policies in the long-run, by encouraging cost reductions over time

Reichardt and Rogge (2016) provide a case study of offshore wind innovation in Germany. Their interviewees suggest that feed-in tariffs were the most important policy supporting offshore wind development. As offshore wind is more expensive than onshore wind, this is consistent with Johnstone *et al*.'s finding that direct financial support is more important for technologies further from the market. Using US time series data, Horner *et al*. (2013) find that renewable portfolio standards increased wind innovation, but that tax-based incentives did not. Böhringer *et al*. (2017) use a panel of patent data for 7 different renewable energy technologies in Germany from 1990-2014. Variation in feed-in tariff rates over time allows them to compare the effect of feed-in tariffs across technologies. Their model does not allow them to compare policy instruments, but rather the magnitude of effectiveness of a single instrument (feed-in tariffs) across different technologies. In their data, wind, rather than solar, experiences the greatest increase in innovation from feed-in tariffs. To assess the importance of the relative mix of policies in a country, the aforementioned Costantini *et al*. (2017) create a measure of policy mix *balance* between demand-pull and technology-push policies and a measure of *comprehensiveness* as the stock of total policies divided by the sum of policy instruments (e.g. are all types of policy instruments represented). Both policy balance and comprehensiveness enhance innovation for energy efficiency.

Two studies consider the role of energy market of market liberalization on innovation. Jamasb and Pollitt (2011) examine descriptive data on patenting in the UK electricity sector, showing that patents for non-nuclear electricity and renewable technologies increased after market liberalization. Nesta *et al*. (2014) ask how market liberalization affects the impact of renewable energy policies on innovation. They create indices for both renewable energy policy and electricity market deregulation, using data from the International Energy Agency (2004) and OECD, and address potential policy endogeneity using both in-sample instruments (e.g. two-year lags of policies) and out-of-sample instruments (age of democratic institutions and share of decentralized energy before liberalization). They find that renewable energy policy and deregulation are complementary – renewable policies induce more innovation in countries with liberalized energy markets.

In addition to policy, firms may pursue environmental protection voluntarily, either in response to perceived consumer pressure or to deter future regulation. Carrión-Flores *et al*. (2013) consider whether the US Environmental Protection Agency's 33/50 program increased environmental innovation. Soon after publicly releasing the Toxic Release Inventory (TRI) database, the EPA created the 33/50 program to encourage the largest polluters to voluntary reduce pollutants by 33 percent in 1992 and by 50 percent by 1995. Using the same simultaneous equations model as Carrión-Flores and Innes (2010), described in section 2.2, they find short-run run increases in environmental patenting among participating firms. However, several years after the program's end, participating firms had fewer environmental patents. The cumulative effect over the entire 11 year period is negative – participating firms were, overall, less innovative than non-participating firms.

Popp *et al*. (2011) use pulp and paper manufacturing to ask whether pressure from consumers for green goods can spur innovation. Efforts to reduce chlorine usage in the bleaching stage of pulp production grew rapidly in the 1990s, after a Greenpeace studies linking dioxin from bleaching process raised awareness of chlorine persisting in paper products after manufacture. The first wave of innovation on technologies to reduce chlorine use occurred before regulations requiring the use of these technologies, suggesting consumer pressure does play an important role. In contrast, product labeling schemes promoted by many countries produced little innovative response. Perhaps because labeling schemes are voluntary, these schemes appear to incorporate existing technologies in their criteria, rather than serving as technology-forcing standards. Regulation in Sweden and Finland did produce a second wave of innovation to perfect these technologies. In contrast, the US and Canada delayed regulation, and appeared to develop regulations based on the availability of existing technologies. Their regulations did not induce new innovation. Thus, regulatory stringency is important.

Kesidou and Demirel (2012) ask how corporate social responsibility (CSR) affects levels of environmental R&D. Using UK survey data, they consider consumer demand for green products, implementation of voluntary environmental management systems, and stringency of environmental regulations. Using a selection model, they find that consumer demand and CSR initiatives work at the extensive margin only – they affect the firm decision to do environmental R&D, but do not increase the level of environmental R&D. In contrast, firm environmental management initiatives affect both intensive and extensive margins. Using quantile regressions, they find that environmental regulation spurs innovation among both the least and most innovative firms, but has less impact on other firms. Instead, the potential of cost-savings spurs environmental innovation among those firms in the middle quantiles.

In sum, the evidence on innovation based on voluntary environmental performance is mixed. Popp *et al*. (2011) find that concerns about negative consumer pressure initiated an initial wave of innovative activity to reduce residual chlorine in manufactured paper products, and Carrión-Flores *et al*. (2013) observe an initial wave of innovation after the US EPA's 33/50 program began. But these effects are short-lived, and cost-savings, rather than corporate social responsibility, are the main drivers of environmental innovation in Kesidou and Demirel's (2012) work.

6. Should policy be technology-neutral or technology-specific?

In addition to choosing from an array of environmental policy instruments, policy makers must also determine the relative balance between policies designed to address environmental market failures (e.g. externalities) versus those designed to address knowledge market failures. As noted earlier, environmentally friendly innovation suffers from two market failures: environmental externalities and knowledge spillovers. Knowledge *spillovers* provide benefit to the public as a whole, but not to the innovator. As a result, private firms do not have incentives to provide the socially optimal level of research activity. Economists studying the returns to research consistently find that knowledge spillovers result in a wedge between private and social rates return to R&D,

suggesting that socially beneficial research opportunities are ignored by firms because they are unable to fully capture the rewards of such innovations.[7]

An important policy question is whether targeted policies addressing knowledge market failures specifically for green innovation are necessary. Because knowledge market failures apply generally across technologies, can these market failures be addressed by economy-wide policies, leaving it to environmental policy to "get the prices right" to encourage green innovation? Or, are there other market failures specific to green innovation that require targeted policies?

