The CO2 Question:

Technical Progress and the Climate Crisis[1]

Patrick Bolton*

Marcin Kacperczyk[Ω]

Moritz Wiedemann[Δ]

December 7, 2024

Abstract

We split green innovation into pure green and fuel efficiency patent filings and study its effects on carbon emissions in a large sample of global firms. Despite a steady rise in green R&D, we find that green innovation does not predict future reductions in emissions of innovating firms. Fuel efficiency innovation improves emission intensity but is also associated with higher future sales and investments, resulting in higher future emissions. At the industry level, countervailing effects in terms of emission intensity improvements and changing market shares of innovators on net result in green (fuel efficiency) innovation predicting higher (lower) future emissions.

JEL codes G12, G23, G30, D62, D83

Keywords: carbon emissions, green patents, fuel efficiency patents, Jevons paradox, displacement effect, path dependence of innovation.

* Columbia University, Imperial College, CEPR, and NBER.

Ω Imperial College and CEPR

Δ Rotterdam School of Management, Erasmus University

[1] We are grateful to Trucost for giving us access to their corporate carbon emissions data. We thank Leonid Kogan, Asaf Bernstein, Lauren Cohen, Antoine Dechezleprêtre, Rob Engle, Mariassunta Gianetti, Stefano Giglio, Po-Hsuan Hsu, Raj Iyer, Mirabelle Muuls, Ramana Nanda, Thomas Philippon, Melissa Prado, Roberto Rigobon, Zach Sautner, Sophie Shive, Johannes Stroebel, and participants at numerous conferences and seminars for their useful feedback. This project has received funding from the European Research Council (ERC) under the ERC Advanced Grant program (grant agreement No. 885552 *Investors and Climate Change*).

We are in the early stages of a sustainability revolution. It will have the magnitude of the industrial revolution yet the speed of the digital revolution. Al Gore (2020)

There is no doubt that the energy sector will only reach net-zero emissions if there is a significant and concerted global push to accelerate innovation Energy Policy Perspectives 2020 IEA

1. Introduction

How are innovation activities and technological advances shaped by the prospect of an approaching climate change crisis? In this paper, we explore corporate green innovation activity around the world and its effects on corporate behavior, in particular on future corporate carbon emission. Nearly all analysts agree that a successful global decarbonization cannot be founded only on stricter carbon emissions regulations. It necessarily entails major technical advances in substitute energy sources and other technologies to reduce or capture carbon emissions. According to the IEA (2020), "Reducing global CO2 emissions will require a broad range of different technologies working across all sectors of the economy in various combinations and applications. These technologies are at widely varying stages of development."

Much R&D that is touted as green mainly takes the form of efficiency improvements in energy use. Primary examples are fuel efficiency gains in transport, electricity efficiency gains in refrigeration, air-conditioning, computing, lighting, and heating. The promise of these technological improvements is that the environmental impact of consumption in terms of carbon emissions will become smaller and smaller. However, as Jevons (1865) first noted about coal consumption, greater energy efficiency—by lowering the energy cost of consumption—could induce an increase in aggregate demand for energy, which could undo the anticipated reduction in energy use: "It is wholly a confusion of ideas to suppose that the economical use of fuel is equivalent to a diminished consumption." Indeed, despite all the technological improvements in fossil energy use, we have still not seen a global decoupling of economic growth and carbon emissions.

The title of our paper is a reference to the title of Jevon's (1865) book, *The Coal Question*, as the same economic problem he saw for the consumption of coal, which is only available in limited supply, arises for CO2 concentration in the atmosphere, which can only be accumulated by a limited amount if we are to avoid global overheating. The main question we are concerned with in this study is the impact of green innovation on future corporate carbon emissions. What has come to be known as the *Jevons paradox* (and is also referred to as the *rebound effect*) is a warning that green technological progress is not necessarily synonymous with carbon emission reductions

because technological improvements that reduce fossil fuel energy reliance also boost economic activity. It is unclear a priori what the net effect is on carbon emissions of respectively green R&D (that is not related to fossil fuels) and fuel efficiency-improving R&D (that improves the energy efficiency of fossil fuel-based technologies), given that consumption and production are endogenous, and that any successful innovation generates additional economic activity. Even pure green innovations, that reduce direct or downstream emissions, may cause an increase in brown electricity production (scope 2 emissions) or emissions in the supply chain (especially upstream), an impact we define as the *displacement effect*.

A related question we are concerned with is the extent to which companies with high carbon emissions move away from fossil fuel-based technologies and embrace green innovation. More generally, how much do corporate characteristics (the line of business the company is in; the technologies it is using) determine the innovation activities a company engages in? What companies, in which sectors, have been the source of most green R&D?

We can address these questions by combining three global datasets on respectively corporate patent filings, corporate financial reports, and corporate (direct and indirect) carbon emissions covering the period from 2005 to 2022. All in all, our data covers more than 1.7 million patents held by more than 800,000 firms. Based on the patent's Cooperative Patent Classification (CPC), we can sort patents into three broad categories, *pure green patents* (which concern technological improvements in the environmental impacts of economic activities), *fuel efficiency-improving patents* (which achieve advances in fossil energy efficiency), and other patents that are not directly related to the environment or to energy. These three categories broadly correspond to the green patent classification of the OECD.

For each firm we can determine the intensity of their green or fuel efficiency innovation activities by calculating the ratio of the number of their green (respectively efficiency) patents to the total number of patents they have filed. We calculate these ratios based on filings with the European patent office, which are known to be more reliable and more impactful. We can also weigh in the importance of each patent based on the number of its future citations and the stock market response to patent announcements (as in Kogan et al., 2017) when publicly listed companies report new patent filings. We find that green patents, on average, are not very different from fuel efficiency improving patents in terms of their market-based impact.

A first contribution of our study is to provide a picture of green innovation activity across countries, sectors, firms, and over time. For example, we find that 19.5% of publicly listed companies engage in innovation, while only 2.3% of private companies on average file patents each year. Furthermore, we find that the distribution of countries contributing at least one green patent is highly skewed, with the top ten countries contributing most green patents. This is also

true for the distribution across sectors and firms, with some sectors, such as multi-Utilities, Electric Utilities, Oil, Gas & Consumable Fuels, and Independent Power and Renewable Electricity production standing out for their high ratios of green to total number of patents. Across sectors just over 1% of all firms have filed at least one green patent. We also find that green innovation activity has steadily risen over our sample period, with the average patent ratio rising from 8.1% in 2005 to 15.3% in 2022.

Given that there has been a steady rise in the number of green patent filings, does this mean that we are on the cusp of a *sustainability revolution*? We explore this question next by looking at the effects of green R&D on future corporate carbon emissions and other policy outcomes. How has green R&D affected corporate carbon emissions, capital expenditures, and other policies? According to the IEA (2020) "Around half of the cumulative emissions reductions that would move the world onto a sustainable trajectory come from four main technology approaches. These are the electrification of end-use sectors such as heating and transport; the application of carbon capture, utilization and storage; the use of low-carbon hydrogen and hydrogen-derived fuels; and the use of bioenergy. However, each of these areas faces challenges in making all parts of its value chain commercially viable in the sectors where reducing emissions is hardest". Another issue is the extent to which the benefits of technological improvements in terms of carbon efficiency are undone by rebound effects (Jevons, 1865). Finally, some of the green innovations may lead to a displacement in emissions.

Our main finding on the effects of *firm-level* green innovation on future carbon emissions is that there has been no significant association of such innovation activity with future carbon emissions. Whether in the medium run (three years ahead) or in the long run, we do not find any significant association of pure green innovation with either direct or indirect corporate carbon emissions in the cross-section of innovating firms. If anything, we find that fuel efficiency innovation is associated with future increases in direct emissions. The observed weak association of green innovation and future emissions is not due to lack of statistical power and can be understood through the lens of the Jevons paradox. To be sure, we find that fuel efficiency innovation does result in lower future carbon intensity of both direct and indirect emissions, but this effect is undone by higher firm sales and higher CAPEX. Further, these results do not depend critically on the economic importance of patents, even though we find that the offsetting forces underlying the Jevons paradox are more precisely measured for economically important patents.

A central idea in the economics of innovation literature is the *Arrow replacement effect* (Arrow 1962), which refers to the lower incentive to innovate for an established firm with market power if the innovation replaces an existing technology that is working and is profitable. Another important idea for our analysis is learning-by-doing (Arrow 1971), which means that companies

master better the technologies they use, the more they have been using them. A key prediction for our analysis that derives from these two effects is that profitable companies with operations based on fossil fuel energy are less likely to engage in green innovation, a new technology they are less familiar with. If a company engages in pure green innovation, it is more likely to be a new entrant that is less dependent on fossil fuel-based technologies.

Consistent with these predictions, we find that companies with greater experience with brown technologies (measured by the stock of fuel efficiency patents they already own) are less likely to engage in green innovation and companies with greater experience with green technologies (measured by the stock of green patents they already own) are less likely to engage in fuel efficiency innovation.[1] Furthermore, we find that brown companies (with higher emissions and that are older) do not tend to engage in green R&D. This is also true for companies with higher indirect (scope 3) emissions. One reason for why companies may not want to switch to alternative technologies is the potentially negative effect of such actions on their competitiveness and market share. Consistent with this hypothesis, we find that firms that improve their green patent ratios tend to lose market share to other firms in their industry. Overall, our results suggest the presence of a replacement effect at work. Notably, that effect is more extensive than Arrow's replacement effect, given that brown companies appear to be locked into fossil-fuel dependent technologies through their production networks. If input suppliers or downstream customers also rely on fossil fuel-dependent technologies, it is more difficult for an individual firm in the supply chain to switch to green technologies. A key implication from this latter finding is that to induce firms to transition from brown to green technologies, industrial policy may be necessary to coordinate this transition across all firms linked through the supply chain.

We also analyze how aggregate sectoral changes in emissions are associated with green R&D on the presumption that firm-level innovation could be of use not just to the innovator but also for other firms operating in the same sector. However, we do not find any significant spillover effects of pure green innovation on the aggregate carbon emissions of firms in the same (GICS-6) sector. If anything, future total emissions of the industry, both direct and indirect, increase when the intensity of green innovation in the industry goes up. In contrast, fuel efficiency innovation does predict slightly smaller future emission in the same sector. The above results are broadly

[1] A case in point is the energy company Halliburton. In response to a recent SEC question on its exposure to carbon transition risk it stated that "We believe that one of the significant risks that we face in energy transition is that we will be unable to innovate in a timely, cost-efficient manner, or at all." (See *Climate risks gain corporate acknowledgment after SEC prodding* by Patrick Temple-West, Financial Times 30 December 2022). We show in Figure IA.I that most of Halliburton's innovation activity in recent years has been in fuel efficiency innovation, which has steadily increased over time.

similar even if we allow for the possibility that innovation could spill over to different sub-industries (GICS-8) within a broadly defined economic sector (GICS-2).

To better understand the economic drivers of these results, it is useful to distinguish between companies that innovate (competitors) and those that simply adopt innovations of others (adopters). When we use such conditioning information in our industry-level tests, remarkable findings emerge. First, we find that absolute direct emissions of adopters go up, and even more so do those of innovators. What is interesting, however, is that the factors driving both effects are very different. Green innovators reduce their emission intensity, but this effect is compensated by their significant increase in size. In turn, green adopters see their future sales decline and their emission intensity increase. One explanation of these different effects could be that adopters are less competitive and more inefficient companies in their sector. These companies face the credible threat of disruptive innovation, also including that from new entrants, which is possibly too costly for them to implement in the short run. Their best response therefore is to run down their brown assets faster before they become obsolete. Hence, their emissions (and emission intensity) go up. In sum, the observed effects for total emissions reflect opposite effects through emission intensity and through redistribution of market shares across the two groups of firms. Second, we observe that the same comparison for fuel efficiency innovations yields slightly different results. We observe that both innovators and adopters reduce their emissions, but the sources of these reductions are improved fuel efficiency and increased sales of innovators, and improved fuel efficiency but reduced sales of adopters. This result suggests that the equilibrium distribution of total emissions is primarily related to changing market shares rather than changing fuel efficiency.

As suggestive as they are, our findings do not establish causality. Accordingly, in the last part of the paper we explore further a possible causal interpretation, taking advantage of the plausibly exogenous and unexpected shock to green innovation in Germany triggered by the political response to the 2011 Fukushima nuclear accident, and the decision by the German government to phase out nuclear energy production (the "Atomausstieg"). An attractive feature of the shock is that it is predominantly supply driven and thus the interpretation of our results is not confounded by possible demand-based explanations. Using a basic difference-in-differences methodology that compares firms and industries in Germany to their peers in Europe, we show that the Atomausstieg has indeed led to a significant relative increase in green innovation in Germany. We further show that this shock has had a significant effect on energy production. As one could predict, Germany has significantly increased its energy production from renewables. However, Germany could not meet its increased demand for energy from this source alone and also had to turn to coal and other fossil fuels. Consequently, within the few years immediately following the Atomausstieg, German economy saw an increase in overall emission intensity, even

though the shock has led to an improved emission intensity excluding fossil fuels. In the longer run, the increased capacity in renewable energy has led to a reduced reliance on coal and thus to an overall improvement in emission intensity, both direct and indirect. Overall, this experiment illustrates potentially interesting unintended consequences of green innovation such as rebound effect and displacement to other sectors.

Related Literature

Earlier studies on rebound effects have focused on specific activities or on sector or country-level data. Our study is the first to explore the effects of technological change on carbon emissions based on firm-level data.[2] The findings on rebound effects in this earlier literature are mixed. For example, Schipper and Grubb (2000) have looked at aggregate data on energy use and found that car use and energy use in other activities have not changed much in response to technological improvements in energy efficiency. Based on these findings they conclude that rebound effects are likely to be small. Sorrell et al. (2009) provide a review of prior empirical studies on rebound effects. They argue that many studies only look at partial rebound effects over limited time periods and over restricted consumption responses. For example, studies on the consumption response to fuel-efficiency improvements in automobiles only measure changes in mileage travelled and do not consider more long-term changes in vehicle size. By looking at firm-level data and at cross-firm and cross-industry effects of green innovation we can identify substantially larger and more diverse forms of rebound effects.

Our paper also contributes to a growing recent literature on the firm-level implications of the transition to a green economy. A closely related study by Cohen et al. (2022), who also look at green innovation by U.S. listed companies, draws somewhat different conclusions. They find that green innovation activity in the energy sector is higher than that in other sectors and conclude that this is evidence against path dependency of innovation. We confirm some of their cross-industry variation, but our main finding is that *within* each sector brown companies (those with higher emissions) do less green R&D. This is true across all sectors and countries. More important, our focus is on carbon emission outcomes and not path dependency alone. In this regard, our paper is related to a recent work by Leippold and Yu (2024) who use NLP methods to classify green innovation and relate it to firm value and measures of emissions.

[2] An important aspect of green innovation is the role of government policies in supporting innovation (for a literature review, see Greaker and Popp, 2022). These policies are important and can induce a shift to green innovation (e.g., Popp, 2002; Aghion et al., 2016). Our study focuses on firm-level responses and how they depend on their characteristics, especially their carbon emissions. We absorb the impact of innovation policies using industry and country fixed effects, making an implicit assumption here that innovation policies are industry-wide and not firm-specific. Our findings reveal how firms in an industry differentially respond to these policy interventions and how their differential response is linked to firm characteristics such as carbon emissions.

Our findings are also consistent with earlier studies on directed technical change that find evidence that innovation is path dependent (Acemoglu, 2002, Popp, 2002, and Aghion et al. 2016). Aghion et al. (2016) consider a panel of automobile manufacturers and explore the extent to which these companies produce innovations on combustion-engine cars versus electric, hydrogen or hybrid engine vehicles. Their main finding is that specialization in innovation activity in clean (vs efficiency) technologies is self-reinforcing. Our study finds that this self-reinforcing specialization effect is present in all sectors, across countries, not just in the automobile sector.

Finally, a parallel literature in finance explores the effect of green innovation of U.S. firms on firm value (e.g., Hege et al. (2022); Kuang and Liang (2022); Reza and Wu (2022)). More broadly, Bolton and Kacperczyk (2021, 2023) show that the transition risk, which embeds technological progress, is already reflected to a large extent in equity markets. Ilhan et al. (2021) show that carbon risk is also priced in options. Engle et al. (2020) have constructed an index of climate news through textual analysis of the Wall Street Journal and other media and show how a dynamic portfolio strategy can be implemented that hedges transition risk with respect to climate change news. Sautner et al. (2023) show that companies that report positive sentiment towards climate in their conference calls subsequently produce a greater number of green patents. In contrast to these studies, our focus is on the effects of green patents in decarbonization.

The remainder of the paper is organized as follows. Section 2 provides the conceptual framing for our analysis. Section 3 describes the data and provides summary statistics. Section 4 discusses the results on the impact of innovation on future emissions and other corporate decisions. In Section 5, we discuss evidence from the German "Atomausstieg". Section 6 concludes.

2. Conceptual Framework

There are three key guiding ideas that help us understand the various connections between green innovation and carbon emissions. The first, as already highlighted, is the Jevons paradox and other rebound effects of green innovation on energy consumption, one of which is the *displacement effect* defined above. The narrow notion of the Jevons paradox is that an energy efficiency gain, or a carbon intensity gain, from a better technology will of course reduce emissions for a given level of operations, but if the new technology invites more users and larger operations then the overall reduction may be limited or may not materialize at all.

We expect to find direct evidence of such rebound effects if a fuel efficiency innovation subsequently not only improves the carbon intensity of operations, but also leads to larger sales and investment. A general reason why one should expect a positive effect on operations and sales from a fuel efficiency innovation is that the innovation improves profitability and the

competitiveness of the innovating company, which are likely to result in an expansion of the business.

There are other, more indirect, and more subtle, displacement effects to be expected. A concrete and highly relevant example is the transition to electric vehicles (EV). This is one of the major new green innovations. If, as is likely to be the case, the share of EV grows significantly in the next few years then scope 1 emissions from transportation should be expected to decline. However, if the increased demand for electricity is met by increased production from coal-fired power plants, as is likely to be the case in states where coal-fired power plants are still responsible for the lion share of electricity production (such as West Virginia, with a 91% share, Missouri with 75%, Wyoming with 74%, and Kentucky with 71%)[3], then the green EV revolution will result in an increase of scope 2 emissions. What does not get burned by the vehicle will get burned by the power company, with a likely net increase in total emissions given that coal is far more carbon intensive than oil. Similarly, the production of all the parts that go into an EV, from the wheels, tyres, chassis, body, engine, and batteries, etc, will generate carbon emissions, so that green innovation could also result in higher upstream scope 3 emissions. These higher emissions will be fully offset by lower scope 1 emissions than a combustion engine vehicle only after the EV has clocked up many thousands of miles.

Other rebound effects operate through product market competition. If green innovation involves higher operating costs relative to an established brown technology that it replaces, then the green innovating firm will be at a cost disadvantage relative to its industry peers. It may as a result lose market share. This would translate into lower carbon emissions for the green innovating firm, but higher carbon emissions for its competitors that are gaining market share. Alternatively, green innovation could spur adoption of green technologies by industry peers, leading to an industry-wide reduction in carbon emissions. In sum, green innovation is likely to have spillover effects, positive or negative, which could affect carbon emissions of non-innovating firms within the industry or across industries. To understand the overall impact of green innovation on carbon emissions it is therefore important to explore the link between green innovation activity and carbon emissions within and across industries.

The second and third guiding concepts for our analysis are closely related. They are both associated with founding ideas first proposed by Kenneth Arrow (1962, 1971). One concept is commonly known as Arrow's replacement effect (Arrow 1962), which refers to the idea that established firms, monopolies, have a lower incentive to innovate because their innovation mostly replaces their existing technology that is working and is profitable. The other concept, learning-

[3] See https://www.eia.gov/todayinenergy/detail.php?id=54919

by-doing (Arrow 1971), has broader applications. But in the context of innovation, it means that companies understand the technologies they already use better, which induces them to continue to improve something they already mastered rather than explore new directions which seem more obscure. One key general prediction that follows from these two concepts is that profitable companies with operations based on fossil fuel energy (brown companies) are less likely to replace their brown operations with green operations and less likely to engage in green innovation, a new technology they are less familiar with. A related general prediction is that innovation is likely to be path dependent: a company that has already been actively researching fuel efficiency innovations is more likely to continue to do brown R&D. Green innovation, therefore is most likely to be undertaken by less established companies, or those in declining industries, and by new entrants.

Arrow (1962) focuses his analysis on an individual firm's technology and the replacement of the firm's own technology. When it comes to green and efficiency innovation, however, replacement has a broader scope and involves complementary technologies upstream and downstream. Replacement is not just confined to one firm. It may require technological changes in an entire ecosystem. Following the development of a new green technology an individual firm might be ready to replace its old technology if all the other firms it depends on also make the switch. A case in point is again electric vehicles. Switching to EV requires major changes not only in the supply chain but also downstream, with new charging station networks, maintenance, servicing, etc. The more dependent on fossil fuels upstream and downstream industries are, the less likely it is that an individual firm in the supply chain will transition to green technologies. A major general prediction that follows from this observation is that an individual company is less likely to do green R&D the higher are its upstream and downstream scope 3 emissions.

Finally, another key consideration in exploring the link between green innovation and future carbon emissions is the timing of deployment of new technologies. There can be a major time-to-build lag between the discovery and development of a new technology and its deployment. Part of this lag may be the time it takes to go from a working prototype to a mature technology.

Given the relatively short and finite time interval of our study, it is not possible to account for impacts that are far into the future. We cannot rule out the possibility that these impacts will eventually be very large, and that green innovation will fully deliver on its promises. Still, it is important to find out whether, and the extent to which, green innovation is already having an impact on reducing carbon emissions, given the small and rapidly shrinking remaining carbon budget. Given that annual energy-related emissions have been around 31.5 GtCO2 in 2020 (IEA 2021) and given that projected annual energy-related emissions for the next few years will remain at that level, there are only a few years left for green innovation to deliver on its promises before it is too late.

3. Data

Our data construction begins with the list of all global firms, both publicly listed and private, identified between 2005 and 2022 in Orbis and Compustat. The financial data (balance sheets and income statements) for public firms is based on both sources. The financial data for private firms is based solely on Orbis. We also complement missing stock price information with data from Datastream. The overall dataset is termed "full sample". We merge these datasets with the Orbis Intellectual Property (Orbis IP) dataset, which provides a comprehensive coverage of patent filings and corporate ownership of patents by listed and unlisted companies in 81 countries. This dataset includes 136 million patents held by 2.3 million firms. It also provides patent citations, which are a good measure of the importance of the innovation protected by the patent.

We further combine the full sample with data from Trucost on firm-level carbon and other greenhouse gas emissions. Trucost reports yearly firm-level carbon and greenhouse gas emissions data for scope 1, 2, and 3 emissions in units of tons of CO2 equivalent. Scope 1 emissions are direct emissions from operations of affiliates that are owned or controlled by the company. Scope 2 emissions are those that come from the generation of purchased heat, steam, and electricity used by the company. Scope 3 emissions are indirect emissions caused by the company's operations and the use of its products. These include emissions from the production of purchased materials, product use, waste disposal, and outsourced activities. Establishing the scope 3 emissions of a company requires a detailed analysis of the share of emissions of producers in the supply chain that is attributable to the company's input purchases. This involves estimating an input-output model with sector-level emission factors. Our data allows us to distinguish between scope 3 emissions coming from upstream and downstream activities although the latter are only available from 2017 onwards; hence, total scope 3 emissions prior to 2017 reflect upstream emissions only. Finally, we include world index constituent data from MSCI. We use the ISIN identifier and company names to match these datasets.

3.1 Aggregate data by country

Internet Appendix Table IA.I provides a breakdown of our aggregate data by country. In Panel A, we report a breakdown of the number of firms in each country that are respectively, publicly listed, privately held, and have carbon emissions data. The total number of firms in our sample is 795,867, of which 41,281 are publicly listed companies and 754,046 are privately held firms. There are 15,837 firms for which we have carbon emissions data through Trucost. The limited coverage reflects the fact that Trucost has collected emissions data mostly from listed and larger companies. Countries with the largest number of firms in the full sample include China, Italy, Denmark, and France, each of them having more than 50,000 companies in the full sample. Even excluding these

countries, our sample has a wide cross-country representation. Notably, in the matched Trucost sample, the U.S. has the largest representation of all countries, which is consistent with the fact that it has the relatively larger fraction of publicly listed companies. In columns 5-8, we further restrict the full sample to observations for which we have patent data from Orbis IP. Throughout our main analysis, we focus on patents registered with the European Patent Office (EPO). As is well known, the filing process is most rigorous at the EPO, so that these filings reflect more significant and enduring innovations. The total number of firms in this subset of patenting firms represents roughly 3% of the universe of companies in our data, which reveals the fact that most companies do not get involved in any innovation activity. Interestingly, publicly listed patenting companies comprise more than one third of the sample with patents. Still, private companies represent a significantly larger population of all firms. These numbers therefore indicate that public firms are significantly more likely to engage in innovative activities.

In Panel B, we report the distribution of patent counts and firm-year observations across countries for the full and the Trucost samples. Notably, the fraction of patents registered by companies that are part of the Trucost data is 75%. The Trucost sample generally comprises publicly listed firms, which provides further evidence that innovation is typically produced within large companies. The two countries with the highest number of patents in our sample are the United States and Japan, each one having more than 300,000 patents registered at the EPO. The next three countries are Germany, France, and South Korea, each with more than 100,000 patents. In columns 3 and 4, we show the average number of patents per firm, for companies that do engage in patenting activity. An average company in our sample registered about 15 patents over the sample period. The fraction is significantly larger for the Trucost sample, in which firms register more than 36 patents per firm.

Columns 5 to 8 show the country-level breakdown into firm-year observations. To be included in the final sample, we require firm-year observations to have values for assets, book leverage, ROE, and country of incorporation. We lose about 5 million firm-year observations due to this restriction. In addition, we require public firms to have records for year of incorporation, capex, PPE, volatility, and market capitalization. This leads to another 400,000 firm-year observations being lost. We refer to this filtered dataset with 6.0 million firm-year observations as the "full sample". Columns 5 and 6 present the numbers for the full set of public and private companies. The number of observations in the full sample is 6,015,426, of which 118,264 are observations from the Trucost sample. In columns 7-8, we restrict the sample to companies with at least one listed patent. That sample includes 110,150 observations, 31% of which are from the Trucost sample.

3.2 Green and fuel efficiency innovation

We make a key distinction between pure green innovation, targeting technologies that substitute carbon dioxide emitting technologies for carbon dioxide-free technologies (or that make carbon-dioxide-free technologies more accessible), and fuel efficiency innovation, which targets improvements in fossil-fuel based technologies. For this patent classification we rely on four technology classification sources on patents relating to the environmental impact of technologies, namely the environmental technologies classified by the Organization of Economic Co-operation and Development (OECD) , the International Patent Classification (IPC) Green Inventory, the efficiency-improving fossil fuel-technology categories of Lanzi et al. (2011), as well as a self-identified classification based on patents from the Corporate Knights Clean 200. Patents are classified based on the subject to which the invention relates. The classification structure is very granular with approximately 250,000 classification entries.[4] We combine the four technology classification sources into three broad categories of respectively "green", "efficiency", and other patents. Innovation that concerns process efficiency improvements in general but is not clearly linked to renewables or fossil fuels is omitted and left "unclassified".

Prior research (e.g., Cohen et al., 2022; Aghion et al., 2016) has relied on the OECD classification of green patents. But the OECD classification does not always distinguish between patents on renewable energy technologies and efficiency improvement patents. This distinction is important because the economic mechanisms resulting from each type of innovation may be quite different. Figure 1 highlights that in the Trucost sample, 21% of patents in the OECD classification are classified as efficiency patents. To illustrate the difference in nature of these innovations, we conduct a cloud-of-words analysis of patent descriptions using the term frequency–inverse document frequency (TFIDF) algorithm. We search for the dominant words in our green patent classifier, stripping out common words in the OECD classification, and we do the same for our efficiency patent classifier. We present the resulting clouds in Internet Appendix Figure IA.II.

In the left figure, we show the words that are uniquely dominant to our classification of pure green patents. Words like "mri", "magnetoresistive", or "magnetometer" are very common to fusion reactions and underlie the green nature of the patent. In the right figure, we show the words dominant to our classification of efficiency patents. The dominant words of this process include "packer", "boring", or "jackup", all three likely attributed to efficiency gains of fossil fuel-based technology. Overall, this analysis suggests that the decomposition of the OECD green

[4] Cooperative Patent Classification overview.

patents into pure green and fuel efficiency may uncover slightly different economics of the implementation process.

In Table IA.II, we report the distribution of firms and patents conditional on a firm filing a green or fuel efficiency patent. In Panel A, we analyze the distribution of firms by country. In columns 1-4, we report the statistics for firms which file a green patent, and in columns 5-8 the statistics for firms which file a fuel efficiency patent. Only about 1% (0.4%) of all firms have at least one green (fuel efficiency) patent. In the cross-section, the U.S., Japan, and Germany (Japan, the U.S., and Germany) have the largest number of firms with green (fuel efficiency) patents, each of them representing 9%-14% (11%-15%) of the total number of patenting firms. The distribution of countries contributing at least one green (fuel efficiency) patent is skewed, with the top 10 countries contributing most green (fuel efficiency) patents. Publicly listed companies account for 51% (54%) of firms with green (fuel efficiency) patents. The fraction of firms with at least one green (fuel efficiency) patent that is covered by Trucost is roughly 41% (48%).

In Panel B, columns 1 to 4, we provide a similar breakdown for the total and average (per firm) number of green patents. In the full sample, over the period 2005-2022, companies have filed 179,067 green patents. Almost 140,000 of green patents have been filed by companies with emissions data in Trucost. The highest numbers of green patents by firm come from South Korea, Japan, Hong Kong, and Germany, each having more than 8 green patents per firm. In columns 5 to 8, we provide the breakdown for fuel efficiency patents. In the full sample, we observe 70,560 fuel efficiency patents in total; the fraction of fuel efficiency patents that is covered by Trucost is roughly 75%. Germany and the United States are the two countries with the highest number of fuel efficiency patents per firm.

In Figure IA.III, Panel A, we show the year-by-year distribution of patenting activity, measured by green and fuel efficiency patent counts, based on the sample of all firms with patent data. We observe a steady increase in patenting activity over time until 2019, especially for green patents. Green patents also represent a larger share of patenting activity. We also separate the data into different regions. The two regions with the largest number of either green or fuel efficiency patents are Asia and Europe. At the peak of 2019, each region contributed almost 6,000 patents each. The equivalent number for North America is significantly less and accounts for about 2,000 patents. Notably, countries outside these three regions, which include Africa, Australia, and South America, contribute almost no patents to the overall patent count. This fact underlies the importance of any innovation spillovers from patenting to non-patenting regions, especially because these non-patenting regions are responsible for significant fraction of global emissions. Panel B presents observations for all firms that are available in Trucost. The subsample quite closely mimics the behavior of the unconditional sample. We observe a steady increase in

observations from 2005 until 2015. More pronounced is the sharp increase in observations starting from 2016. This increase can be largely explained by the change in firm coverage by Trucost that took place post-Paris agreement. When we restrict our observations to firms that are featured in Trucost prior to 2016, we still observe the increase in firm observations over time but the sharp increase in 2016 is no longer as pronounced.

3.3 Green and fuel efficiency innovation ratios

Patenting activity in any given year is limited by a firm's innovation capacity. Accordingly, to get an accurate picture of the intensive margin of innovation activity, we relate new patent filings to the firm's innovation capacity, as proxied by the firm's accumulated stock of patents. The intensive margin is then measured by the ratio of the firm's new green (and fuel efficiency) patent filings in any given year over the firm's total patent filings. Another reason why we measure incremental innovation with these patent ratios (as opposed to just keeping track of the total patent count) is that green innovation activity could conceivably happen concurrently with other innovation that could increase the firm's carbon footprint (a good example of such R&D is innovation in artificial general intelligence). Accordingly, we normalize the number of green (respectively fuel efficiency) patent filings by the total number of a firm's patent filings and define the following two variables: GREENRATIO, which is the ratio of granted and purchased green patents over the total number of granted and purchased patents in that year; and, EFFRATIO, which is the ratio of granted and purchased fuel efficiency patents over a similar total number of patents in that year.[5]

Following Kogan et al. (2017), we take the grant date rather than the application date for patent filings because the grant date reflects certified innovations that are closer to commercialization. Although the application date is closer to the actual point of innovation, the grant date is closer to development and is more likely to pick up patents that have real impact. Nonetheless, Lerner and Seru (2022) highlight that the gap between application date and grant date is noisy, which introduces truncation bias. We further address this latter concern by measuring patenting activity over a three-year interval, which reduces timing noise. Following the Lerner and Seru (2022) checklist, we also show that our results are robust to the alternative specification based on the application date, and to the introduction of industry-year fixed effects at different industry levels, as well as to dropping industries that experience a surge in patent filings.

Table IA.III, Panel A provides information on the ratios of green or efficiency patent filings for each country. In columns 1-4 we focus on green patent ratios. The average green patent ratio equals approximately 11%. Interestingly, the ratios do not differ greatly between publicly

[5] For robustness, some of our results scale the number of patents by total firm assets; the results are mostly unaffected by using this alternative normalization.

listed and private companies, with the former having an average ratio of 11.9% and the latter 10.5%. For the Trucost sample, the numbers are slightly higher. Furthermore, innovation activity (as measured by the number of firms with at least one patent) is proportional to the size of the economy. Among the countries with more than 2,000 public or private firm-year observations, some of the ones with the highest ratios of green to total number of patents are: Norway with a ratio of 18.3%, Denmark with a ratio of 15.7%, and Canada with a ratio of 14.6%. In comparison China has a ratio of 13.1%, and the U.S. an even lower ratio of 10.7%. Notably, Australia reports a large fraction of green patents 13.8%, and the Russia Federation an even higher ratio of 19.2%, which is interesting given their strong reliance on fossil fuel production. In columns 5-8 we provide respective summary statistics for fuel efficiency patents. On average, fuel efficiency ratios are significantly smaller. The average number equals 3.3%. The unconditional numbers do not deviate much from those based on the Trucost sample. Notable countries for significant fuel efficiency patenting activity include Croatia, Cyprus, Finland, Hungary, Lithuania, Norway, Romania, and Singapore. The numbers for the U.S. and China are about the same 2.6%.

Panel B breaks patent activity down by sector (GICS-6-industry). In columns 1-4, we present the results for green patents. Some sectors stand out for the intensity of their innovation activities. The Independent Power and Renewable Electricity Producers industry has the highest ratio of green patents filed at EPO, with 57.2%, followed by Electric Utilities, Multi-Utilities, and Gas Utilities. These results are broadly consistent with those in Cohen et al. (2022) for the U.S. On the other end of the green R&D spectrum, IT and healthcare sectors are the two industry groups with the lowest green patent ratios. The ratios are broadly within the same range for public and private firms. They are also not markedly different when we restrict our sample to Trucost observations, which is reassuring about any selection concerns one might have. In columns 5-8 we report the results for fuel efficiency patents. The ratios are generally larger for publicly listed firms, especially in those sectors with higher ratios. Among the most active industries, Energy Equipment & Services leads with the highest ratio of 19.3%, followed by Multi-Utilities with 12.4%, and Electric Utilities with 12.1%.

In Panel C, we report the distribution of patenting activity by year, with columns 1-4 providing green patenting activity over time and columns 5-8 providing fuel efficiency patenting activity. Green patent ratios have steadily increased over time. For example, in column 1 we see that this ratio was below the average of 11% in 2005, with a ratio 8%, but above average in 2022 with a ratio of 15.3%. The same increasing trend in green patent activity can be observed for listed companies (in column 2), private companies (column 3), and for Trucost companies, which are mostly listed companies (in column 4). When it comes to fuel efficiency patent filings, we see a relatively stable ratio and do not observe much of a change in R&D activity over time for these

technologies. In Figure IA.IV, we display the patent ratios across time by region and find broadly similar patterns.