Three recent applied theoretical papers provide guidelines for when targeted policies may be needed. Lehmann and Söderholm (2018) present a partial-equilibrium model of the electricity sector that illustrates when targeted, rather than technology-neutral, renewable energy policies are justified. This model provides the framework for a review of existing literature to determine when evidence supports such policies. Their work highlights the importance of additional market failures, such as:

- Learning-by-doing, which justifies additional deployment policies to hasten technology development
- Path dependency, where switching costs lead to lock-in of established technologies
- Capital market failures, such as risk aversion, that limit the amount of private capital available for renewable energy

Fischer *et al*. (2017) model technology choice in the US electricity sector. They extend the work of Fischer and Newell (2008), allowing for additional details such as improved energy efficiency and distinguishing between "conventional" and "advanced" renewable energy sources to capture differences in costs and innovation potential. Their results suggest governments should supplement broad-based polices with limited subsidies for technologies furthest from the market. Such subsides will be most effective if they target other market failures. For example, if learning-by-doing is important, the experiences of early entrants provide lessons for future technology development, suggesting subsidies for emerging technologies would help. R&D subsidies help lower future costs and are particularly valuable when knowledge spillovers are high. Their simulation results suggest R&D market failures are more important than learning-by-doing, so that R&D spending is more effective than targeted deployment policies. However, current policy efforts favor deployment schemes justified through learning-by-doing.

Acemoglu *et al*. (2016) present an endogenous growth model with both clean and dirty technologies. Their model emphasizes the technology-push role of science policy. Innovation provides new research opportunities that stimulate future innovations. If the clean technology is far behind, initial R&D subsidies are needed to make private R&D on clean technology profitable. This may be due to path dependencies and to the potential for higher returns to research for a still emerging technology.

As all three papers highlight cases when targeted support for renewables is justified, either though deployment support or increased R&D spending, evidence from empirical studies is

[7] Examples of such studies include Mansfield (1977, 1996), Pakes (1985), Jaffe (1986), Hall (1996), and Jones and Williams (1998). Typical results include marginal social rates of return between 30 and 50 percent. In comparison, estimates of private marginal rates of return on investments range from 7 to 15 percent (Bazelon and Smetters 1999, Jones and Williams 1998, Hall 1996).

important to guide policy decisions. Below I review evidence on each of the potential knowledge market failures mentioned above: differential spillovers from green R&D, spillovers from learning by doing, path dependency, and potential capital market failures.

6.1. Spillovers

Government investment in R&D is justified by the high social returns to R&D investment. However, this is true for all technologies, not just green technologies. Thus, an important question becomes whether spillovers from green innovation are larger, so that government R&D should play a *larger* role for green technologies. Here I review empirical literature relevant to these concerns.

Several recent papers use patent citations to study spillovers from energy innovations. Patents contain citations to earlier patents that are related to the current invention. The citations are placed in the patent after consultations among the applicant, his or her patent attorney, and the patent examiner. Citations received by a patent, known as *forward citations*, indicate that the knowledge represented in the patent was utilized in a subsequent invention. These citations can be seen as evidence of knowledge flows, and thus potential spillovers. Similarly, *backward citations*, or citations made to earlier parents, provide evidence of the building blocks of knowledge used in creation of a new invention.[8]

Spillovers from energy research need not only benefit future energy researchers. Nemet (2012a) uses patent citations to study inter-technology knowledge flows for energy patents granted between 1976 and 2006. He uses forward citations as a measure of quality and backward citations to determine the fields upon which patents draw inspiration. A citation is considered "external" if it is to a patent in a different technical classification. Energy patents with more backward citations to external patents receive more forward citations within the 10 years after patent issue, suggesting that such patents provide greater social value. Notably, most forward citations come from non-energy patents, suggesting that energy research has general application. However, Nemet does not provide similar analysis for non-energy patents, and thus cannot determine whether energy patents are *more* general than other innovations.

A working paper by Dechezleprêtre *et al*. (2017) addresses this question by comparing the magnitude of knowledge spillovers from clean and dirty technologies in electricity production and the transportation sectors. They find evidence that clean patents generate larger knowledge spillovers than the dirty technologies they replace. Moreover, the magnitude of knowledge spillovers in clean technologies is comparable to other emerging technological fields such as IT or nanotechnology. Popp and Newell (2012) find similar evidence, comparing alternative energy patents to other patents from the same firms. Alternative energy patents are cited more frequently and are more general than all patents in all technologies except computers.[9] The results of both

[8] The key assumption here is that a citation made to a previous patent indicates a flow of knowledge from the cited patent to the citing patent, so that patents cited more frequently are considered more valuable to future inventors. Jaffe, Fogarty, and Banks (1998) investigate the validity of this assumption, using evidence from citations made to NASA patents. They conclude that, although there is noise in the citation process, aggregate citation patterns represent knowledge spillovers, although the spillover may be indirect.

[9] Generality is measured using a Herfindahl index of the various patent classes cited by the patent.

papers provide support for public R&D funding of clean technologies, as underinvestment due to knowledge externalities might be particularly high these technologies.

Bjørner and Mackenhauer (2013) provide contrasting evidence, using data on Danish companies from 2000-07. Rather than simply focusing on patent citations, they use survey data to estimate stocks of knowledge related to R&D spending. They include both internal and external knowledge in their models, where external knowledge represents spillovers from other firms' R&D. While external knowledge provides spillover benefits, they find no evidence that energy R&D provides greater spillovers than other types of R&D. Unlike Dechezleprêtre *et al*. (2017) or Popp and Newell (2012), they do not distinguish between clean energy R&D and other types of energy R&D. Still, their results suggest that the evidence for favoring energy over other technologies when determining levels of government support is not clear cut, and that more research is needed.

R&D is highly uncertain. The returns to R&D are highly skewed. While most innovations generate little social value, a few highly successful innovations may generate millions of dollars of value (e.g. Pakes 1986). Popp *et al*. (2013) address the uncertainty, studying the determinants of patent citations for six different energy technologies: wind, solar, fuel cells, nuclear, hybrid vehicles, and energy efficiency. They compare regression results pooling all six technologies to models estimated separately for each, as well as comparing models estimating the conditional mean effect to quantile regression results. Differences across technologies, rather than differences across quantiles within technologies, are more important. The value of successful technologies, such as wind and hybrid vehicles, persists longer than those of less successful technologies. They conclude that their results provide evidence that success is the culmination of several advances building upon one another, rather than resulting from one single breakthrough. Moreover, they find evidence of diminishing returns at high levels of research activity. Combined, these results suggest that long-term sustained research support may be more effective than short bursts.

Noailly and Shestalova (2017) provide further evidence knowledge spillovers are technology specific. Using European patent data from 1978-2006, they compare patent citations to innovations in energy storage, solar, wind, marine energy, hydropower, geothermal, waste energy, and biomass energy. They ask which technologies generate the most spillovers and consider where these spillovers go. Using solar energy as the base technology, both wind (10% more) and energy storage (40% more) generate more forward citations than solar patents. All other patents generate fewer citations. For wind, these spillovers are generally within the same technological domain. Solar and energy storage generate spillovers both within and outside their own technology domain. They conclude that wind will need less policy support once its internal knowledge base is large enough, whereas the larger external spillovers for solar and energy storage suggest government support will play a more crucial role for those technologies.

6.2. Learning-by-Doing

Knowledge market failures may also result from learning-by-doing (LBD). Learning-by-doing occurs when the costs to manufacturers or users fall as cumulative output increases (Arrow, 1962, Rosenberg, 1982). LBD commonly is measured in the form of "learning" or "experience" curves that estimate how much unit costs decline as a function of experience or production. A typical learning curve estimation regresses costs of installation (or production) at different points in time as a function of cumulative installed capacity (or sometimes cumulative output) in log-log fashion. The resulting elasticity coefficient on cumulative capacity in these models (α) is often translated into a so-called "learning rate" ($1-2^{\alpha}$) giving the percentage change in costs resulting from a doubling in cumulative capacity. Typically, studies on new energy technologies find faster learning for younger technologies, with estimates clustering around 15-20% for alternative energy sources such as wind and solar energy (McDonald and Schrattenholzer 2000).

While learning curves provide useful information on changing costs, simple learning curves have limited ability to establish causation between experience and costs. Thompson (2012) notes that standard learning curve models collapse a complex set of processes into a single reduced form equation.[10] This is important, as the relative contributions of learning from experience versus R&D determine both the optimal timing of policy (e.g. Goulder and Mathai 2000) and the choice of policy instruments (Fischer *et al*. 2017). If learning is present, the early producers of a technology generate knowledge through the production and usage of technology, rather than through R&D activity. If these benefits of learning spill over to other producers, policy should subsidize early actors.[11]

Several recent papers address these concerns by developing richer models that identify different channels of learning. Kellogg (2011) uses oil well productivity data in Texas from 1991 to 2005. He observes experience for both oil production companies and drilling contractors. Productivity increases with joint experience – a drilling rig improves productivity twice as fast if it works with a single producer, rather than switching between partners. A working paper by Covert (2015) uses data on hydraulic fracturing in North Dakota from 2005-2012. Because he observes data on well location and inputs, Covert argues that endogeneity from omitted variables are unlikely to be a concern, since engineering limitations prevent firms from selecting inputs using information he does not observe. He estimates a semi-parametric production function using a two-step process that first estimates productivity conditional on location, and then integrates out unobserved location characteristics. Oil companies exhibit some learning, but increased future profits by only 20-60% of what was possible by improving fracking design over time. Firms appear to overweight data from their own operations relative to competitors when making drilling decisions.

A recent working paper by Fetter *et al*. (2018) develops links between environmental disclosure regulations, learning, and innovation. Because of concerns over the effects of toxic chemicals used during hydraulic fracturing, several states require well operators to disclose the chemicals used in drilling. Fetter *et al.* study such a law enacted in Pennsylvania in 2011, finding evidence of learning in response to public disclosure. The chemical mixtures used at different wells became more similar after disclosure. However, the increase in similarity appears to dampen

[10] A set of papers by Klaasen *et al.* (2005), Söderholm and Sundqvist (2007), and Söderholm and Klaasen (2007) address this concern by attempting to disentangle the separate contributions of R&D and experience by estimating "two-factor" learning curves for environmental technologies. These two-factor curves model cost reductions as a function of both cumulative capacity (learning-by-doing) and R&D (learning-by-searching, or LBS). Söderholm and Sundqvist address potential endogeneity between investments in capacity and R&D and find LBD rates around 5 percent, and LBS rates around 15 percent, suggesting that R&D, rather than learning-by-doing, contributes more to cost reductions. However, these results are very sensitive to the model specification, illustrating the difficulty of sorting through the various channels through which costs may fall over time.

[11] In addition to positive externalities from LBD cost reductions, subsidizing deployment of technology may address other market failures, such as peer effects among consumers (e.g. Bollinger and Gillingham 2012) that help encourage diffusion, even if costs do not fall over time.

innovation. The most productive well operators, and thus those most likely to be imitated by others, decrease experimental activity after the disclosure requirement.