3.4 Patent impact measures

Patents are not all equal. Those that enable a larger technological advancement should have greater potential in shaping future production and emission reductions. This fundamental patent heterogeneity means that just counting the number of patents may give a distorted image of the importance of innovation within a firm. Accordingly, we also construct two ratios that weigh patents by their economic impact, specifically their private economic value (Kogan et al., 2017), our benchmark specification, and their influence as reflected in how widely cited they are. The private economic value of patents is determined based on the stock market reactions to the announcement of the patent grant. We follow their methodology to calculate the patent value of all patents of our publicly listed firm sample.[6] An important advantage of this measure is its relative immunity to truncation bias, in that the value of the patent is instantaneously captured by market participants; the downside is that it can only be applied to listed companies. We describe our procedure in detail in the Internet Appendix.

We provide a replica of Table 1 in Kogan et al. (2017) for our sample for both patents granted and purchased by the USPTO and EPO to facilitate comparison with their results. In Table IA.IV, we report the sample distribution of citations and variables related to the patent value. In line with Kogan et al. (2017), we find that the distributions of citations and patent value are highly skewed for patents from the USPTO and EPO. Interestingly, we also find that the economic value of patents granted by the EPO, which is equal to $48.88 million on average, is more than twice as large as the value for patents filed at the USPTO, which is equal to $21.98 million on average. This finding is consistent with the general perception that the filing process at the EPO is more rigorous, so that these patents likely reflect more significant innovations, and further justifies our use of this patent types in our main tests.

We further show in Table 1 that the economic value of green and fuel efficiency patents is similar. The average increase in firm value following a green patent announcement equals $47.6 million, and following the announcement of a fuel efficiency patent grant the increase is similar, on average $45.8 million. Notably, the similarities between the two groups of patents hold at all quantiles of the empirical distribution we report. These results set a context that indicates that any differences in economic impact between green and fuel efficiency patents are unlikely due to an

[6] In contrast to Kogan et al. (2017), we consider both granted and purchased patents and focus on the EPO rather than the USPTO. Our paper therefore also shows how their methodology can be applied and how it carries over in different settings.

unequal distribution of the economic importance of each patent type. We also show that both types of patents, in aggregate, are economically important. Table IA.V reports the time-series variation in cumulative economic value of all patents, broken down by green and fuel efficiency categories. As can be seen, for example, in 2022 the global value of all patents, using 1982 dollars, equalled $5.3 billion, of which green patents accounted for $656 million, and fuel efficiency patents for $169 million. As for the count-based patent ratios, we calculate respectively patent-value based green and fuel efficiency ratios: GREENKPSSRATIO (EFFKPSSRATIO) is the ratio of the sum of patent values of green (fuel efficiency) patents over total patent values in that year.

Table 1 also shows that the distribution of citations and patent value is highly skewed. A small proportion of patents represents major technological breakthroughs while most patents reflect only incremental innovations. The second measure zooms in on these blockbuster patents. We define blockbuster patents, as those that are in the last 5th percentile of the empirical distribution of forward citations (up to 2023) in a given grant year and technology classification (green or fuel efficiency). In line with the other measures, we focus on the EPO and calculate a ratio again and scale green (fuel efficiency) blockbusters for a given firm by the total number of patents of that firm in that year. GREENBBRATIO (EFFBBRATIO) denote the respective variables of the two.

3.5 Summary statistics

In this section we provide summary statistics for the main variables in our models, conditional on whether firms file patents. In addition, we report complete summary statistics for publicly listed firms with carbon emissions data (those matched to the Trucost dataset). Our empirical analysis in the subsequent sections is based on this restricted sample. Accordingly, these summary statistics provide information on how the broader universe of firms may differ from the Trucost universe.

We begin by defining all the variables. Our first category is variables related to innovation activity. In our second category we include variables measuring corporate carbon emissions (direct and indirect) when available, and standard variables capturing key corporate characteristics. Thus, LOGS1TOT, LOGS2TOT, LOGS3UPTOT, and LOGS3DOWNTOT respectively stand for the natural logarithm of firm-level scope 1, 2, 3 upstream and downstream total carbon emissions, and S1INT, S2INT, S3UPINT, and S3DOWNINT are firm-level scope 1, 2, and 3 emission intensity variables defined as the level of emission divided by firm sales. In our third category we include the main variables reflecting key corporate characteristics: i) LOGSIZE stands for the natural logarithm of a listed company's market capitalization (price times shares outstanding); ii) LOGASSETS is given by the natural logarithm of the firm's assets (in $ million); iii) LOGPPE is given by the natural logarithm of the firm's property, plant, and equipment (in $ million); iv)

LEVERAGE is the ratio of debt to book value of assets; v) ROE is given by the ratio of firm i's net yearly income divided by the value of its equity; vi) M/B is the end of year market cap divided by the firm's book value; vii) INVEST/A is the firm's capital expenditures divided by the book value of its assets; viii) LOGAGE is given by the natural logarithm of the firm's age based on its year of incorporation; ix) BETA is the market beta of individual companies calculated over the preceding 12-month period; x) VOLAT is the standard deviation of returns based on the past 12 monthly returns; xi) MSCI is an indicator variable equal to one if a stock is part of the MSCI ACWI index in year *t*, and zero otherwise. To mitigate the impact of outliers we winsorize M/B, LEVERAGE, INVEST/A, and ROE at the 2.5% level, and VOLAT at the 0.5% level.

In Table IA.VI, we report the sample averages, medians, and standard deviations of these variables. Panel A is based on all public and private firms, and Panel B on firms with available emission data. Columns 1 to 3 aggregate all firms with at least one patent. Columns 4 to 6 aggregate firms without any patents. Columns 7 to 9 aggregate firms in the bottom decile based on firms' average GREENRATIO across the whole period. The bottom decile covers only firms with no green patents and represents around 35% of observations. Columns 10 to 12 aggregate firms in the top decile based on firms' average GREENRATIO across the whole period. Both Panels A and B reveal considerable heterogeneity in innovative activity. Among the firms that hold at least one patent, there is a wide dispersion in green innovation as reflected in the standard deviation of GREENRATIO of 25.0%, the standard deviation of GREENKPSSRATIO is 25.1%, and of GREENBBRATIO is 17.7%. Interestingly, the average level of emissions of innovating firms is significantly larger than that of non-innovating firms, with the mean of LOGS1TOT equal to 10.8 for innovating firms but only 9.9 for non-innovating firms. A similar difference holds for scope 2 and 3 emissions. Partly this difference could be attributed to the fact that innovating firms are slightly larger (mean LOGSIZE is 8.0 for innovating firms versus 6.9 for non-innovating firms). Patenting firms have also greater values of LOGASSETS and LOGPPE, and slightly higher values of M/B than non-patenting firms do. At the same time, they do not differ much in terms of their ROE, INVEST/A, LOGAGE, and VOLAT.

We now turn to the analysis of innovation and the carbon transition. Our analysis will be guided by three fundamental insights, the Arrow replacement effect (Arrow, 1962), Jevons' paradox (Jevons 1865), and the displacement effect. Arrow (1962) has pointed out that "The pre-invention monopoly power acts as a strong disincentive to further innovation." More generally, the incentive to innovate is reduced if the innovation replaces an existing technology that is working and is profitable. By that principle one should expect companies that master technologies based on fossil fuels to be less motivated to engage in green innovation that would replace a technology and know-how that is already working. This is even more likely if green innovation

involves retooling and abandoning a knowledge base around fossil fuel-based technology. If there is an incentive to innovate for an incumbent firm with a fossil fuel-dependent installed base it is more likely to take the form of efficiency improvements in the use of fossil fuels, what we refer to as fuel efficiency improvements. Indeed, this innovative activity plays into the strengths of the incumbent firm, its expertise with particular technologies, which it has built through learning by doing (Arrow 1971).

Carbon emissions can be reduced by replacing brown with green energy or by improving the carbon efficiency of brown energy. Thus, both green and fuel efficiency innovations are central to the drive to decarbonize the economy. But, as Jevons (1865) has pointed out, fuel efficiency improvements do not necessarily translate into carbon emission reductions because the very efficiency gain is also inviting greater use. Furthermore, the displacement effect from green innovation may displace scope 1 emissions to scope 2 and scope 3 emissions, as is for example the case for electric vehicles.

In the next section we explore the link between green innovation and the future decarbonization of the economy.

4. The effects of innovation on future carbon emissions

In this section, we systematically estimate the effects of (green and fuel efficiency) innovation on future carbon emission reductions. Do green and fuel efficiency innovation significantly reduce future carbon emissions? The archetypal image of a technological change that drastically reduces carbon emissions is the substitution of a coal-fired power plant by a photovoltaic power station, or the substitution of a combustion-engine car by an electric vehicle. Yet even these obvious examples come with questions about the net effects of these technological changes on carbon emissions, since solar panel and electric vehicle production require inputs and use energy that causes upstream and downstream carbon emissions, giving rise to displacement effects. Similarly, with efficiency-improving innovation, the effect on carbon emission reductions may be limited because of rebound effects. Fuel economy innovations for combustion engine cars may be undone by people driving longer distances. Battery life improvements for cell phones may simply result in more intense phone usage. It is therefore unclear a priori how much green and fuel efficiency innovation has affected direct and indirect carbon emissions. We explore in turn the effects of innovation on: i) the companies' own future direct and indirect emissions; ii) the effects on other companies' direct and indirect emissions in the same industry; and iii) the effects on carbon emissions across other, broadly related industries.

4.1 Green innovation and the CO2 problem at the firm level

We begin our analysis of the impact of green R&D on carbon emissions by estimating the regression model linking future firm-level total emissions (in log scale) to firm-level measures of green and fuel efficiency patent ratios, both measured at an annual frequency. The log scale for emissions controls for the possibility that the impact on emission levels may be unequal across the distribution of patent ratios, and greater in absolute terms for firms with higher patent ratios. Our model takes the following form:

$$\text{Log Emissions}_{i,t:t+2} = a + b*\text{Patent Ratio}_{i,t-3:t-1} + c*\text{Controls}_{i,t-1} + FE + \varepsilon_{i,t} \quad (1)$$

where *Log Emissions* is a generic response variable that includes scope 1, scope 2, and scope 3 emissions (both upstream and downstream). We cumulate emissions over 3 years to reflect the possibility that there may be a "time to build" lag in corporate adjustments. The variable *Patent Ratio* is defined as before and includes either green or fuel efficiency innovation. The average patenting activity over the previous 3 years accounts for the fact that innovation breakthroughs are lumpy. *Controls* is a vector of the following time-varying firm-specific variables: LOGSIZE, LOGASSETS, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, LOGAGE, and MSCI, all lagged one year. All regressions include GICS-6 industry-year and firm-fixed effects. Including firm-fixed effects allows us to study the effect of innovation within a firm over time. We double cluster standard errors at the firm and year dimensions. Our coefficient of primary interest is *b*, which measures the impact of *Patent Ratio* on future emissions.

The results are reported in Table 2. Panel A reports the effects of green innovation (GREENRATIO). As shown in column 1, green innovation has no significant effects on firms' direct emissions up to three years later. The same is true for indirect emissions (scope 2 emissions in column 2, upstream scope 3 emissions in column 3, and downstream scope 3 emissions in column 4). Based on these findings it appears that green innovation has not resulted in significant carbon emission reductions for innovating firms. Panel B reports results from similar tests for fuel efficiency innovation (EFFRATIO). We find few significant effects of innovation on future emissions, except for a small increase in direct emissions with a 10% statistically significant positive coefficient of 0.108 (in column 1). This finding suggests that far from reducing future emissions, fuel efficiency innovations have resulted in higher future emissions.

In a second step, to gain further insights into the above results we decompose total emissions into two parts: emission intensity and sales (and investments) and estimate the regression model in (1) with these new dependent variables. We present the results in Table 3 (Panel A for green innovation and Panel B for fuel efficiency innovation). Again, there is no significant effect

of green innovation on direct or indirect emission intensity, firm sales, and CAPEX. These results again suggest that green technical progress has not materialized in any significant carbon efficiency gains, or any changes in the scale of innovating firms' operation. However, we do find an improvement in scope 2 emission intensity, with a 5% statistically significant negative coefficient of –0.058 for scope 2 emission intensity, as well as in upstream scope 3 emission intensity, with a 1% statistically significant negative coefficient of –0.143 following fuel efficiency patent filings. Yet, these latter effects must be set against the significant positive effects on sales and CAPEX, both significant at least at 5%. Overall, what emerges from these findings is a picture that is consistent with the Jevons paradox: although fuel efficiency innovation produces carbon intensity efficiency gains (particularly for scope 2 and upstream scope 3 emissions), these gains are offset by operating expansions (sales), which on net result in higher scope 1 emissions. The results from the emission decomposition tests shed further light on our results in Table 2. Importantly, it is less likely that the insignificant results for total emissions are an artifact due to a possible weak power of our statistical tests, for if the lack of power were the main driver of our results, we would expect that it would have a similar impact on our findings when we decompose total emissions into emission intensity and sales.

An important consideration for any study of innovation is the inherent heterogeneity in the economic importance of patents. This feature of the patent data could introduce a downward bias in our estimates in Tables 2 and 3, since only important patents may possibly contribute to any efficiency gains among all patents we consider. To address this concern, we consider two measures of patent impact defined in Section 3: the market-based measure of Kogan et al. (2017), henceforth termed KPSS, our benchmark measure, and the citation-based measure, which focuses on blockbuster patents (that is, patents in the last 5th percentile of the empirical distribution of patent citations), henceforth termed BB. We calculate the ratios of impact of a given patent, green or fuel efficiency, relative to similar impact measures for all patents for both measures. Next, we estimate the model in (1) using these new innovation variables.

In Table 4, we present the results when the dependent variable is total emissions, and the KPSS ratios are our measures of impact. Consistent with our unconditional results, we find that firms with greater values of GREENKPSSRATIO do not perform significantly differently in terms of their future emissions, whether direct and indirect, for up to 3 years into the future. Further, we find slightly higher scope 1 emissions for firms with higher EFFKPSSRATIO, and no difference for other types of emissions.

In Table 5, we report further results for these impact-based measures when we break down total emissions into emission intensity and sales (and CAPEX). As in Table 3, we find a strong negative association between measures of fuel efficiency impact and future scope 2 and upstream

scope 3 emission intensities, and a strong positive association of this impact measure with future sales and CAPEX. At the same time, the association of the impact measures based on green patents with future intensities and sales is statistically and economically weak.

The results reported in Tables IA.VII and IA.VIII highlight that these findings are robust to several alternative patent ratio specifications. First, in Panel A of each table, we present similar results for the citation-based impact measure and the blockbuster-based patent ratios. Second, in Panel B of each table, we scale the number of green (respectively, fuel efficiency) patent filings by total firm assets (and winsorize the asset-based patent ratio at the 0.5% and 99.5% levels), to address any concerns that firms with little innovation activity may be misconstrued as very green under our main patent ratio variable. We still observe a strong significant negative association between fuel efficiency innovation and future upstream scope 3 emission intensities, and a significant positive association (although weaker) with future sales and investments. Third, we report additional robustness checks on possible truncation bias in the patent data. Lerner and Seru (2022) note that the gap between a patent's application and grant date is noisy and depends on the technology field (as well as the state of the patent office). We calculate the patent ratio based on the application dates (conditional on patents being granted) and lag the patent ratios by one additional year. The latest application date is thus 2019, several years before the end of the sample. Panel C of each table corroborates our findings.

So far, we have analysed the separate impact of green and fuel efficiency innovation on emissions. However, companies may be involved in both types of innovation activities, and these activities could jointly contribute to the firm's overall carbon footprint. For example, a car company may improve on its brown technology, increasing the fossil fuel energy efficiency of its combustion engine vehicles and simultaneously innovate with new green technologies in the production and assembly of its cars. Accordingly, we study next the impact of such technological complementarity using a new variable, *JOINTRATIO*, which is calculated as a sum of *GREENRATIO* and *EFFRATIO*. Similarly, we calculate equivalent ratios for our measures of patent impact. We estimate the model in (1) using the different variants of these variables. Our results, in Table IA.IX, indicate that there is no significant difference in the qualitative findings of our analysis. The results for total emissions, in Panel A, show no significant predictive power for future emissions. If anything, the positive effect of blockbuster patents on scope 1 emissions is even stronger than before. The results from the decomposition of emissions into their intensities and scale of production show some improvement for carbon intensities, but the effects are comparably weaker than before, which may suggest that the complementarity benefit of green and fuel efficiency patents may not be that strong.

Overall, we conclude that, by and large, firm-level green innovation does not predict significant reductions in future total emissions. The disaggregated effects paint a more nuanced picture, in that pure green innovation does not predict emission intensities, or firm sales, whereas fuel efficiency innovation is associated with significant reductions in emission intensities, especially indirect ones, but this efficiency gain is offset by an increase in operational activity, which results in no reduction in total future emissions. It is surprising at first sight that pure green innovation does not predict any significant emission reductions. This result could possibly reflect a lower quality of pure green patents, but this explanation would be at odds with the increasing trend in green innovation and the fact that green patents generate similar market values as fuel efficiency patents. An alternative, more plausible, explanation could be that green innovators are already low emitters, so that any additional innovation would not materially change future emissions.

The sustainable energy technological revolution could also involve substituting fossil fuel-based technology for green technology. Is this substitution taking place within firms (with the greening of brown firms) or across firms (with the replacement of brown firms by green firms)? Our working definition of a *brown* firm is a firm with high carbon emissions, that is older, may have larger assets, and may be a value company. Similarly, a *green* firm is one that has low carbon emissions, is younger, may have smaller asset size, and may be a growth firm. These characteristics are not the only possible ways to define a firm type, these are more to illustrate the point that companies' emissions may be systematically driven by some ex-ante metrics. Our question, rephrased with reference to these two firm types, then is how much we see green innovation activity at *green* versus *brown* firms, and whether we see brown firms greening themselves through green R&D. Given that firms have limited innovation capacities and given that the research projects that are most promising in view of individual firms' accumulated know-how tend to crowd out other R&D, it is natural to measure the amount of green (resp. fuel efficiency) R&D in terms of the ratio of green-to-total patent filings (resp. fuel efficiency-to-total patent filings).