A working paper by Bollinger and Gillingham (2014) develops a model of installer pricing behavior that considers the role of economies of scale, market power, and dynamic pricing, which they apply to solar photovoltaic installations in California. They instrument for on-going contracts using variation in mean solar radiation, assuming that consumers are more likely to consider installing solar power in sunnier months, and county-level monthly housing prices. They find evidence of both internal and external learning. Using their results to calibrate an optimal subsidy for solar PV, the subsidy initially increases to take advantage of learning, but declines as the LBD externality becomes less relevant. Their results suggest that California's solar PV subsidy cannot be justified by learning externalities alone.

Nemet (2012b) looks for evidence of learning and knowledge spillovers in California wind turbines, using data on turbines installed between 1982 and 2003. His data is a panel that includes annual production for each wind farm. To look for potential learning spillovers, he includes three measures of experience: (1) cumulative electricity produced by time *t*, (2) cumulative experience produced by the time of installation, to capture learning relative to wind farm siting decisions and technology choice, and (3) cumulative turbines installed by the time of installation. For each, he includes both internal and external experience. Nemet finds evidence of both internal and external learning. However, learning is subject to diminishing returns and decays quickly. Thus, technology-specific subsidies become ineffective and expensive at some point, suggesting that deployment subsidies should be part of a policy mix, but not the only policy instrument chosen.

Finally, Tang (2018) considers the role of learning from both wind turbine producers and operators. Her model includes learning through R&D, wind farm operation experience, turbine manufacture experience, and previous collaborations between operators and turbine manufacturers. Similar to Kellogg's results for oil wells, wind farm operation improves with experience, and these improvements are greater if the wind farm developer collaborates with the same turbine manufacturer. The regulatory framework also matters. Learning effects are greatest when the transmission system is operated by an independent system operator or regional transmission organization, rather than vertically integrated transmission systems owned by major utilities. Independent system operators face no competing interests when dispatching generation sources on the grid, reducing barriers for renewable energy adoption.

In sum, recent evidence on learning-by-doing provide some evidence of external benefits from learning, but not of a magnitude sufficient to be the only justification for deployment subsidies. Moreover, papers such as Kellogg (2011) and Tang (2018) suggest that these externalities can be partially internalized through lasting partnerships between suppliers and downstream users of technologies.

6.3. Path Dependency

Notably fewer empirical studies address path dependency explicitly. Notable exceptions are the previously cited papers by Aghion *et al*. (2016) on the auto industry and Stucki and Woerter (2017) on green innovation, both of which find evidence of path dependency. These papers use a firm's previous patents on both green and non-green innovation to see how previous research results affect the direction of current research. While not a main focus of their paper asking whether policy shifts innovation from fossil fuels to renewable energy, Noailly and Smeets (2015) note that the importance of knowledge stocks in their work could be interpreted as evidence of path dependency. Similarly, while Popp *et al* (2013) do not explicitly mention path dependency in their analysis of energy patents, Lehmann and Söderholm (2018) interpret the result that successful clean energy innovation depends on a sequence of incremental inventions that build upon one another as evidence of path dependency. As these examples illustrate, studying path dependency for green innovation requires detailed data, so as to distinguish between green and non-green innovation histories.

Rexhäuser and Löschel (2015) compare the importance of technology-push factors for renewable energy and energy efficiency innovation. They link patent data to firm-level survey data from the Mannheim Innovation Panel for 376 German companies active in energy R&D between 1992 and 2009. Using patent counts for each type of innovation as the dependent variable, the lagged dependent variable has a larger effect on renewable energy innovation, which they interpret as a more important role for path dependency. They explain that the average renewable firm likely specializes in a specific technology (e.g. wind), whereas most firms do not specialize in energy efficiency *per se*, but rather products where energy efficiency is just one relevant feature. They are careful to note, however, that a lagged dependent variable may pick up other individual effects not picked up by controls, so that path dependency is not the only possible interpretation.

Because successful innovation depends on both demand-side and supply-side motivations, the simple finding that innovators follow research paths that appear more promising is not a market failure. 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 (Lehmann and Söderholm, 2018). Aghion *et al*. (2016) conclude their paper with a numerical simulation showing that path dependency creates lock-in for dirty innovation in a world without policies supporting clean technology (such as a carbon tax or R&D subsidy), but that path dependency reinforces the growth of clean technology once such policies are in place. However, none of the aforementioned empirical papers explicitly test whether the observed path dependency results from high switching costs or are simply a reaction to better research. Given the importance of path dependency as a justification for technology-specific policy interventions, more research on path dependency, particularly connecting path dependency to switching costs, is needed.

6.4. Capital Market Failures

Particularly for the clean energy sector, capital market imperfections that impede the transition of innovations from the laboratory to commercialization may also justify government funding for green innovation. Such concerns are often described as a "Valley of Death". Both Mowrey *et al*. (2010) and Weyant (2011) argue that government research helps new energy technologies overcome roadblocks to commercialization. For instance, significant energy innovations typically have disproportionately large capital expenses, leaving a role for collaboration with the public sector to provide support for both initial project development and demonstration projects.

Howell (2017) provides evidence of financing barriers for clean energy technology. She provides a quasi-experimental evaluation of US Department of Energy (DOE) Small Business Innovation Research (SBIR) program. Founded in 1982, SBIR requires federal agencies to allocate 2.7% of their extramural R&D budgets to small firms. DOE officials rank grant applicants, using a cutoff exogenous to the ranks. This allows Howell to use a regression discontinuity design comparing successful and rejected applicants just above and below the cutoff. Receiving an SBIR grant from DOE increases a firm's chance of receiving private venture capital investment from 10% to 19%, and nearly doubles the probability of firm survival and successful exit. Recipient firms earn more revenue and receive more patents. As a result, reallocating support from larger, later stage grants to more numerous small, early stage grants to younger firms may achieve better outcomes and help smaller firms move new ideas from the initial research stage to technology commercialization. Moreover, the effects of SBIR funding are largest for newer clean energy firms. Grants are ineffective for older technologies such as coal, natural gas, and biofuels.

Two other recent works also emphasize the importance of access to financing. Al Mamum *et al*. (2017) uses panel data from 25 OECD countries to show that growth of equity and credit markets promotes clean energy production. The effect is larger in countries with higher rates of innovation. Brunnschweiler (2010) shows that underdeveloped financial sectors hinder deployment of renewable energy in developing and transition economies. While not directly related to innovation, the results illustrate how underdeveloped credit and finance markets reduce demand for clean energy, thus reducing incentives for innovation as well.

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

Popp (2017) provides evidence of the long time frame needed to bring new energy technologies to market. He uses citations made by patents to earlier scientific publications to trace the evolution from more basic research represented in a scientific article to a commercializable idea. The probability of a scientific article being referenced by a patent peaks 15 years after article publication. This lag is longer than found in studies of other fields (e.g. Branstattter and Ogura, 2005; Finardi, 2011), suggesting that the length of time necessary for commercialization of energy R&D creates another barrier to raising financial support.

Overall, the evidence on capital market failures for energy is limited but suggestive of such market failures. Howell's work provides specific evidence of financial constraints mattering for small businesses, and recent descriptive work on clean technology venture capital suggests venture capital is not ideally suited for clean technologies. Evidence of long citation lags between publications and patents for energy technologies suggests investors will need to wait longer for investments to pay off than they will in other sectors. Further research in a wider range of settings could help here. For example, while demonstration projects are an important recipient of government investment, most research on demonstration projects remains descriptive (e.g. Nemet *et al*. 2018). In addition, Howell's (2017) finding that SBIR funding is most effective for clean energy technologies raises the question of the extent to which financial constraints hinder clean energy investment, relative to a lack of demand for emerging clean technologies that historically have not been cost-effective without government support. That is, is the Valley of Death for energy research really due to the special characteristics of energy innovation, or simply a result of historically underpriced environmental externalities reducing demand for cleaner technology? Both falling costs and increased policy support from governments may provide future researchers evidence needed to better identify the effects of financial constraints from other market failures holding back clean technology.

7. Effectiveness of Government R&D

Independent of whether market failures justify more green R&D investments from the public sector, such investments are growing. For example, the "Mission Innovation" pledge signed by a coalition of 20 governments at the December 2015 Paris climate meeting promised a doubling of government renewable energy R&D budgets to over $30 billion by 2021 (Sanchez and Sivaram 2017). Thus, evaluating the impact of public R&D investments on innovation is important.

Most studies addressing government R&D simply include public R&D expenditures as one of several variables in more general studies of the drivers of innovation. For example, Johnstone *et al.* (2010), Verdolini and Gaelotti (2011), Peters *et al*. (2012), Dechezleprêtre and Glachant (2014), and Nesta *et al.* (2014) include public R&D expenditures in models testing the role of energy prices and or policy on renewable energy patenting. All but Nesta *et al*. (2014) report a positive effect of R&D spending on patenting.

Costantini *et al.* (2015) provide evidence that the state of technology development matters for government R&D effectiveness. They compare patenting in conventional first-generation biofuels to patenting in more advanced second generation biofuels. Combining keyword and patent classification analysis, they identify biofuels patents in 35 countries from 1990-2010. In addition to the role of public R&D, they consider two demand-side policy instruments: a quantity based mandates of biofuel usage, and excise tax exemptions as an example of price instruments. For first generation biofuels technology, public R&D spending has no effect on country-level patent count, but both fuel mandates and the excise exemption induce patenting. However, for more advanced second generation biofuels, public R&D plays an important role, as do excise exemptions. Fuel mandates have no impact on second generation biofuels innovation. Thus, technology-push policies are not important for more mature technologies, but are needed to foster development in emerging, more advanced technologies.

To more directly focus on the effectiveness of public energy research, Popp (2016) links data on scientific publications to public energy R&D funding. For evaluating public research funding efforts, publication data provide a more appropriate outcome measure than patents, thus shedding light on the process through which public R&D helps develop scientific knowledge. To account for potential endogeneity in R&D funding decisions, instrumental variables for R&D spending are used, including spending on related technologies (e.g. using biofuels R&D as an instrument for solar energy R&D spending) and instruments modeling the political process determining R&D funding. The paper provides three key results. First, $1 million in additional government R&D funding leads to 1-2 additional publications, but with lags as long as ten years between initial funding and publication. Second, including either non-linear terms for R&D spending or dummy variables representing years with large R&D increase, adjustment costs associated with large increases in research funding are of little concern at current levels of public energy R&D support. These results suggest that there is room to expand public R&D budgets for renewable energy, but that the impact of any such expansion may not be realized for several years. Finally, as the ultimate goal of government energy R&D funding is not an article, but rather a new technology, Popp uses citations from patents to scientific literature to link these articles to new energy patents. While public funding does lead to new articles, lags in both the creation of a new publication and the transfer of this knowledge to applied work mean that public R&D spending may take over a decade to go from new article to new patent.

Moving forward, the long lags before the full effect of R&D spending are realized have important implications for future work on public R&D programs. Most studies evaluating the effect of government R&D on innovation consider just contemporary or one-year lagged energy R&D.[12] While these studies often find small effects of energy R&D on private sector innovation, failure to consider sufficient lags call these results into question, suggesting instead that these papers are merely picking up spurious relationships between the factors determining energy R&D funding and those driving renewable energy innovation in the private sector, such as changes in energy prices. Future researchers should thoroughly explore the potential lagged effects of public R&D programs.