To answer this question, we estimate the following Pseudo Poisson Maximum Likelihood model with firm (*i*) and year (*t*) as units of observation[7]:

$$\text{Patent Ratio}_{i,t} = a + b*\text{Firm Type}_{i,t-1} + c*\text{Controls}_{i,t-1} + \text{Fixed Effects} + \varepsilon_{i,t} \qquad (2)$$

where *Patent Ratio* is a generic variable that allows for different types of patents to be related to the total number of patent filings. *Firm Type* (a continuous variable measuring the share of a firm's green and brown activities) is proxied by a combination of i) LOGS123UPTOT (the sum of scope

[7] Since many companies do not report any green patents a standard OLS regression is not suitable to estimate this relationship.

1, scope 2, and upstream scope 3 carbon emission variables); ii) GREENSTOCK and EFFSTOCK, and iii) AGE/100. *Controls* is a vector of the following variables: LOGSIZE, LOGASSETS, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, and MSCI. We include country and year fixed effects. In some specifications, we also include industry-year or firm fixed effects. Our baseline specification uses the GICS-6 sector classification of 74 industries. To allow for the cross-sectional and serial dependence in the residuals we double cluster standard errors at the firm and year dimensions. Our coefficient of primary interest is *b*.

We report our findings for the extensive margin (which includes all firms, whether they own any green, respectively brown, patents or not) in Table 6. In columns 1-3, we present the results for green innovation activity (GREENRATIO), and in columns 4-6 the results for fuel efficiency innovation activity (EFFRATIO). When industry fixed effects are not included (column 1) the coefficients of LOGS123UPTOT and GREENSTOCK are positive and statistically significant. The coefficient of AGE and EFFSTOCK are negative and statistically significant. Not controlling for industry, however, is misleading because technological differences (and differences in emissions) across industries are huge. The results of the regressions without industry fixed effects are therefore difficult to interpret. For this reason, we consider specifications that absorb the time-varying differences across industries through industry-year fixed effects. When industry-year fixed effects are included (column 2) the coefficient of LOGS123UPTOT is highly significant and negative. The other three coefficients retain the same sign and significance as before. When we further include firm-fixed effects, in column 3, all coefficients become insignificant. This evidence, however, does not invalidate our inference because our hypothesis is mostly cross-sectional in nature.

The results flip when we look at fuel efficiency innovation activity (EFFRATIO), in columns 4-6. For this type of innovation activity, the association with direct carbon emissions is positive across firms within the same industry. When we include firm-fixed effects, in column 6, the association for LOGS123UPTOT becomes negative, suggesting that when direct emissions increase firms tend to reduce their innovation activity.

Overall, the combination of these results has a clear interpretation: green companies do more R&D that is green, and brown companies do less; instead, the latter do more fuel efficiency R&D. These are cross-firm rather than within-firm effects (when we substitute industry*year FE for firm FE neither the coefficients for carbon emissions nor for the stock of patents are significant). These results further confirm the path-dependency hypothesis for R&D. To the extent that brown companies engage in innovation activities, their innovations are less likely to be directed towards green patents (and the opposite is true for green companies). In addition, green innovation is most likely to be undertaken by new entrants. By and large, incumbents, far from

embracing renewable energy technological change, respond by seeking to improve the efficiency of fossil fuel-based technology. The auto industry provides a good illustration of these findings. Indeed, the EV revolution has been driven by new entrants (Tesla, BYD) and initially incumbents have responded by improving the carbon efficiency of their vehicles.

The results in Table 6 suggest that companies find it on average more beneficial to stick to their existing technologies, perhaps because these are cheaper for them, or they have higher costs of switching. We further explore the nature of the cost-benefits by looking at the effects of changing innovation on market power of an average firm. We consider two measures of the company's market power: one measures a firm-level market share in terms of sales relative to the total sales of both public and private firms within the same GICS-6 industry (MARKETSHARE SALES); the other one uses asset values instead (MARKETSHARE ASSETS). Both measures are averaged over the period of three years to allow for any transitory shocks to firm operations. We relate each of the two measures of market share to our patent ratios, while including all the same controls as before, as well as firm fixed effects. Notably, our sample in this test involves both public and private companies, which we control for by using the indicator variable PUBLIC. We present the results from estimating the model in Table 7. Columns 1 and 2 use measures based on sales, while columns 3 and 4 measures based on assets.

Our results indicate that green innovation, and the adoption of green technologies, can be a handicap in product market competition if green firms have higher production costs than brown firms. As is shown in columns 1 and 3, a firm's future market share is significantly negatively impacted by its increased green innovation activity. In contrast, there is a positive but not significant effect of fuel efficiency innovation activity on firms' future market share. This finding could explain the path dependency results of Table 6 and suggests that any expansion of green innovation would likely be through the entry of new firms rather than through the switching of innovation type by incumbents.

4.3 Innovation and emissions at the industry level

If green or brown innovation does not lead to future carbon emission reductions by the innovating firms, could it be that these innovations are adopted by other firms so that green innovation activity *spills over* to the industry as a whole and materializes in industry-wide emission reductions? Similarly, could it be that entry and exit into innovation activity determine the aggregate output and emissions of the sector? Finally, could it be that in some industries a subset of companies focuses on green technologies, while another subset focuses on fuel efficiency innovation, and that these technologies are complementary in the production process?

We begin our analysis of these hypotheses by exploring the extent to which green and fuel efficiency innovation are complementarity. Figure 2 shows the relationship between green and fuel efficiency innovation at the industry level. We can see a strong positive relationship between the two variables, which suggests that a typical industry does not specialize in a given type of technology, but instead attracts both types of technology at the same time. When it comes to the impact on emissions, we explore these hypotheses by linking industry-level direct and indirect carbon emissions, carbon intensity, and investment, to respectively green and fuel efficiency innovation activity by the listed companies of the industry. Our baseline specification uses the GICS-6 industries classification. We aggregate all the patent, financial and emission data for all publicly listed firms that have filed at least one European patent, or that have emissions data in our sample period. Patent measures are now calculated as industry patent ratios for all publicly listed firms. All regressions include the same controls as before, except that they are now measured at the industry level, either as simple market capitalization value-weighted averages or totals. The dependent variables are either industry level total emissions, or intensities, based on all publicly listed firms. We also include year and industry fixed effects. We double cluster standard errors at the industry and year levels. We report our findings for the industry-wide effects of innovation on the level of emissions in Panel A of Table 8. In Panel A1, we consider the measures based on quantity of innovation, while in Panel A2 the results based on quality of innovation. Columns 1-4 correspond to green innovation while columns 5-8 correspond to fuel efficiency innovation.

Consider first the effects of green innovation. We find that green innovation is positively associated with future scope 1, scope 2, and upstream scope 3 emissions in the same industry, and negatively associated with future downstream scope 3 emissions. The positive effects are largely statistically significant, especially for the impact-based measures of innovation. The results on scope 2 and upstream scope 3 emissions are consistent with the presence of a displacement effect, either due to increased consumption of energy, or to an increased reliance on less efficient suppliers. On the other hand, the results for downstream emissions point to the potential improved usage of green technology by consumers. For example, even though Tesla is generally a green car company in that its scope 3 downstream emissions are close to zero, its reliance on electricity consumption and different parts it assembles that are purchased from suppliers may contribute to an increased production of indirect emissions. When we consider fuel efficiency patents instead, we find a mostly negative effect of such innovation on future emissions, but the effects are estimated with more noise. Both direct and indirect emissions are negatively correlated with fuel efficiency patent filings, except for downstream scope 3 emissions for which the effect of quantity-based innovation is positive but statistically insignificant.

A potential limitation of this within-industry analysis is that innovation spillovers may reach beyond a narrowly defined economic cluster. While the GICS-6 classification is quite broad, it is still possible that not all innovation spillovers have been captured. Accordingly, we further consider specifications that include potential innovation spillovers across GICS-8 segments within a given GICS-2 sector. The benefit of this industry classification is that GICS-2 specifies much broader sectors that allow for significantly more spillovers. Specifically, we estimate the effects of innovation activity in a given GICS-8 sub-industry on future emission levels of the corresponding GICS-2 sector, excluding the specific GICS-8 sub-industry. Our regression model has the same structure as the one in Panel A. We present the results from this model in Panel B of Table 8, for quantity-based measures of innovation in Panel B1, and the quality-based innovation in Panel B2. Our results from this model largely mirror those in Panel A, except that some of the coefficients are estimated with less precision.

A more nuanced view of innovation emerges when we break down industry effects by looking separately at firms that innovate and those that do not. The reason why we make this distinction is that spillovers among innovating firms could be driven by competition, whereas spillovers from innovating firms to non-innovating firms are driven by adoption of the new technologies. To tease out these differential effects, we define a new variable, INNOVATORS, which is an indicator variable equal to one if the firm is a patenting company, and equal to zero if it is not, within the same industry. We then interact this indicator variable with the respective measures of patenting activity and estimate the model in (1) using measures of emissions separated into the two groups of companies within a given industry. We present the results from this model in Table 9.

In Panel A of Table 9 we report the results of the effects of KPSS measures of innovation on future emissions levels at the industry level. Across all specifications, we do not find statistically significant differences in emissions, both direct and indirect, between firms that innovate and those that do not, irrespective of the type of innovation. In other words, there is no evidence of any within-industry *spillover* between green/fuel efficiency innovators and non-innovators. In Panel B of Table 9, we further look at the emission decomposition into intensity metrics and operational scale. Several interesting results emerge from this analysis. First, green patenting activity is associated with a reduction in future scope 1 intensity of innovating firms, and a parallel increase in intensity for non-innovating firms. If anything, innovators seem to be the primary beneficiaries of the patenting activity they engage in. Simultaneously, we observe that the group of patenting companies subsequently increases its sales and investments while the opposite is true for the possible adopters. These offsetting forces can explain the earlier effect of positive significant differences in total emissions across these two groups of companies. One explanation of this

industry effect could be that adopters are less competitive and more inefficient companies in their sector, which face the credible threat of disruptive innovation. Adopting these new technologies could possibly be too costly in the short run. It may be less costly to simply run down their brown assets more quickly, thereby increasing their emission intensity. We further confirm the presence of such heterogeneity across the two groups of firms in Table IA.X. In sum, the observed effects for total emissions result both from opposite effects on emission intensity and redistribution of market shares across the two groups of firms.

When we in turn consider fuel efficiency innovation, we find that intensity of scope 1 emissions goes down for both patenting and adopting companies, but this reduction is met with a relative increase in sales and operations for innovators (which is consistent with the Jevons paradox that we observed at the firm level), and a reduction in sales for non-innovators. This latter result suggests that the equilibrium distribution of total emissions is a result of changing market shares rather than changing emissions efficiency of production. A slightly different picture emerges for indirect emissions. Here, we find that patenting companies observe increases in their emission intensities relative to non-innovating firms. Given that they also grow in scale, that could explain a much more significant dispersion in emissions across the two groups of firms. One reason why this reverse pattern may occur is that companies typically have less control over the impact of their innovation in the production network. Therefore, even if they achieve improvements in intensities of their direct emissions, they may generate leakage into the supply network.

Overall, we conclude that, by and large, innovation improves innovators' carbon efficiency, but these benefits are more visible for the operations that are under their direct control. At the same time, these companies tend to also increase their sales, so that some of the benefits of improved carbon efficiency may be wasted at the expense of increased scale. These effects are more pronounced for fuel efficiency patents, even though considerable differences can also be noted for green patents. These findings suggest that the success of decarbonization depends on the relative distribution of emissions across firms and the ability of firms to control any spillovers via their production networks.

4.5 The long-term impact of green innovation on emissions

A key factor in the effects of innovation is the speed with which new patent filings propagate into technological implementation. Consequently, it is important to look at the effects of innovation in the long run to the extent possible. While this lag between invention and adoption applies to many different economic activities, in the context of the climate crisis time is also a risk factor, and long lags between invention and adoption have a higher cost. Nevertheless, as a general test of the viability of innovations it may be useful to assess any long-term effects. To this end, we look at

the relationship between the stock of innovation and subsequent long-term changes in emissions. Specifically, we predict firm-level absolute changes in average emission levels (and their intensities) between the periods 2005-2014 and 2015-2020, using measures of the stock of innovations (measured as KPSS patent value-based ratios) over the period 1990-2004. We perform the tests separately for green and fuel efficiency innovation. We report the results of this test in Table IA.XI. Panel A presents the results based on the firm-level analysis, while Panel B reports similar results at the industry level.

We find that the long-term stock of green fuel efficiency innovation measured by impact-based patent ratios is not related to long-term changes in emissions at the firm level. In contrast, we do find that the long-term stock of fuel efficiency innovation is associated with lower upstream scope 3 emissions at the firm level. At the industry-level, we find that the long-term stock of green innovations predicts higher scope 2 emissions and lower upstream scope 3 emissions. This result points to some emission displacements in the long-rum, possibly due to greater consumption of energy, although suppliers are able to lower their emissions. Interestingly, the long-run firm-level results for fuel efficiency innovation do not carry over to the long-run industry-level results. Indeed, we find that the long-term stock of fuel efficiency innovations predicts higher scope 1 emissions. These results highlight again the complex nature of innovation at the industry level, involving subtle composition and changing market share effects. Overall, the general conclusion that emerges from this analysis is that even though we find some evidence that over the long-run, green innovation may lead, in some cases, to reductions in emissions, the link between green (and fuel efficiency) innovation and future decarbonization is too tenuous to support an unconditional directed technical change policy exclusive of any other broader policy interventions to regulate greenhouse gas emissions.

5. Evidence from the German "Automausstieg"

Our findings above paint a consistent picture of the lack of significant decarbonization driven by green innovation. As suggestive as they are, these findings do not establish causality. In this section we make an attempt to provide a more causal link between green innovation and future carbon emissions, taking advantage of the plausibly exogenous shock to green innovation in Germany triggered by the political response to the 2011 Fukushima nuclear accident, and the decision by the German government to phase out nuclear energy production (the "Atomausstieg"). In the announcement of the policy, the then Chancellor Angela Merkel committed to the doubling of energy use from renewable sources from 17 to 35% by 2020[8]. Given that the Fukushima accident

[8] Wiesmann, G. (2011, May 30). "Germany to scrap nuclear power by 2022". Financial Times.

was truly unexpected, we can trace down its impact on patenting activity, energy production, and carbon emissions. The methodological advantage of this shock is that it is a supply-driven shock, thus ruling out the possibility that any response in green innovation and emissions we identify could reflect demand-driven shocks to the economy.

Our full sample, unless otherwise noted, includes observations at the GICS-8 sub-industry, country, and year level. The composition of each industry requires firms that have a European patent or emissions data at some point during the entire sample period. We further drop any industry that does not have patent and emissions data in the period immediately following the shock. Our empirical analysis follows a standard difference-in-differences methodology in which we compare to each other the treated and control groups around the policy shock. The treatment sample involves industries in Germany, while our control group includes the equivalent counterparts in European countries relying on nuclear energy prior to the shock (as of 2010), but not subjected to any subsequent change in energy policy. These include Bulgaria, the Czech Republic, Finland, France, Great Britain, Hungary, Netherlands, Romania, Russia, Slovakia, Slovenia, and Ukraine. Among nuclear producers, we exclude companies/industries located in Belgium, Spain, Switzerland, and Sweden because each of these countries responded with some form of policy change, even if short lasting, around the same period. We conduct a standard balance test for treatment and control groups, with results reported in Table IA.XII. The results indicate that the two subsamples are largely comparable on most observable characteristics, which we further include in our regression models. This result is consistent with the hypothesis that the policy shift was not a response driven by a particularly unusual composition of the economy but rather a politically motivated decision.

We begin by estimating the impact of the Atomausstieg shock on the creation of green patents (excluding patents related to nuclear energy). In Figure 3, we plot the time-series evolution of GREENRATIO, calculated separately for Germany and the control group countries. These ratios are given by the aggregated sum of pure green patents granted (or purchased) for both publicly listed and private companies to total patent filings and acquisitions. We observe that prior to 2011 the two subgroups of countries have been closely tracking each other in terms of their green patenting activity. This observation supports the assumption of the difference-in-differences setting, which is the presence of parallel trends. Following the Atomausstieg, however, we observe a differential increase in green patenting activity in Germany, consistent with the intended policy shift away from nuclear energy and towards renewables.

We support this evidence with additional tests in which we look at the presence of a differential treatment at the level of GICS-8 industries. Specifically, for each year between 2005 and 2020 and each industry, we multiply GREENRATIO and GREENKPSSRATIO (both net of

nuclear energy patents) by the indicator variable, TREAT, which is equal to one for industry observations from Germany and equal to zero for industry-country observations (separately from each country) in the control group. To absorb any additional variation across different industries and countries, and over time, we include the same set of control variables as in Table 8, set at their pre-determined values as of the end of 2008, and interacted with each year indicator variable. We also include GICS-8-country and year fixed effects. Given that the measures of innovation involve both extensive and intensive margins, we estimate the model using the Poisson pseudo-maximum likelihood method. We double cluster standard errors at the industry and year dimensions.

The results, presented in Figure 4, show the point estimates of TREAT along with the 90% confidence intervals. These results indicate an increase in relative green ratios, both quantity and quality-based, for German industries. Note that the effect is not immediate, but typically occurs 2-3 years after the shock, which is consistent with the idea that the policy would take some time to take effect. In Panel D, we construct a placebo test for the fuel efficiency patents, which are largely not related to renewable energy. Consistent with our hypothesis, the evidence does not show any strong differential effect for German vs. non-German companies.

We further corroborate our findings on differential green patent filings by estimating a Poisson model, which additionally controls for any presence of pre-trends. The results are presented in Table 10. Columns 1-4 present the results for the patent ratios, while columns 5-7 are for intensity metrics. In column 1, we present the results based on the sample of public and private firms. For any variables that are available for both groups of firms we aggregate information into a combined characteristic. If the data are available only for public firms, we use the control corresponding to this group only. In columns 2-7, we restrict our sample to public firms only. Consistent with our plots, we find a strong positive effect of the Atomausstieg policy on GREENRATIO and GREENKPSSRATIO. The results are insignificant for EFFRATIO, which is consistent with the policy intent targeting green innovation only. Across all specifications we find no evidence of pre-trends, as can be seen through the coefficients of the lagged TREAT variables. Overall, we conclude that the German policy shift has had a differentially positive effect on the intensity of green innovation (ex-nuclear) of German industries.