Governments can also support research by facilitating flows of knowledge across research institutions. Popp (2017) examines citation patterns between journal articles and patents, focusing on the value of knowledge from different institutions, including universities, private sector, and government laboratories. Better understanding of the value of knowledge from these institutions can help decision makers target R&D funds where they are most likely to be successful. Research performed at government institutions appears to play an important translational role linking basic and applied research, as government articles are more likely to be cited by patents than any other institution, including universities. Universities play a less important role in wind research than for solar and biofuels, suggesting that wind energy research is at a more applied stage where commercialization and final product development is more important than basic research.

Networks that result from R&D cooperation also help transfer knowledge and drive innovation (Powell *et al*., 1996). There is emerging evidence that collaborative research produces higher-quality research output, which in turn can translate into innovation. For example, in a study of papers and patents, Wuchty *et al*. (2007) show that teams of researchers tend to produce more highly cited and higher impact outputs compared to individuals. Popp (2017) finds that for alternative energy technologies, both scientific articles and patents with authors from multiple types of institutions (e.g., university and corporations) are cited more frequently, suggesting that collaborations may have positive impacts on research quality.

Fabrizi *et al.* (2018) study participation in research networks promoted by the European Union, hypothesizing that that larger research networks complement the effects of demand-side policies. These networks can help overcome imperfect information and provide coordination of

[12] Exceptions include Peters *et al*. (2012), who state that they test multiple lags and stocks of public R&D in unreported results, and Popp (2002), which uses an adaptive lag model for government R&D. In their study of biofuels innovation, Costantini *et al*. (2015) test policy lags up to three years but determine that a one-year lag best fits the data. However, they apply the same lag to all policy variables, rather than allowing for potentially longer lags for public R&D spending.

research among firms. They use data on participation in European Framework Programmes on green innovation to measure research cooperation among EU countries. While research networks do enhance the effect of demand-side policies, the effect is strongest when high scientific profile network members, such as universities, are included in the network. They speculate that the complex nature of green innovation makes these actors important.

In a study of wind and solar PV inventor networks in Germany, Canter *et al*. (2016) find both that the level of R&D funding increases network size and that requirements for collaboration as part of receiving public research funding increase connections within networks. While Canter *et al*. do not explicitly link network size to research outcomes, combining their results with those of Popp (2017) and Fabrizi *et al*. (2018) suggests that supporting collaborative R&D efforts is important (Hepburn *et al*. 2018).

These studies provide *ex post* evaluations of government R&D programs. However, policy makers deciding on future R&D levels must make judgements on which investments hold the most future promise. Determining how much to spend on public energy R&D requires an interdisciplinary approach. While economics can provide guidelines as to how funding increases can be implemented, engineers are better suited to determine which projects are most deserving from a technical standpoint. Expert elicitation studies offer one method for projecting future technological progress. Expert elicitation uses surveys of technology experts to provide insights on what investments look most promising. Anadon *et al*. (2016) provide an example of this work. The authors combine the results of separate expert elicitations to provide guidelines for future R&D investments in nuclear, solar, carbon capture and storage, bioelectricity, and biofuels. In these studies, researchers propose R&D spending levels in a survey of technology experts, who respond with predicted cost savings or productivity improvements. While their panel of experts predict median cost savings around 20%, there is much uncertainty in the predictions, and no technology stands out as receiving consistently better predicted results. Verdolini *et al*. (2018) review expert elicitation studies on energy technology. They conclude that experts mostly believe increased R&D expenditures will reduce technology costs by 2030, and that diminishing returns to R&D are a concern. Possible breakthroughs suggest potential annual rates of cost reduction around 10 percent per year.

8. What's Next?

While the previous discussions highlight some of the most popular research areas in green innovation over the past decade, many questions remain to be answered, and new areas of research are emerging. Here I highlight three topics with the potential for research growth: green innovation in emerging countries, innovation addressing adaptation to environmental problems such as global climate change, and the use of big data techniques to study changing innovation patterns.

8.1. The Role of Emerging Economies

Historically, most R&D took place in a few high-income countries. In 2002, OECD nations accounted for 81% of global R&D, with just the United States and Japan together accounting for 45%. At the time, China performed about 6% of global R&D (National Science Board, 2008). The dominance of high-income countries among the top R&D performers held true for environmental innovation as well. Using patent data from 1987-2005, Dechezleprêtre *et al*. (2011)

found that most climate-friendly innovation occurs in developed countries. The United States, Japan, and Germany together accounted for two-thirds of the innovations in their sample. While Dechezleprêtre *et al*. did find some evidence of innovation in emerging economies, innovation in emerging economies is often of a different nature. For example, the most prevalent innovations in China, South Korea, Russia, and Brazil include technologies designed primarily for local markets, such as geothermal and cement manufacture. Fort technologies of wider use globally, measured by the percentage of patents that have corresponding applications in other countries, nearly all were from developed economies. As such, most of the studies cited so far have focused on high-income countries.

However, the global distribution of global R&D expenditures is changing. By 2015, OECD nations' share of global R&D fell to 65%. China alone performed 21% of global R&D. Only the US, with 26%, performed more (National Science Board, 2018). As such, studying the drivers and impact of environmental R&D from emerging economies is important. Over the past decade, researchers have begun to assess environmental innovation in emerging economies, particularly in China. However, much of the focus has been on policies designed to increase innovation in China, such as joint venture requirements, rather than the effect of environmental policy on innovation *per se*.