We further explore the effect of this policy on emission intensities across industries. We present the results for three different types of emissions in Figure 5. Our methodology mimics the one we use for Figure 4. We find several interesting results. First, following the shock, we observe that emission intensities generally go down, but the effect only occurs a few years after the Atomausstieg, and much later than the first visible increase in green patenting activity. Second, if anything, for the first few years, intensities of scope 1 emissions increase, contrary to what one would expect from a green innovation shock. Finally, we do not find any strong pre-trend in the

data prior to 2011. We further confirm the robustness of these results, by estimating the model in Table 10. Columns 5-7 document the estimated coefficients, which are generally in line with our evidence in Figure 5.

We supplement our analysis with external data on energy production to get a better understanding of the sources of observed variation in our data. We look at the different energy sources at the country level and estimate a similar model as in Figures 4 and 5, except that our only time-varying control is the country's GDP per capita. We also include country and year fixed effects. Figure 6 presents the results respectively for: production emission intensity (Panel A), nuclear electricity share (Panel B), renewables electricity share (Panel C), coal electricity share (Panel D), other fossil fuel electricity share (Panel E), and the proportion of electricity consumption from net imports (Panel F). Several interesting results emerge from this analysis. First, consistent with the substance of the Atomausstieg shock, we do observe that the share of renewable electricity increases significantly, and that the share of nuclear electricity decreases. These two effects are exactly the intended effects of the policy makers. Second, and somewhat unexpectedly, we find that this increase in the renewable share has not been accompanied by a similar decrease in fossil fuel energy. If anything, the share of fossil fuel consumption has gone up. In particular, the share of coal energy has increased, even though this effect has been temporary. Finally, we surprisingly observe that Germany has not met this increase in brown energy consumption with imports. On the contrary, net energy imports are significantly reduced in the post-shock period. One explanation of these joint effects is that the shift in policy has also coincided with an expansion in the German economy that could not be met through an increase in renewable energy alone. Consequently, in the few years immediately following the Atomausstieg, the German economy as a whole saw an increase in overall emission intensity, even though the shock has led to an improved emission intensity excluding fossil fuels and an increase in renewable energy supply. Eventually, the increased capacity in renewable energy has led to a reduced reliance on fossil fuels and thus to an overall improvement in emission intensity, both direct and indirect. As before, we further corroborate these results with the regression estimates reported in Panel B of Table 10. The results are consistent with the plots.

In sum, the exogenous shock to German energy policy has had a positive impact on green innovation that likely resulted in more energy being produced from such sources. However, the scale of the German economy's expansion has resulted in an unintended consequence of compensating any energy shortfalls with fossil fuel energy. As a result, the intended overall impact of the Atomausstieg shock on emission intensity has not immediately materialized, a result that is consistent with a form of Jevons paradox and displacement of inefficiency into other parts of economic activity.

6. Conclusion

What emerges from our analysis of green innovation is that the predicted sustainability revolution has not yet begun. Although there has been a steady increase in green and fuel efficiency innovation, these technological advances have not materialized in lower carbon emissions at the firm level. Most of the green innovation is done by firms that are already green (with low carbon emissions) but brown companies (with high carbon emissions) tend to engage in fuel efficiency innovation. Much of the promise of the latter technological advances in terms of lower carbon intensity has been undone by rebound effects. Furthermore, where we see significant decarbonization, it has little to do with green technological advances, and some of the reductions in emissions at the industry level result from the reduction in output of companies that lose their competitive edge rather than improved emission intensities.

We cannot determine what the counterfactual would be, had there been much less green innovation. It is possible that in the absence of all this innovation activity, carbon emissions might have been much higher. Also, as the IEA (2020) report contends, the path to decarbonization "will require a broad range of different technologies working across all sectors of the economy in various combinations and applications." What we have found, however, is that green innovation has not yet put the economy on a net zero compatible trajectory. Green innovation may be necessary, but it is not sufficient on its own to bring about a renewable energy transition.

A major obstacle to green innovation is Arrow's (1962) replacement effect. Fossil fuel-based profitable businesses have little incentive to engage in green innovation that might undermine their business model. But we have found a much more pervasive replacement effect at work, through companies' supply chains and ecosystems. When upstream suppliers and downstream clients have fossil-fuel based operations it is very difficult and costly for individual companies to switch to a green technology. Hence, their lack of interest in green innovation. Not a day goes by without some major announcement of a promising technological breakthrough that might solve the CO2 problem, whether it is molten-salt nuclear reactors, power-to-gas (P2G) renewable hydrogen production, nuclear fusion, modular carbon capture systems, or sodium-sulphur batteries, etc. Yet, as promising as these technological breakthroughs sound, what ultimately matters for the transition to net zero is adoption of these green technologies at scale. And for this to happen in an accelerated way to avoid further overheating of the planet, what may be required is public policy intervention to coordinate adoption. This calls for a new form of industrial policy that breaks through the replacement obstacle by coordinating green technology adoption upstream and downstream throughout firms' ecosystems. Moreover, subsidies for green innovation must be more carefully targeted to where they help unlock a general adoption of green technologies throughout the supply chain. Blanket subsidies for green innovation without regard

to the likely adoption of new technologies and future decarbonization may simply be too wasteful and costly.

References

Acemoglu, Daron, 2002, "Directed technical change" *Review of Economic Studies* 69, 781—810.

Aghion, Philippe, Antoine Dechezlepretre, David Hemous, Ralf Martin, and John Van Reenen, 2016, "Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry" *Journal of Political Economy* 124, 1—51.

Andriosopoulos, Dmitris, Pawel Czarnowski, and Andrew Marshall, 2021, "Do investors care about green innovation?" Working Paper University of Strathclyde.

Arrow, Kenneth, 1962, "Economic Welfare and the Allocation of Resources for Invention" *National Bureau of Economic Research, Inc.*

Arrow, Kenneth, 1971, "The Economic Implications of Learning by Doing" *Palgrave Macmillan* UK, London, pp. 131–149.

Bolton, Patrick and Marcin Kacperczyk, 2021, "Do investors care about carbon risk?" *Journal of Financial Economics* 142(2), 517—549.

Bolton, Patrick and Marcin Kacperczyk, 2023, "Global pricing of carbon-transition risk" *Journal of Finance* 78(6), 3677—3754.

Busch, Timo, Matthew Johnson, and Thomas Pioch, 2018, "Consistency of corporate carbon emission data" University of Hamburg Report WWF Deutschland, Hamburg.

Cohen, Lauren, Umit Gurun, and Quoc Nguyen, 2022, "The ESG-innovation disconnect: Evidence from green patenting" Working Paper Harvard Business School.

Engle, Robert, Stefano Giglio, Heebum Lee, Bryan Kelly, and Johannes Stroebel, 2020, "Hedging climate change news" *Review of Financial Studies* 33, 1184–1216.

Greaker, Mads and David Popp, 2022, "Environmental economics, regulation, and innovation" NBER Working Paper 30415.

Hege, Ulrich, Sebastien Pouget, and Yifei Zhang, 2022, "The impact of corporate climate action on financial markets: Evidence from climate-related patents" Toulouse School of Economics Working Paper.

IEA (International Energy Agency), 2020, "Energy Technology Perspective 2020 Special Report on Clean Energy Innovation", *IEA*, Paris.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov, 2021, "Carbon tail risk" *Review of Financial Studies* 34(3), 1540–1571.

Jevons, William S., 1865, "The Coal Question; An Inquiry Concerning the Progress of the Nation, and Probable Exhaustion of Our Coal Mines." London: Macmillan and Co.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, "Technological innovation, resource allocation, and growth" *The Quarterly Journal of Economics* 132(2), 665—712.

Kuang, Huan and Bing Liang, 2022, "Climate-related innovations: Economic value and risk mitigation" University of Massachusetts Working Paper.

Lanzi, Elisa, Elena Verdolini, and Ivan Hascic, 2011, Efficiency-improving fossil fuel technologies for electricity generation: Data selection and trends. *Energy Policy*, 39(11), 7000–7014.

Leippold, Marcus and Tingyu Yu, 2024, "Are green innovations priced? Evidence beyond patents." Working Paper.

Lerner, Josh, and Amit Seru. "The use and misuse of patent data: Issues for finance and beyond." *The Review of Financial Studies* 35.6 (2022): 2667-2704.

Popp, David, 2002, "Induced innovation and energy prices," *American Economic Review* 92, 160—180.

Redding, Stephen, 2002, "Path dependence, endogenous innovation, and growth" *International Economic Review* 43(4), 1215—1248.

Reza, Syed and Yanhui Wu, 2022, "Green innovation", SUNY Binghamton Working Paper.

Sautner, Zacharias, Laurence Van Lent, Grigory Vilkov, and Ruishen Zhang, 2023, "Firm-level climate change exposure" *Journal of Finance* 78(3), 1449—1498.

Schipper, Lee and Michael Grubb, 2000, "On the rebound? Feedback between energy intensities and energy uses in IEA countries" *Energy Policy* 28, 367—388.

Sorrell, Steve, John Dimitropoulos, and Matt Sommerville, 2009, "Empirical estimates of the direct rebound effect: A review" *Energy Policy* 37, 1356—1371.

1 Tables

TABLE 1: ESTIMATES OF KPSS PATENT VALUE: GREEN AND FUEL-EFFICIENCY PATENTS

The table replicates Table 1 from Kogan et al. (2017) for our sample. Our sample is based on patents granted or purchased by the European Patent Office (EPO) between 2005 and 2022. In Panel A, we report estimates for green patents and in Panel B estimates for fuel-efficiency patents. We report the distribution of the following variables: the number of future citations till the end of our sample period C, the number of citations scaled by the mean number of cites to patents within the given patent type, i.e. green and fuel-efficiency, issued in the same year $\bar{C}$, the market-adjusted firm returns R_f on the three-day window following the patent issue date; the filtered component of returns $E[v|R_f]$ related to the value of innovation using Kogan et al. (2017)'s equation 4; and the filtered dollar value of innovation ζ using Kogan et al. (2017)'s equation 3 deflated to 1982 (million) dollars using the CPI. Market adjusted returns are computed as the difference between the firm return (Compustat) minus the return of the country-specific market index. We restrict attention to the patents for which we have nonmissing data on three-day announcement return, market capitalization, and return volatilities - inputs needed to compute the economic value.

Moment	C	$\frac{C}{\bar{C}}$	$R_f(\%)$	$E[v\|R_f](\%)$	ζ
Panel A: Green patents					
Mean	39.13	1.00	0.05	0.40	47.58
Std. dev.	457.13	11.19	3.59	0.18	135.03
Percentiles					
p1	0.00	0.00	-9.89	0.14	0.14
p5	0.00	0.00	-5.18	0.18	1.02
p10	1.00	0.03	-3.56	0.21	2.08
p25	4.00	0.15	-1.63	0.28	6.33
p50	12.00	0.40	-0.07	0.36	16.96
p75	33.00	0.90	1.60	0.49	42.08
p90	75.00	1.87	3.75	0.64	103.52
p95	125.00	2.97	5.65	0.74	182.84
p99	364.00	8.39	11.04	0.99	505.88
Panel B: Fuel-efficiency patents					
Mean	24.46	1.00	-0.01	0.39	45.80
Std. dev.	73.86	2.28	3.66	0.20	108.62
Percentiles					
p1	0.00	0.00	-10.06	0.13	0.11
p5	0.00	0.00	-5.22	0.16	0.83
p10	0.00	0.00	-3.49	0.19	2.62
p25	3.00	0.19	-1.61	0.26	8.50
p50	10.00	0.52	-0.10	0.35	20.11
p75	26.00	1.11	1.46	0.48	43.43
p90	55.00	2.13	3.54	0.63	97.23
p95	85.00	3.26	5.34	0.78	165.10
p99	212.00	7.89	11.46	1.06	449.73

TABLE 2: PATENT RATIOS AND TOTAL EMISSIONS (FIRM-LEVEL ANALYSIS)

The unit of observation is firm(f)-year(t). The sample period is 2005 to 2022. The dependent variables are natural logarithms of 3-year averages (*t to t+2*) of *S1TOT*, *S2TOT*, *S3UPTOT* and *S3DOWNTOT*. The key independent variable is *GREENRATIO* in Panel A, which is a 3-year cumulative sum of green patent counts over total patent counts from *t-3 to t-1*. Similarly, the key independent variable in Panel B, *EFFRATIO*, is based on efficiency patents. Controls include: *LOGSIZE*, *LOGASSETS*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *LOGAGE*, *BETA*, *VOLAT*, and *MSCI* and are lagged by one year. *LOGSIZE* is the natural logarithm of market capitalization (in $ million); *LOGASSETS* is the natural logarithm of total assets (in $ million); *LOGPPE* is the natural logarithm of plant, property & equipment (in $ million); *LEVERAGE* is the book value of leverage defined as the book value of debt divided by the book value of assets; *ROE* is the return on equity; *M/B* is the market value of equity divided by the book value of equity; *INVEST/A* is CAPEX divided by the book value of assets; *LOGAGE* is the natural logarithm of the firm's age based on its year of incorporation; *BETA* is the firm-level market beta estimated over the one year period; *VOLAT* is the monthly stock return volatility calculated over the one year period; *MSCI* is an indicator variable equal to one if a stock is part of the MSCI ACWI in a given year and zero otherwise. The model is estimated using pooled regression model. All regressions include GICS-6 industry-year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) $LOGS1TOT_{f,t:t+2}$	(2) $LOGS2TOT_{f,t:t+2}$	(3) $LOGS3UPTOT_{f,t:t+2}$	(4) $LOGS3DOWNTOT_{f,t:t+2}$
Panel A: Green innovation				
$GREENRATIO_{f,t-3:t-1}$	0.011	0.024	0.023	−0.027
	(0.034)	(0.034)	(0.017)	(0.079)
R2	0.968	0.967	0.985	0.953
Observations	39450	39450	39450	21751
Panel B: Efficiency innovation				
$EFFRATIO_{f,t-3:t-1}$	0.108*	−0.016	0.022	0.228
	(0.059)	(0.064)	(0.028)	(0.166)
R2	0.968	0.967	0.985	0.953
Observations	39450	39450	39450	21751
Controls	yes	yes	yes	yes
Industry-Year F.E.	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes

TABLE 3: PATENT RATIOS AND EMISSION FACTORS (FIRM-LEVEL ANALYSIS)

The unit of observation is firm(f)-year(t). The sample period is 2005 to 2022. The dependent variables are 3-year (*t to t+2*) emission intensities *S1INT*, *S2INT*, *S3UPINT* and *S3DOWNINT*, which is the 3-year cumulative sum of emissions over the 3-year cumulative sum of sales, as well as natural logarithms of 3-year averages (*t to t+2*) of *SALES* and *CAPEX*. The key independent variables are *GREENRATIO* in Panel A and *EFFRATIO* in Panel B. Controls include: *LOGSIZE*, *LOGASSETS*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *LOGAGE*, *BETA*, *VOLAT*, *MSCI*. All independent variables are defined in Table 2 and are lagged by one year. The model is estimated using pooled regression model. All regressions include GICS-6 industry-year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) $S1INT_{f,t:t+2}$	(2) $S2INT_{f,t:t+2}$	(3) $S3UPINT_{f,t:t+2}$	(4) $S3DOWNINT_{f,t:t+2}$	(5) $LOGSALES_{f,t:t+2}$	(6) $LOGCAPEX_{f,t:t+2}$
Panel A: Green innovation						
$GREENRATIO_{f,t-3:t-1}$	0.200	0.013	0.003	0.287	0.009	−0.010
	(0.141)	(0.018)	(0.037)	(0.517)	(0.015)	(0.028)
Observations	39450	39450	39450	21751	39450	39359
R2	0.940	0.864	0.938	0.903	0.985	0.955
Panel B: Efficiency innovation						
$EFFRATIO_{f,t-3:t-1}$	−0.069	−0.058**	−0.143***	−0.093	0.066***	0.132**
	(0.244)	(0.027)	(0.046)	(1.207)	(0.021)	(0.057)
Observations	39450	39450	39450	21751	39450	39359
R2	0.940	0.864	0.938	0.903	0.985	0.955
Controls	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes

TABLE 4: PATENT IMPACT AND TOTAL EMISSIONS (FIRM-LEVEL ANALYSIS)

The unit of observation is firm(f)-year(t). The sample period is 2005 to 2022. The dependent variables are *LOGS1TOT*, *LOGS2TOT*, *LOGS3UPTOT*, and *LOGS3DOWNTOT* as defined in Table 2. The key independent variables are *GREENKPSSRATIO* and *EFFKPSSRATIO*, which is a 3-year cumulative sum of green, respectively fuel-efficiency, patent values over total patent values from *t-3 to t-1* following the methodology of Kogan et al. (2017). Controls include: *LOGSIZE*, *LOGASSETS*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *LOGAGE*, *BETA*, *VOLAT*, *MSCI*. All control variables are defined in Table 2 and are similarly lagged by one year. The model is estimated using pooled regression model. All regressions include GICS-6 industry-year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) $LOGS1TOT_{f,t:t+2}$	(2) $LOGS2TOT_{f,t:t+2}$	(3) $LOGS3UPTOT_{f,t:t+2}$	(4) $LOGS3DOWNTOT_{f,t:t+2}$
Panel A: Green innovation				
$GREENKPSSRATIO_{f,t-3:t-1}$	0.032	0.013	0.018	−0.040
	(0.036)	(0.033)	(0.017)	(0.078)
R2	0.967	0.967	0.986	0.953
Observations	38568	38568	38568	21175
Panel B: Efficiency innovation				
$EFFKPSSRATIO_{f,t-3:t-1}$	0.099	−0.022	0.028	0.192
	(0.062)	(0.066)	(0.028)	(0.168)
R2	0.967	0.967	0.986	0.953
Observations	38568	38568	38568	21175
Controls	yes	yes	yes	yes
Industry-Year F.E.	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes

TABLE 5: PATENT IMPACT AND EMISSION FACTORS (FIRM-LEVEL ANALYSIS)

The unit of observation is firm(f)-year(t). The sample period is 2005 to 2022. The dependent variables are *S1INT*, *S2INT*, *S3UPINT*, *S3DOWNINT*, *LOGSALES*, and *LOGCAPEX* as defined in Table 3. The key independent variables are *GREENKPSSRATIO* and *EFFKPSSRATIO* as defined in Table 4. Controls include: *LOGSIZE*, *LOGASSETS*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *LOGASSETS*, *LOGAGE*, *BETA*, *VOLAT*, *MSCI*. All control variables are defined in Table 2 and are similarly lagged by one year. The model is estimated using pooled regression model. All regressions include GICS-6 industry-year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) $S1INT_{f,t:t+2}$	(2) $S2INT_{f,t:t+2}$	(3) $S3UPINT_{f,t:t+2}$	(4) $S3DOWNINT_{f,t:t+2}$	(5) $LOGSALES_{f,t:t+2}$	(6) $LOGCAPEX_{f,t:t+2}$
Panel A: Green innovation						
$GREENKPSSRATIO_{f,t-3:t-1}$	0.204	0.010	−0.016	0.722	0.010	−0.007
	(0.139)	(0.018)	(0.038)	(0.595)	(0.014)	(0.028)
Observations	38568	38568	38568	21175	38568	38478
R2	0.940	0.865	0.938	0.903	0.985	0.954
Panel B: Efficiency innovation						
$EFFKPSSRATIO_{f,t-3:t-1}$	−0.093	−0.073**	−0.168***	−0.556	0.073***	0.136**
	(0.251)	(0.027)	(0.045)	(1.228)	(0.022)	(0.056)
Observations	38568	38568	38568	21175	38568	38478
R2	0.940	0.865	0.938	0.903	0.985	0.954
Controls	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes

TABLE 6: PATENT RATIOS AND FIRM TYPE

The unit of observation is firm(f)-year(t). The sample period is 2005-2022. The dependent variable is $GREENRATIO$ in columns 1 to 3 and $EFFRATIO$ in columns 4 to 6. $GREENRATIO$ is the number of green patents over the total number of patents granted or purchased at the firm and year level based on European Patent Office patents. $EFFRATIO$ similarly is the number of fuel efficiency patents over the total number of patents at the European Patent Office. $LOGS123UPTOT$ is the natural logarithm of firm-level scope 1, 2, and upstream 3 emissions. $LOGAGE$ is the natural logarithm of the firm's age based on its year of incorporation. $GREENSTOCK$ and $EFFSTOCK$ is the firm's patent stock of all (green and fuel efficiency) granted or purchased patents by the EPO from 1990 up to year t. Controls include: $LOGSIZE$, $LOASSETS$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $BETA$, $VOLAT$, and $MSCI$. All independent variables are lagged by one year and control variables are defined in Table 2. The model is estimated using Poisson pseudo-maximum likelihood. Columns 1 and 4 include year and country fixed effects. Columns 2 and 5 include country and GICS-6 industry×year fixed effects and columns 3 and 6 GICS-6 industry×year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	$GREENRATIO_{f,t}$			$EFFRATIO_{f,t}$		
$LOGS123UPTOT_{f,t-1}$	0.048**	−0.053***	−0.002	0.256***	0.010	−0.006
	(0.024)	(0.018)	(0.022)	(0.044)	(0.043)	(0.086)
$LOGAGE_{f,t-1}$	−0.198***	−0.154***	−0.075	0.098	0.074	−0.097
	(0.036)	(0.031)	(0.116)	(0.066)	(0.061)	(0.211)
$GREENSTOCK(/100)_{f,t-1}$	0.054***	0.059***	−0.001	−0.110***	−0.103***	−0.016
	(0.011)	(0.011)	(0.005)	(0.026)	(0.034)	(0.011)
$EFFSTOCK(/100)_{f,t-1}$	−0.033***	−0.056***	0.009	0.148***	0.126***	−0.001
	(0.012)	(0.013)	(0.011)	(0.026)	(0.032)	(0.012)
Controls	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes
Year F.E.	yes	no	no	yes	no	no
Industry X Year F.E.	no	yes	yes	no	yes	yes
Firm F.E.	no	no	yes	no	no	yes
Observations	32438	31811	23646	32319	27968	13696
Pseudo R2	0.0365	0.110	0.222	0.0749	0.169	0.273

TABLE 7: PATENT RATIOS AND MARKET SHARE

The unit of observation is firm(f)-year(t) and covers both public and private firms, as we do not rely on public firms' emission data. The sample period is 2005 to 2022. In columns 1 and 2 the dependent variable is $MARKETSHARE\ SALES$, which is a firm's market share based on its sales relative to total public and private firms' sales in a given GICS-6 industry. Similalry, in columns 3 and 4 the dependent variable is is $MARKETSHARE\ ASSETS$ and is based on assets. The key dependent variable is $GREENRATIO$ and $EFFRATIO$. Control variables include only those financial variables that are also available for private firms, specifically: $LOGASSETS$, $LOGPPE$, $LEVERAGE$, ROE, $INVEST/A$, $LOGAGE$, and $PUBLIC$. $PUBLIC$ is an indicator equal to one for public firms. All other variables are defined in Table 2. All independent variables are lagged by one year. The model is estimated using pooled regression model. All regressions include firm fixed effects and GICS-6 industry×year fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1)	(2)	(3)	(4)
	$MARKETSHARE\ SALES_{f,t:t+2}$		$MARKETSHARE\ ASSETS_{f,t:t+2}$	
$GREENRATIO_{f,t-3:t-1}$	−0.015**		−0.011*	
	(0.006)		(0.006)	
$EFFRATIO_{f,t-3:t-1}$		0.014		0.006
		(0.009)		(0.009)
Observations	115892	115892	122107	122107
R2	0.967	0.967	0.965	0.965
Controls	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes
GICS6-Year F.E.	yes	yes	yes	yes

TABLE 8: PATENT RATIOS AND TOTAL EMISSIONS (INDUSTRY-LEVEL ANALYSIS)

The sample period is 2005 to 2022. The unit of observation is GICS-6(j)-year(t) in Panel A. The dependent variables are natural logarithms of GICS-6 industry-level 3-year averages (t *to* t+2) of $S1TOT$, $S2TOT$, $S3UPTOT$ and $S3DOWNTOT$. In Panel A.I, the key independent variable is $GREENRATIO$ and $EFFRATIO$, which is a GICS-6 industry-level 3-year cumulative sum of green, respectively fuel-efficiency, patent counts over total patent counts of public firms from *t-3 to t-1*. In Panel A.II, the key independent variable is $GREENKPSSRATIO$ and $EFFKPSSRATIO$, which is a GICS6 industry-level 3-year cumulative sum of green, respectively fuel-efficiency, patent dollar values over total patent dollar values of public firms from *t-3 to t-1* following the methodology of Kogan et al. (2017). Controls include: $LOGSIZE$, $LOGASSETS$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $LOGAGE$, $BETA$, $VOLAT$,$MSCI$. The controls are either industry level logs of sums ($LOGSIZE$, $LOGASSETS$, and $LOGPPE$), sum over sums ($LEVERAGE$, ROE, M/B, and $INVEST/A$), market capitalization-weighted averages ($BETA$, $VOLAT$, $MSCI$, $LOGAGE$). All control variables are lagged by one year. The model is estimated using pooled regression model. All regressions include year and GICS-6 industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. In Panel B, the unit of observation is GICS-8 (j)-year(t). We aggregate the dependent variables at a given GICS-8 industry's higher GICS-2 level including all GICS-8 industries but the given GICS-8 industry used for the independent variables. The dependent variables are thus natural logarithms of GICS-2 (minus the given GICS-8 industry) industry-level 3-year averages (t *to* t+2) of $S1TOT$, $S2TOT$, $S3UPTOT$ and $S3DOWNTOT$. The key independent variables are $GREENRATIO$ and $EFFRATIO$, which is a GICS-6 industry-level 3-year cumulative sum of green, respectively fuel-efficiency, patent counts over total patent counts from *t-3 to t-1* in Panel B.1. In Panel B.2, the key independent variable is $GREENKPSSRATIO$ and $EFFKPSSRATIO$ and similarly defined 3-year cumulative sum of green, respectively fuel-efficiency, patent dollar values over total patent dollar values of public firms. Controls include: $LOGSIZE$, $LOGASSET$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $LOGAGE$, $BETA$, $VOLAT$, $MSCI$. The controls are either GICS-8 industry level logs of sums ($LOGSIZE$, $LOGASSET$, $LOGPPE$) or market capitalization weighted averages ($LEVERAGE$, ROE, M/B, $INVEST/A$, $BETA$, $VOLAT$, $MSCI$, $LOGAGE$). All control variables are lagged by one year. The model is estimated using pooled regression model. All regressions include GICS-8 industry and year fixed effects. We double cluster standard errors at the GICS-8 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) $LOGS1-TOT_{j,t:t+2}$	(2) $LOGS2-TOT_{j,t:t+2}$	(3) $LOGS3-UPTOT_{j,t:t+2}$	(4) $LOGS3-DOWNTOT_{j,t:t+2}$	(5) $LOGS1-TOT_{j,t:t+2}$	(6) $LOGS2-TOT_{j,t:t+2}$	(7) $LOGS3-UPTOT_{j,t:t+2}$	(8) $LOGS3-DOWNTOT_{j,t:t+2}$
Panel A: Within-industry analysis								
Panel A.1: Count-based ratios								
$GREENRATIO_{j,t-3:t-1}$	0.771*	0.958*	0.271	−0.268				
	(0.417)	(0.458)	(0.244)	(0.949)				
$EFFRATIO_{j,t-3:t-1}$					−1.490	−1.858*	−0.473	5.802*
					(0.961)	(0.987)	(0.461)	(2.384)
Observations	1114	1114	1114	412	1114	1114	1114	412
R2	0.985	0.975	0.987	0.970	0.985	0.975	0.987	0.971
Panel A.2: KPSS-based ratios								
$GREENKPSSRATIO_{j,t-3:t-1}$	0.840**	0.857**	0.407*	0.053				
	(0.303)	(0.315)	(0.229)	(0.890)				
$EFFKPSSRATIO_{j,t-3:t-1}$					−1.495*	−1.149	−0.461	2.983
					(0.815)	(0.890)	(0.428)	(2.470)
Observations	1114	1114	1114	412	1114	1114	1114	412
R2	0.986	0.975	0.987	0.970	0.985	0.974	0.987	0.971
Panel B: Cross-industry analysis								
Panel B.1: Count-based ratios								
$GREENRATIO_{j,t-3:t-1}$	0.146	0.231*	−0.017	−0.455				
	(0.104)	(0.111)	(0.063)	(0.250)				
$EFFRATIO_{j,t-3:t-1}$					−0.206	−0.363*	−0.317*	0.207
					(0.283)	(0.172)	(0.161)	(0.441)
Observations	2439	2439	2439	904	2439	2439	2439	904
R2	0.993	0.973	0.988	0.984	0.993	0.972	0.988	0.983
Panel B.2: KPSS-based ratios								
$GREENKPSSRATIO_{j,t-3:t-1}$	0.147*	0.177**	0.029	−0.003				
	(0.084)	(0.076)	(0.061)	(0.150)				
$EFFKPSSRATIO_{j,t-3:t-1}$					−0.236	−0.234	−0.232	−0.131
					(0.227)	(0.148)	(0.161)	(0.512)
Observations	2435	2435	2435	904	2435	2435	2435	904
R2	0.993	0.973	0.988	0.983	0.993	0.973	0.988	0.983
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes

TABLE 9: PATENT RATIOS AND INNOVATOR VS NON-INNOVATOR EMISSIONS (INDUSTRY-LEVEL ANALYSIS)

The unit of observation is innovator(p)-GICS-6 industry(j)-year(t). We group firms into innovators and non-innovators and aggregate at the innovator×GICS-6 industry level annually. The sample period is 2005 to 2022. Innovators are defined within each patent class, i.e. separately for green and fuel-efficiency innovation. A firm that has at least one green, respectively fuel-efficiency, patent within the sample period is considered to be an innovator. The dependent variables are natural logarithms of innovator×GICS-6 industry-level 3-year averages (t *to* t+2) of $S1TOT$, $S2TOT$, $S3UPTOT$ and $S3DOWNTOT$ in Panel A. In Panel B, the dependent variables are natural logarithms of innovator-GICS6 industry level 3-year (t *to* t+2) emission intensities $S1INT$, $S2INT$, $S3UPINT$ and $S3DOWNINT$, which are calculated as 3-year cumulative averages of emissions over the 3-year cumulative averages of sales, as well as natural logarithms of 3-year averages (t *to* t+2) of $SALES$ and $CAPEX$. The key independent variables are $GREENKPSSRATIO$ and $EFFKPSSRATIO$. Both patent variables are defined in Table 8 and are naturally based on the GICS-6 innovation subset. We interact the patent variables with the indicator $INNOVATORS$, which is equal to one if the industry aggregate is based on green, respectively fuel-efficiency, patenting firms. Innovator×industry-level controls include: $LOGSIZE$, $LOGASSETS$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $LOGAGE$, $BETA$, $VOLAT$, and $MSCI$ and are interacted with the indicator $INNOVATORS$. All control variables are lagged by one year and are defined in Table 8. The model is estimated using pooled regression model. All regressions include year and GICS-6 industry fixed effects. We double cluster standard errors at the GICS-6 industry and year dimension. *** 1% significance, ** 5% significance * 10% significance.

Panel A: Total Emissions

	(1) $LOGS1-TOT_{j,t:t+2}$	(2) $LOGS2-TOT_{j,t:t+2}$	(3) $LOGS3-UPTOT_{j,t:t+2}$	(4) $LOGS3-DOWNTOT_{j,t:t+2}$	(5) $LOGS1-TOT_{j,t:t+2}$	(6) $LOGS2-TOT_{j,t:t+2}$	(7) $LOGS3-UPTOT_{j,t:t+2}$	(8) $LOGS3-DOWNTOT_{j,t:t+2}$
$GREENKPSSRATIO_{j,t-3:t-1}$	0.038	0.493	−0.033	−0.058				
	(0.392)	(0.399)	(0.292)	(0.555)				
$GREENKPSSRATIO_{j,t-3:t-1}\times$	0.224	−0.175	0.240	−0.084				
$INNOVATORS$	(0.435)	(0.400)	(0.242)	(0.384)				
$EFFKPSSRATIO_{j,t-3:t-1}$					−1.524	−1.285	−1.378	0.869
					(1.263)	(0.821)	(0.803)	(1.919)
$EFFKPSSRATIO_{j,t-3:t-1}\times$					−0.585	0.650	1.045	−0.019
$INNOVATORS$					(1.179)	(0.817)	(0.949)	(1.196)
Observations	2217	2217	2217	822	2220	2220	2220	819
R2	0.953	0.949	0.962	0.962	0.951	0.942	0.960	0.962
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes

Panel B: Emission Factors

	(1) $S1INT_{j,p,t:t+2}$	(2) $S2INT_{j,p,t:t+2}$	(3) $S3UPINT_{j,p,t:t+2}$	(4) $S3DOWNINT_{j,p,t:t+2}$	(5) $LOGSALES_{j,p,t:t+2}$	(6) $LOGCAPEX_{j,p,t:t+2}$
Panel B.1: Green innovation						
$GREENKPSSRATIO_{j,t-3:t-1}$	6.833*	0.245	0.195	6.879	−0.124	−0.590*
	(3.516)	(0.164)	(0.299)	(5.730)	(0.267)	(0.319)
$GREENKPSSRATIO_{j,t-3:t-1}\times$	−11.216**	−0.068	0.182	−6.127	0.280*	0.176
$INNOVATORS$	(4.962)	(0.226)	(0.408)	(6.711)	(0.159)	(0.202)
Observations	2217	2217	2217	822	2217	2216
R2	0.962	0.809	0.860	0.816	0.978	0.946
Panel B.2: Fuel-efficiency innovation						
$EFFKPSSRATIO_{j,t-3:t-1}$	−5.745	−0.037	−3.217***	3.272	−0.718	0.638
	(5.490)	(0.353)	(0.920)	(17.741)	(0.595)	(1.063)
$EFFKPSSRATIO_{j,t-3:t-1}\times$	−9.191	0.363	1.601	−14.646	1.104**	0.618
$INNOVATORS$	(5.842)	(0.241)	(1.089)	(15.477)	(0.443)	(0.514)
Observations	2220	2220	2220	819	2220	2219
R2	0.967	0.800	0.860	0.883	0.979	0.942
Controls	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes

TABLE 10: IMPACT OF THE ATOMAUSSTIEG ON INNOVATION AND EMISSIONS

The sample period is 2005 to 2020. We drop the years 2011 and 2012, which coincide with the year of and the year after the Atomausstieg. In Panel A, the unit of observation is GICS-8 industry(j)-country(c)-year(t). Treated observations are all firms that have their headquarter in Germany. Control observations are all firms that have their headquarter in a nuclear energy producing European country other than Germany. We additionally exclude firms from Belgium, Spain, Sweden and Switzerland, as these countries also responded to the Fukushima nuclear accident with nuclear energy reductions, but reversed or weakened their decision in subsequent years. We require all industries to have emission and patent data in t=-1, the base period. The dependent variables are $GREENRATIO$, $GREENKPSSRATIO$, and $EFFRATIO$ in columns 1 to 4. We exclude nuclear patents for the green innovation variables. We consider patents from public and private firms in column 1 and patents from public firms only in columns 2 to 5. $GREENRATIO$ and $EFFRATIO$ are annual sum over sums of the given patent counts. $GREENKPSSRATIO$ takes patent values in the numerator and denominator. In columns 5 to 7, the dependent variables are industry level sum over sum sales based intensities ($S1INT$, $S2INT$, $S3UPINT$), which we winsorize at the 5% level. The key independent variables are $TREATPOST$, $TREAT\ T = -2$, and $TREAT\ T <= -3$. $TREATPOST$ is a dummy equal to one for industry-country-year observations from Germany from 2011 onwards and zero otherwise. $TREAT\ T = -2$ is a dummy equal to one for industry-country-year observations from Germany in 2009 (i.e. two years before treatment). $TREAT\ T <= -3$ is a dummy equal to one for industry-country-year observations from Germany before 2009 (i.e. two years before treatment and onwards). Private controls are based on the public and private sample and include $LOGASSETS$, $LOGPPE$, $LEVERAGE$, ROE, $INVEST/A$, $LOGAGE$, and $PUBLIC$. Public controls are based on the public sample and include $LOGSIZE$, $LOGASSETS$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $LOGAGE$, $BETA$, $VOLAT$, and $MSCI$. All controls are based on 2008 and are interacted by year. *Public* is an asset-weighted average of the public indicator. All other control variables are defined in Table 4. We estimate the model in columns 1 to 4 by using Poisson pseudo-maximum likelihood and in columns 5 to 7 by using pooled regression model. All regressions include GICS-8 industry×country and year fixed effects. We double cluster standard errors at the GICS-8 industry times country and year dimension. In Panel B, the unit of observation is country(c)-year(t). As in Panel A, Germany is considered to be the treated country. All other European nuclear producing countries except for Belgium, Spain, Sweden and Switzerland are considered control countries. The dependent variables are $POWERGENINTENSITY$, which is the emission intensity of the total electricity produced (power generated), $NUCLEARSHARE$, $RENEWABLESHARE$, $COALSHARE$, and $OTHERFOSSILSHARE$, which are the share of electricity produced by nuclear energy, renewable energy sources (including solar, wind, biofuels, geothermal, waste, and hydro), coal, and other fossil fuel energy sources. The key independent variables are as in column A $TREATPOST$, $TREAT\ T = -2$, and $TREAT\ T <= -3$. We additionally include the 2008 country-level GDP per capita interacted by year as control. The model is estimated using pooled regression model. All regressions include year and country fixed effects. We use robust standard errors. *** 1% significance, ** 5% significance * 10% significance.