The impact of technology transfer into China has received particular interest. Luo *et al*. (2017) show that solar PV firms whose leaders studied abroad patent more frequently and provide knowledge spillovers to other local firms. Howell (2018) studies potential technology transfer from joint ventures between Chinese and foreign auto manufacturers. Chinese regulations require foreign manufacturers to produce autos as part of a joint venture with domestic firms. High-tariffs limit imports, so that these joint ventures are the main entrance point into the Chinese market for foreign firms. In 2009, China increased fuel economy standards. To comply, firms would either need to improve technology or sacrifice quality (e.g. reducing torque). While joint ventures are expected to increase access to foreign technology, Howell finds that firms with joint ventures were more likely to reduce quality in response to the fuel economy regulations than firms without joint ventures, suggesting actual technology transfer was limited.

Groba and Cao (2015) use a gravity trade model to study drivers behind increased exports of wind and solar PV technology from China. Not surprisingly, demand from high income countries, typically driven by policy support, plays an important role. Technological advances play a limited role. Groba and Cao use patent data to create two knowledge stocks. Available foreign knowledge, based on patent applications from foreign inventors in China, represent potential technology transfer. Patent applications from Chinese inventors are aggregated into a national knowledge stock. They also control for government R&D spending. Provincial R&D growth increases Chinese PV exports, but R&D spending from the central government has no effect. They argue this is because central government R&D more often focuses on basic research. However, neither the national nor foreign knowledge stocks affect trade flows. Thus, technology plays just a limited role increasing exports.

These results are consistent with recent work by Lam *et al*. (2017), who use patent citation data to study the quality of wind innovation in China. China dramatically increased the deployment of wind energy during the 2000s, so that by 2012 it had the most installed wind capacity of any country. Similarly, the number of Chinese wind energy patents awarded to domestic firms increased dramatically during this time period. However, few of these patents were of sufficient quality to be awarded protection abroad, and Chinese wind energy patents are cited less frequently than patents from other countries. Nonetheless, while early evidence suggests the quality of green innovation from emerging countries such as China has been low, future research should consider whether these countries become important players in the next wave of green innovation.

Given the dramatic increase in Chinese wind energy deployment, several studies use learning curves to look for evidence of technological progress. Tang and Popp (2016) consider the role of knowledge spillovers, using data on the projected costs of wind projects financed through the Clean Development Mechanism (CDM). These data allow them to measure both cost reduction and productivity improvements of wind power in China. They consider different channels through which learning may occur: through research & development, from a firm's previous experience, from spillovers in industry-wide experience, and through network interaction between project developers and turbine manufacturers to determine the impact of these learning channels on improving wind projects. Tang and Popp find that wind project developers benefit from their past experiences with both wind farm installation and wind power generation. More importantly, their study is the first to empirically test and find evidence for learning-by-interaction effects in wind power. Previous collaborative experience between a project developer and foreign turbine manufacturer leads to the greatest reduction in both project costs and improvement of productivity. Their results provide evidence that joint learning occurs between partners during interactions on wind farm installations, and that the CDM helped achieve this goal by encouraging collaboration between project developers and foreign turbine manufacturers.

Hayashi *et al*. (2018) update the work of Tang and Popp using actual, rather than predicted, performance of CDM wind turbines. They find less evidence of learning when using actual performance data. Huenteler *et al*. (2018) provide potential explanations. Comparing the productivity of wind turbines in China and the US, they offer several reasons for poor performance of wind energy in China, including delays in grid connection, curtailment of energy due to grid management, and suboptimal turbine selection and wind farm citing. These last features are locked-in for the life of a wind farm, suggesting improving the overall performance of Chinese wind production will take time.

Fewer studies address the links between environmental policy and innovation in emerging economies. One exception in Chakraborty and Chatterjee (2017). As environmental policy is an important driver for environmental innovation, and environmental policies are often more stringent in high-income countries, policies in high-income countries may influence environmental innovation in emerging markets. Chakraborty and Chatterjee provide an example from India. In 1994, Germany banned the use of 'Azo-dyes' in the production of leather and textile goods. Because Germany was one of India's two largest consumers of textiles, Indian firms were forced to respond to the German regulations. While downstream textile producers did not increase R&D in response to the ban, upstream dye-producing chemical firms did. The average dye-producing firm increased R&D by 21.5% after the German ban, illustrating how regulations in one country may influence production, even in countries with weaker environmental regulation. Given increased pressure on reducing the growth of greenhouse gas emissions from emerging economies, additional research on the links between environmental policy and innovation in emerging economies, including how foreign regulations may affect local innovation, is warranted.

8.2. Innovation for Adaptation

Nearly all the research on green induced innovation focuses on technologies designed to reduce pollution. However, concerning climate change, innovation to reduce pollution may not be enough. Climate change is already occurring, and the political will to reduce greenhouse gas emissions sufficiently to fully prevent further changes appears lacking. Thus, adapting to climate change will be an important part of any climate policy, and new technologies may play important roles in future adaptation. There is a large literature on climate change adaptation and the potential of new technology to help. For example, Blanc and Reilly (2017) review studies on the impacts of climate change on agriculture and on the potential of new crops to improve yields in the face of increased heat and drought. However, few studies consider what is necessary to further encourage and support such innovation.

To provide some insights into how innovation may respond to increased climate damages, Miao and Popp (2014) study the impact of natural disasters on innovation. They consider innovative responses to three natural disasters: earthquakes, flooding, and drought. Because past disaster experience not only leads to further innovation, but may also lead to other adaptive behavior that reduces the damages resulting from a disaster, they construct instruments based on the frequency and location of natural disasters. Using a panel of patent data from 1974-2009, they find that a billion dollars of damage in a country from natural disasters increase innovation by 18 to 39 percent. They find little evidence of spillover effects on innovation in foreign countries, although disentangling such an effect from other year fixed effects is difficult. While these innovative responses to disasters may suggest potential benefits from technological change for adaptation, it also raises an important question for future research: how can such innovation be promoted *before* climate damages are realized, so that technologies are in place when adaptation begins?