Panel A: Innovation and emissions at the GICS-8 industry-country level

	(1) $GREENRATIO_{j,c,t}$ ex. nuclear	(2) $GREENRATIO_{j,c,t}$ ex. nuclear	(3) $GREENKPSSRATIO_{j,c,t}$ ex. nuclear	(4) $EFFRATIO_{j,c,t}$	(5) $S1INT_{j,c,t}$	(6) $S2INT_{j,c,t}$	(7) $S3INT_{j,c,t}$
TREATPOST	0.350*	0.442**	0.401**	0.632**	−0.193	−0.031	−0.146**
	(0.191)	(0.184)	(0.181)	(0.279)	(0.193)	(0.053)	(0.067)
TREAT T=-2	0.116	−0.086	−0.384	−0.022	−0.128	−0.062**	−0.179**
	(0.257)	(0.249)	(0.262)	(0.371)	(0.087)	(0.028)	(0.080)
TREAT T<=-3	0.180	0.248	0.046	0.552*	0.062	−0.118***	−0.114
	(0.216)	(0.217)	(0.238)	(0.331)	(0.119)	(0.032)	(0.078)
Sample	private/public	public	public	public	public	public	public
Controls	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes
Industry-Country F.E.	yes	yes	yes	yes	yes	yes	yes
Observations	2557	2010	1998	1985	2673	2673	2673
Pseudo R2 / R2	0.164	0.195	0.208	0.220	0.901	0.842	0.939

Panel B: Electricity production at the country-level

	(1) $POWERGEN-INTENSITY_{c,t}$	(2) $NUCLEAR-SHARE_{c,t}$	(3) $RENEWABLES\ SHARE_{c,t}$	(4) $COALSHARE_{c,t}$	(5) $OTHERFOSSIL-SHARE_{c,t}$	(6) $ELECTRICITY-IMPORT_{c,t}$
TREATPOST	18.374	−0.107***	0.066***	0.000	0.041**	−0.100***
	(21.596)	(0.009)	(0.022)	(0.024)	(0.016)	(0.025)
TREAT T=-2	11.906	−0.012	−0.002	0.010	0.004	−0.004
	(21.666)	(0.010)	(0.025)	(0.023)	(0.019)	(0.030)
TREAT T<=-3	5.043	0.012	−0.021	0.008	0.001	−0.043*
	(21.035)	(0.012)	(0.021)	(0.023)	(0.017)	(0.026)
Controls	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes
Observations	182	182	182	182	182	182
Pseudo R2	0.944	0.982	0.927	0.924	0.969	0.865

2 Figures

FIGURE 1: PROPORTION OF OECD PATENTS CLASSIFIED AS GREEN OR FUEL EFFICIENCY

We document the proportion of OECD env-tech identified patents that we have classified as green, respectively fuel efficiency. We include all patents from the European Patent Office (EPO) between 2005 and 2022 that have been granted or purchased by firms from the sample of public firms with emission data. We document both the number of patents as well as the proportion relative to all OECD env-tech identified patents. A third group of patents are not strictly related to carbon neutral technology or fossil fuel technology and therefore remain unclassified.

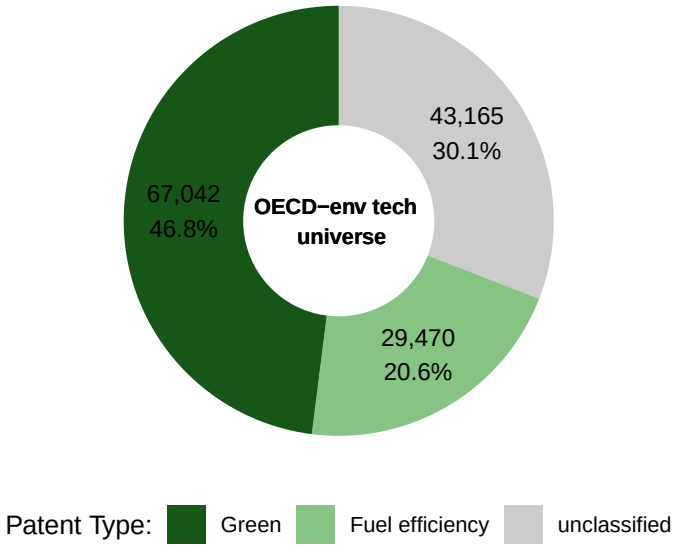
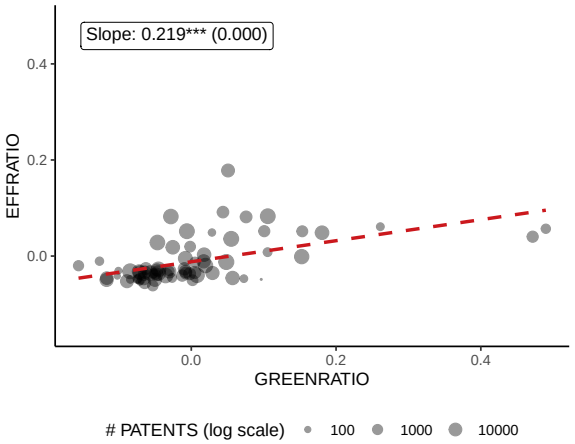
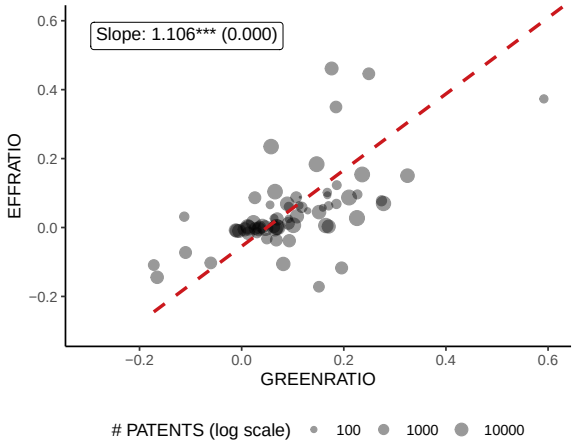


FIGURE 2: INDUSTRY INNOVATION AND EMISSION DISPERSION

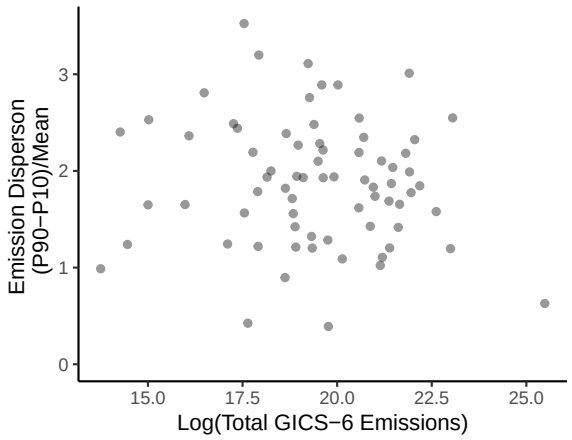
In Panel A and B, we focus on the distribution of green and fuel efficiecny innovation within GICS-6 industries. The unit of observation is GICS-6 industry. We plot normalized *GREENRATIO* and *EFFRATIO* per GICS-6 industry and scale the size of the points by the total number of patents between 2005 and 2022. In Panel A, we calculate the patent ratios by normalizing for country-level innovation at the industry×country level. We first calculate the country level patent ratios as the sum of green, respectively fuel efficiency, patents over all patents. We next similarly calculate patent ratios at the industry×country level and normalize these ratios by deducting the respective country ratio. Lastly, we aggregate the data at the GICS-6 level by value-weighting average the industry-country ratios based on the total number of patents. In Panel B, we calculate the patent ratios by normalizing for country-level innovation at the firm level. To do so, we first calculate country average green, fuel efficiency, and all patent counts. We next normalize patent counts at the firm level by deducting country patent counts. Lastly, we aggregate at the GICS-6 industry level by calculating value-weighted green, fuel efficiency, and any patent counts and subsequently take ratios. We drop three industry observations with ratios larger than 1 in Panel B. We also report a linear regression slope estimate of EFFRATIO on GREENRATIO. In Panel C and D, we focus on emission dispersion within industires. The unit of observation is GICS-6 industry in Panel C and GICS-8 industry in Panel D. We restrict the sample to 2022, the last year in our sample. The scatter plot relates industry emission dispersion to total industry emissions. Total emissions include scope 1, 2, upstream 3 and downstream 3 emissions. Emission dispersion is calculated as the industry p10 to p90 range scaled by average industry emissions.



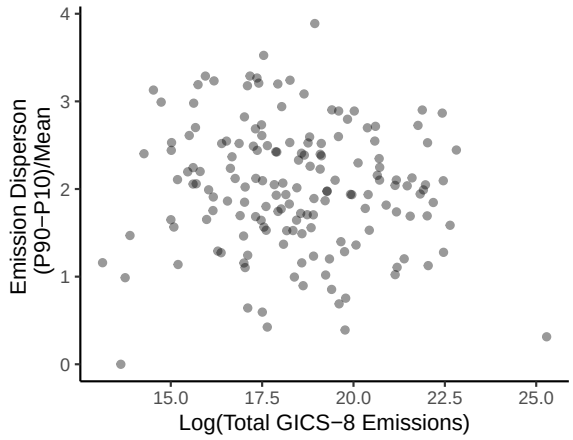
(A) INNOVATION DISTRIBUTION: NORMALIZED AT INDUSTRY×COUNTRY LEVEL



(B) INNOVATION DISTRIBUTION: NORMALIZED AT FIRM LEVEL



(C) EMISSION DISPERSION WITHIN GICS-6



(D) EMISSION DISPERSION WITHIN GICS-8

FIGURE 3: THE ATOMAUSTIEG AND GREEN (EX. NUCLEAR) INNOVATION IN GERMANY (RAW DATA)

We calculate green (ex. nuclear) ratios for Germany (treatment group) and all European Nuclear Energy producing countries except Belgium Spain, Sweden and Switzerland (control group). We first aggregate green (ex. nuclear) and all patents for the treatment and control group per annum and then calculate the green patent ratio. We include patents from all firms, i.e. both public and private firms. We plot the green patent ratio for the treatment group in red and the control group in grey. The shaded area represents the year of 2011, when the Fukushima nuclear accident and the Atomausstieg occurred.

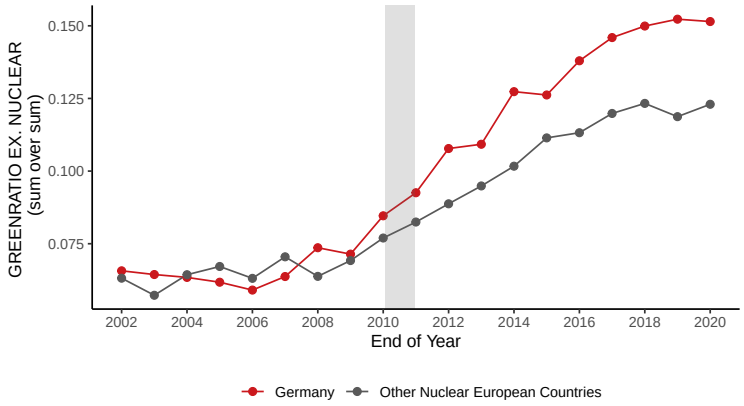
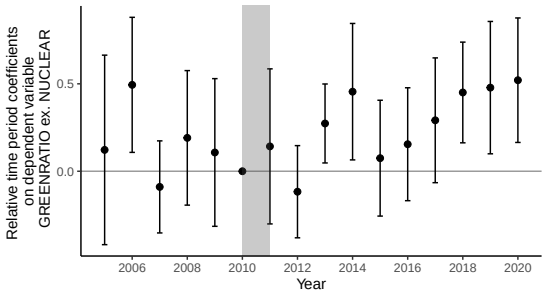
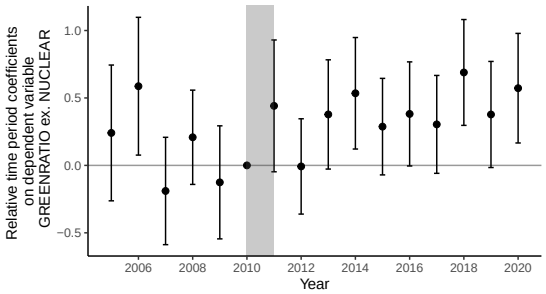


FIGURE 4: THE ATOMAUSSTIEG AND INNOVATION

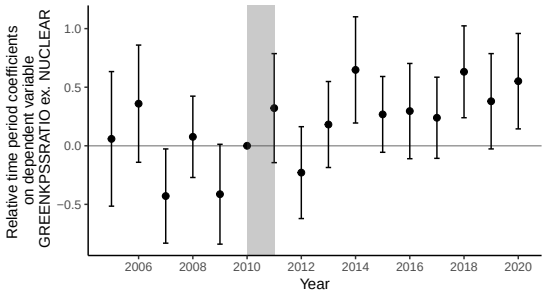
The unit of observation is GICS-8 industry-country-year. The sample period is 2005 to 2020. This figure follows Table 10 Panel A, but reports the corresponding dynamic DiD estimation. Industry observations from Germany are the treatment group, while industry observations from other European nuclear energy producing countries except Belgium, Spain, Sweden, and Switzerland are the control group. We define relative time treatment dummies ($\sum_{rt \in 2005:2020; \neq 2010} TREAT_{rt}$) that are equal to one for the treatment group in the given year, and zero otherwise. The dependent variables are based on the green and fuel efficiency classifications, but exclude nuclear patents in the case of green innovations. In Panel A, the dependent variable is *GREENRATIO* (excluding patents related to nuclear energy) and is based on public and private firms. In Panel B to D, the patent ratios (*GREENRATIO* in Panel B, *GREENKPSSRATIO* in Panel C, and *EFFRATIO* in Panel E) are based on public firms only. All patent variables are defined in Table 10. We estimate the model with Poisson pseudo-maximum likelihood and report point estimates and 90% confidence intervals for relative time treatment dummy coefficients ($TREAT_{rt}$). We additionally include the controls *LOGASSETS*, *LOGPPE*, *LEVERAGE*, *ROE*, *INVEST/A*, *LOGAGE*, and *PUBLIC* in Panel A, respectively the controls *LOGSIZE*, *LOGASSETS*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *LOGAGE*, *BETA*, *VOLAT*, and *MSCI* in Panel B to E. All controls are based on 2008 and are interacted with individual year dummies. All regressions include GICS-8 industry×country and year fixed effects. We double cluster standard errors at the GICS-8 industry×country and year dimensions.



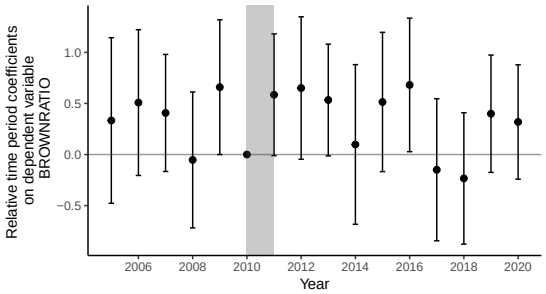
(A) GREENRATIO EX. NUCLEAR (PUBLIC AND PRIVATE)



(B) GREENRATIO EX. NUCLEAR (PUBLIC)



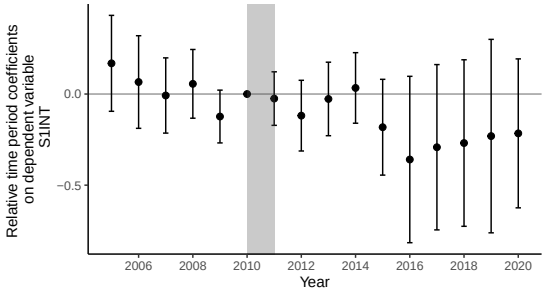
(C) GREENKPSSRATIO EX. NUCLEAR (PUBLIC)



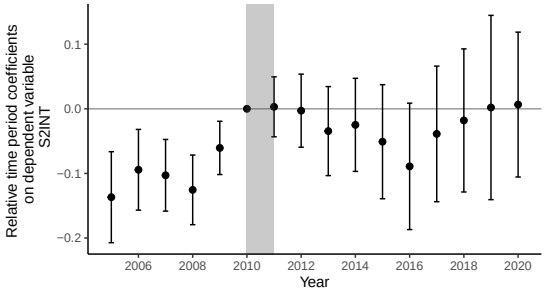
(D) EFFRATIO (PUBLIC)

FIGURE 5: THE ATOMAUSSTIEG AND EMISSIONS

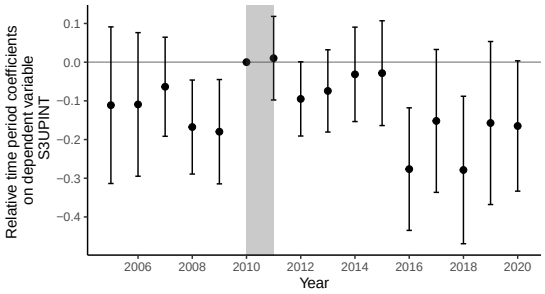
The unit of observation is GICS-8 industry-country-year. The sample period is 2005 to 2020. This figure follows Table 10 Panel A, but reports the corresponding dynamic DiD estimation. Industry observations from Germany are the treatment group, while industry observations from other European nuclear energy producing countries except Belgium, Spain, Sweden, and Switzerland are the control group. We define relative time treatment dummies ($\sum_{rt\in 2005:2020;\neq 2010} TREAT_{rt}$) that are equal to one for the treatment group in the given year, and zero otherwise. The dependent variables is $S1INT$ in Panel A, $S2INT$ in Panel B, and $S3UPINT$ in Panel C and are defined in Table 10. We estimate the model with Poisson pseudo-maximum likelihood and report point estimates and 90% confidence intervals for relative time treatment dummy coefficients ($TREAT_{rt}$). We additionally include the controls $LOGSIZE$, $LOGASSETS$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $LOGAGE$, $BETA$, $VOLAT$, and $MSCI$, that are based on 2008 and are interacted with individual year dummies. All regressions include GICS-8 industry×country and year fixed effects. We double cluster standard errors at the GICS-8 industry×country and year dimensions.