As an example of technologies that may become more important as the climate changes, Conway *et al*. (2015) provide a descriptive look at innovation pertaining to water. They identify over 50,000 patent addressing either water supply or demand from 1990-2010. Water patents make up just 0.2% of all patents during this period. While counts of both demand-side and supply-side patents have grown, growth has been more rapid for supply-side technologies such as desalinization. As with other green innovations, most patents during this period come from high-income countries, particularly the US, Japan, and Germany. Although some water-stressed countries, such as Spain, Australia, and Israel, are relatively specialized in water efficiency technologies, between 80 and 90 percent of water patents come from countries with low or moderate water scarcity. While this occurs partially because most developed countries do not suffer severe water stress, it poses challenges moving forward to direct innovation towards the needs of lower-income countries more likely to suffer increased water stress due to climate change.

8.3. The Potential of Big Data

New data analytic techniques also open new doors for exploring green innovation. For example, most studies using patent data historically identified relevant green patents using classifications found on patents. Now, new techniques such as machine learning enable researchers to make full use of the descriptions embedded in patents and scientific publications. This allows researchers to distinguish between ever smaller differences in technology development. Venugopalan and Rai (2015) demonstrate the possibilities of machine learning to classify green patents. They use topic modeling of patent claims and descriptions to classify solar PV balance of system (BOS) patents into four relevant components. Solar PV balance of system components are the non-module components of a PV system, such as monitoring, power inverters, installation, and site assessment. This allows them to identify trends in innovation, such as convergence between solar inverter and monitoring hardware. While they do not attempt to establish links between technology trends and policy in the paper, their work demonstrates the potential for using data mining techniques to learn more about technology evolution.

Dugoua (2018) takes machine learning a step further, developing a database of innovation on chlorofluorocarbon (CFC) substitutes to estimate the effect of the Montreal Protocol on innovation. While the prevailing wisdom is that CFC substitutes that were readily available prior to signing the Protocol facilitated the agreement (e.g. Heal 2016, Sustein 2007), Dugoua provides evidence that this is not the case. Identifying research on such substitutes is a challenge, however, as no pre-existing patent classifications exist for chemicals that are CFC substitutes. To overcome this, Dugoua applies machine learning to the full text of articles and patents to identify scientific outputs pertaining to 14 molecules identified as substitutes for CFCs. Using both difference-in-difference and synthetic control models, she demonstrates that the Montreal Protocol lead to more than a doubling of patents and articles on CFC substitutes.

9. Conclusions

Recent history provides many successful examples of environmental innovation. Better pollution control technologies, such as catalytic converters for automobiles, led to dramatic reductions in air pollution in the developed world. The costs of clean energy sources such as wind and solar power are now low enough to be competitive with fossil fuel sources, reducing emissions from the electric power sector. This paper has reviewed the recent empirical evidence on environmental innovation. These studies provide evidence of successful innovation in new technological domains and across a wider range of countries. They make use of new data sources, such as survey data, and highlight key differences across policy instruments. Nonetheless, these studies also suggest new research questions deserving attention.

As reviewed earlier, the expanded use of cross-country data, firm-level studies, and survey data offer new insights on environmental innovation. Reconciling these results is important. Firm-level studies often separately identify treated and untreated firms. Yet environmental innovation may occur at upstream suppliers. Moreover, because of market-size effects, innovators may respond to policy incentives outside of domestic territory. Consumer pressure may also matter, as may the perceived likelihood of policy to remain consistent and predictable across time. Understanding what each type of study can and cannot identify is important to create a truly broad picture of the full potential of environmental innovation.

Further study can also say more on the role of different policy instruments. Evidence discussed in section 6 suggests cases where targeted policy support may be justified. But, this section also highlights the need for further research. For example, do high switching costs lead to path dependency and lock-in of existing technologies? As the costs of clean technologies fall, will private venture capital investment increase, or do other barriers to capital result in a “Valley of Death” for environmental technology?

The changing nature of technology suggests still other questions for future research. For example, much of the innovation successfully lowering the costs of wind and solar power occurred in the private sector. But, as the share of electricity generated by intermittent renewable power grows, managing the electric grid becomes more complicated. 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 advances in energy storage could have spillover effects to multiple sectors, will public sector R&D play a more important role? Similarly, innovation for public infrastructure, such as charging stations for electric vehicles, will also be needed. Better understanding the potential role of private vs. public sector innovation in a changing technological environment will be valuable.

Finally, a better understanding of the role of state and local policies provides yet another avenue for future research. In the current US political climate, much of the action on climate and energy policy comes at the state, rather than federal level. How does a patchwork of state policies affect energy innovation? What can we learn from variation in policies across states? What role can states play supporting basic innovation? Such questions are important beyond the US, as Canadian energy policy also differs across provinces, and co-ordination of innovation across EU countries is of interest to policymakers (e.g. Conti *et al.* 2018). The relative influence of state policies compared to overall market size also raises questions about links between green innovation and employment, as creating high-paying green jobs in local communities is often a secondary interest of local policy makers supporting environmental innovation (e.g. Vona *et al*. forthcoming, 2018). Recent political events have raised awareness among economists of the importance of the distributional effects of policy. Scholars are now giving increased attention to the effects of automation and globalization on different sets of workers (Autor and Dorn 2013, Autor *et al*. 2013). The effects of green innovation on employment merit similar attention.

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