(A) S1INT



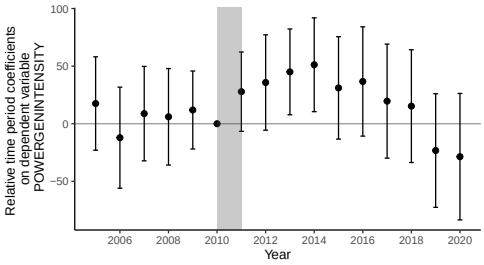
(B) S2INT



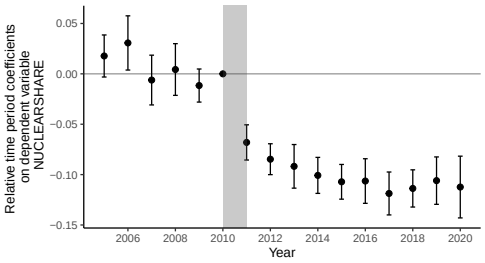
(C) S3UPINT

FIGURE 6: THE ATOMAUSSTIEG AND ELECTRICITY PRODUCTION

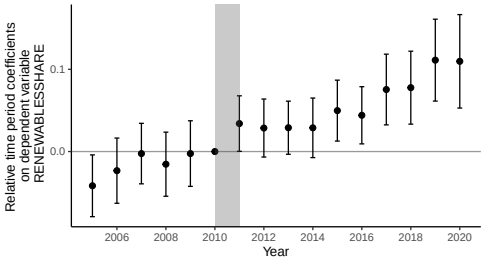
The unit of observation is country-year. The sample period is 2005 to 2020. This figure follows Table 10 Panel B, but reports the corresponding dynamic DiD estimation. Germany is treatment group, while other European nuclear energy producing countries except Belgium, Spain, Sweden, and Switzerland are the control group. We define relative time treatment dummies ($\sum_{rt \in 2005:2020; \neq 2010} TREAT_{rt}$) that are equal to one for the treatment group in the given year, and zero otherwise. The dependent variable is *POWERGENINTENSITY* in Panel A, *NUCLEARSHARE* in Panel B, *RENEWABLESHARE* in Panel C, *COALSHARE* in Panel D, *OTHERFOSSILSHARE* in Panel E and *ELECTRICITYIMPORT* in Panel F. All dependent variables are defined in Table 10. We estimate the model by using the pooled regression model and report point estimates and 90% confidence intervals for relative time treatment dummy coefficients ($TREAT_{rt}$). We additionally include the 2008 country-level GDP per capita interacted with individual year dummies. All regressions include country and year fixed effects. We use robust standard errors.



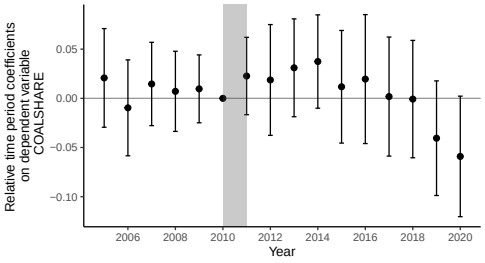
(A) POWER GENERATION INTENSITY



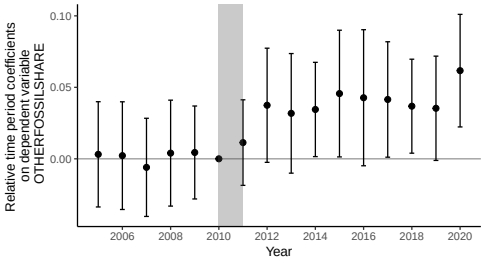
(B) NUCLEAR ELECTRICITY SHARE



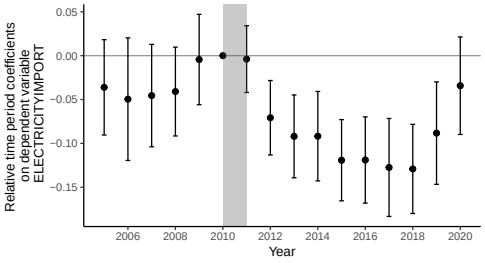
(C) RENEWABLES ELECTRICITY SHARE



(D) COAL ELECTRICITY SHARE



(E) OTHER FOSSIL FUEL ELECTRICITY SHARE



(F) NET ELECTRICITY IMPORT PROPORTION

IA Internet Appendix

IA.1 Internet Appendix; Tables

TABLE IA.I: PATENT DATA BY COUNTRY

The sample period is 2005-2022. In Panel A, we report the number of firm observations by country for the full (public and private), public, private and Trucost sample. Columns 1 to 4 report unconditional numbers and columns 5 to 8 condition on having at least one granted or purchased patent at the EPO. In Panel B, we report patent counts, average patent counts by firm conditional on patenting and the number of firm-year observations. We report the total number of granted or purchased patents at the EPO in a given country in columns 1 and 2, the average number of patents at the EPO per firm conditional on having at least one patent by country in columns 3 and 4, the firm-year observations for the entire sample covering patenting and non-patenting firm-year observations in columns 5 and 6, as well as firm-year observations with at least one granted or purchased patent at the EPO in columns 7 and 8. The full sample is based on firms from Orbis and Compustat. We report countries with less than 2000 firm-year observations in the full sample aggregated by region under "Others". "Others North America" include ANGUILLA, ANTIGUA & BARBUDA, BAHAMAS, BARBADOS, BELIZE, BRITISH VIRGIN ISLANDS, COSTA RICA, CURACAO, DOMINICA, DOMINICAN REPUBLIC, EL SALVADOR, GREENLAND, GRENADA, GUATEMALA, HONDURAS, JAMAICA, MARTINIQUE, MARSHALL ISLANDS, NICARAGUA, PANAMA, SAINT BARTHELEMY, SAINT KITTS & NEVIS, SAINT LUCIA , SAINT MARTIN, SAINT PIERRE & MIQUELON, TRINIDAD & TOBAGO; "Others Asia" include ARMENIA, AZERBAIJAN, BAHRAIN, BANGLADESH, BHUTAN, CAMBODIA, IRAQ, KAZAKHSTAN, KUWAIT, KYRGYZSTAN, LAO PEOPLE'S DEMOCRATIC REPUBLIC, LEBANON, MACAO S.A.R, MONGOLIA, MYANMAR/BURMA, NEPAL, OPAN, PALESTINIAN TERRITORIES, QATAR, SAUDI ARABIA, SYRIAN ARAB REPUBLIC, UNITED ARAB EMIRATES, UZBEKISTAN; "Others Europe" include ALBANIA, BELARUS, FAROE ISLANDS, GEORGIA, GIBRALTAR, GUERNSEY, ISLE OF MAN, JERSEY, LIECHTENSTEIN, MONACO, SAN MARINO, SVALBARD and "Others Rest of the World" include ALGERIA, ARGENTINA, BOLIVIA, BOTSWANA, BURKINA FASO, CAMEROON, CAPE VERDE, COLOMBIA, CONGO, COTE D'IVOIRE, ECUADOR, ESWATINI, ETHIOPIA, FIJI, FRENCH GUIANA, GABON, GAMBIA, GHANA, GUYANA, KENYA, LIBERIA, MALAWI, MALI, MAYOTTE, MOZAMBIQUE, NAMIBIA, PAPUA NEQ GUINEA, PARAGUAY, PERU, REUNION, SENEGAL, SEYCHELLE, SIERRA LEONE, SUDAN, TUNISIA, URUGUAY, UNITED REPUBLIC OF TANZANIA, VENEZUELA, ZAMBIA, ZIMBABWE.

Panel A: Firm count	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample				Patenting sample			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
Australia	6233	2276	3957	518	508	335	173	140
Austria	1791	81	1710	47	254	49	205	36
Belgium	26854	163	26691	80	792	63	729	52
Bermuda	383	268	115	238	45	40	5	39
Bosnia and Herzegovina	1739	3	1736	0	1	0	1	0
Brazil	1169	332	837	195	91	51	40	39
Bulgaria	15689	81	15608	6	44	7	37	3
Canada	4377	1548	2829	338	393	355	38	134
Cayman Islands	723	253	470	242	73	53	20	55
Chile	303	181	122	38	24	20	4	8
China	84590	3860	80730	2185	1187	671	516	551
Croatia	2448	77	2371	2	11	5	6	0
Cyprus	1569	102	1467	8	21	1	20	0
Czechia	14693	19	14674	11	154	3	151	4
Denmark	71642	209	71433	73	969	62	907	40
Egypt	672	148	524	31	7	3	4	1
Estonia	7477	20	7457	3	37	0	37	0
Finland	11250	171	11079	74	574	80	494	50
France	52518	836	51682	389	2090	331	1759	245
Germany	16278	877	15401	302	2424	357	2067	212
Greece	1618	240	1378	34	30	15	15	6
Hong Kong	787	584	203	128	55	46	9	22
Hungary	4751	39	4712	10	47	4	43	4
Iceland	2734	28	2706	5	29	4	25	1
India	13294	3995	9299	694	388	232	156	179
Indonesia	509	496	13	137	4	4	0	3
Iran (Islamic Republic of)	462	0	462	0	0	0	0	0
Ireland	2339	89	2250	52	107	29	78	32
Israel	513	342	171	116	197	180	17	74
Italy	70001	389	69612	190	3032	131	2901	109
Japan	6968	3882	3086	2186	2076	1553	523	1162
Latvia	2568	31	2537	0	12	2	10	0
Lithuania	1335	41	1294	3	18	2	16	0
Luxembourg	5584	61	5523	33	276	22	254	15
Malaysia	10282	814	9468	184	80	46	34	29
Malta	4106	27	4079	1	27	1	26	0
Mauritius	737	70	667	4	6	5	1	0
Moldova, Republic of	981	0	981	0	0	0	0	0
Montenegro	504	0	504	0	0	0	0	0
Netherlands	10364	179	10185	101	515	72	443	66
New Zealand	386	172	214	52	41	31	10	13
North Macedonia	1149	4	1145	0	1	0	1	0
Norway	43163	309	42854	114	796	88	708	55
Pakistan	605	390	215	55	1	1	0	0
Peru	246	103	143	18	3	3	0	1
Philippines	294	91	203	45	10	5	5	5
Poland	12780	385	12395	69	293	95	198	28
Portugal	14615	51	14564	21	128	11	117	9
Republic of Korea	5186	2047	3139	1244	1072	674	398	593
Romania	8184	60	8124	9	18	3	15	1
Russian Federation	44105	239	43866	67	171	29	142	17
Serbia	5506	45	5461	2	6	1	5	0
Singapore	4331	550	3781	119	143	63	80	33
Slovakia	5708	17	5691	1	41	4	37	0
Slovenia	3142	35	3107	7	70	6	64	2
South Africa	430	346	84	131	47	44	3	35
Spain	46670	246	46424	111	932	68	864	61
Sri Lanka	262	246	16	5	2	2	0	1
Sweden	47737	506	47231	252	1401	320	1081	191
Switzerland	494	276	218	172	195	148	47	125
Taiwan	2621	2082	539	868	596	553	43	340
Thailand	2249	275	1974	86	28	20	8	13
Turkey	2159	411	1748	114	96	42	54	29
Ukraine	27552	26	27526	2	0	0	0	0
United Kingdom	35705	2036	33669	601	1570	396	1174	263
United States of America	10809	6681	4128	2605	2816	2413	403	1490
Viet Nam	2332	34	2298	3	3	2	1	0
Others Asia	1755	723	1032	211	26	22	4	18
Others Europe	600	71	529	48	32	18	14	18
Others North America	616	33	583	19	14	11	3	6
Others Rest of the World	1690	519	1171	128	46	33	13	26
Total	795867	41821	754046	15837	27195	9940	17255	6684

Panel B: Patent count and firm-year count

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patent count		Average number of patents conditional on patenting		Firm-year observations: unconditional		Firm-year observations: conditional on patenting	
	Full	Trucost	Full	Trucost	Full	Trucost	Full	Trucost
Australia	3520	1727	2.3	3.8	43693	3927	1506	459
Austria	14452	6498	10.6	24.9	12391	384	1359	261
Belgium	19106	6427	7.1	21.4	268765	602	2697	301
Bermuda	1838	769	7.9	6.0	4066	1585	234	128
Bosnia and Herzegovina	3	.	1.5	.	15447	0	2	0
Brazil	1487	657	4.5	4.5	8037	1419	334	146
Bulgaria	74	3	1.1	1.0	123372	30	68	3
Canada	20651	12469	14.0	23.0	33415	2907	1476	542
Cayman Islands	6660	4635	19.6	23.5	5032	1518	340	197
Chile	1539	807	14.5	16.5	2891	439	106	49
China	41172	25726	10.8	17.3	312914	13264	3826	1487
Croatia	28	0	1.5	.	23061	21	19	0
Cyprus	56	0	1.7	.	6210	29	33	0
Czechia	547	22	1.7	2.2	99138	51	330	10
Denmark	14771	6386	6.4	18.0	390506	574	2321	354
Egypt	353	2	12.6	2.0	2895	244	28	1
Estonia	78	0	1.2	.	66466	25	64	0
Finland	28345	22694	13.4	60.7	102202	619	2117	374
France	128353	79473	16.1	55.8	447757	2831	7987	1424
Germany	187514	112955	16.0	76.9	115002	2385	11724	1468
Greece	96	14	1.2	1.0	15661	268	82	14
Hong Kong	5680	5222	21.4	36.8	7832	1131	266	142
Hungary	350	142	3.2	6.5	45795	71	108	22
Iceland	926	53	8.5	13.2	25708	13	109	4
India	7968	5521	5.0	7.8	104812	4686	1607	708
Indonesia	4	3	1.0	1.0	5013	1017	4	3
Iran (Islamic Republic of)	0	.	.	.	4549	0	0	0
Ireland	19086	10465	35.0	47.6	13729	395	546	220
Israel	3886	2251	5.0	8.2	4777	781	780	275
Italy	28088	7002	3.1	15.4	658630	1201	9043	456
Japan	375969	336194	25.8	47.1	82458	17360	14580	7145
Latvia	48	.	1.7	.	20849	0	28	0
Lithuania	81	0	1.7	.	8069	21	48	0
Luxembourg	6390	631	6.2	6.5	25200	264	1028	97
Malaysia	637	385	2.7	3.7	91586	1348	233	105
Malta	97	0	1.8	.	23235	6	54	0
Mauritius	9	0	1.0	.	2298	24	9	0
Moldova, Republic of	0	.	.	.	5930	0	0	0
Montenegro	0	.	.	.	3828	0	0	0
Netherlands	50767	36625	26.8	79.1	51759	827	1896	463
New Zealand	528	237	3.3	6.6	3212	401	159	36
North Macedonia	1	.	1.0	.	9814	0	1	0
Norway	4263	1610	2.2	6.6	400718	659	1931	245
Pakistan	2	0	1.0	.	5279	396	2	0
Peru	4	1	1.3	1.0	2030	188	3	1
Philippines	141	65	2.3	2.2	2768	470	62	30
Poland	3907	1785	5.6	22.9	82340	496	698	78
Portugal	496	45	1.6	1.6	129736	193	301	28
Republic of Korea	112206	106005	25.5	46.9	54231	8885	4397	2259
Romania	33	0	1.3	.	74319	31	26	0
Russian Federation	771	158	2.1	3.0	324592	528	370	52
Serbia	265	0	17.7	.	44903	18	15	0
Singapore	1411	679	3.1	4.3	21724	875	455	158
Slovakia	92	.	1.3	.	52038	0	69	0
Slovenia	413	76	2.2	6.3	28130	34	185	12
South Africa	1506	1419	9.1	10.8	3755	1418	166	131
Spain	7917	3250	3.1	10.4	417541	928	2573	312
Sri Lanka	2	1	1.0	1.0	2692	45	2	1
Sweden	68000	51605	14.4	63.1	426953	1623	4711	818
Switzerland	46642	41924	30.2	43.8	5162	1632	1546	957
Taiwan	16904	14293	7.1	11.4	32103	6740	2385	1249
Thailand	548	457	4.5	6.1	20861	690	122	75
Turkey	4023	3246	12.2	23.7	14186	836	329	137
Ukraine	0	0	.	.	200517	13	0	0
United Kingdom	46031	23962	7.7	14.2	236828	5584	5958	1688
United States of America	338129	277017	20.9	33.5	79830	20651	16157	8278
Viet Nam	3	0	1.0	.	19830	22	3	0
Others Asia	6156	3737	82.1	133.5	13993	992	75	28
Others Europe	3184	439	20.8	5.9	2968	339	153	74
Others North America	2517	2336	33.1	50.8	4180	111	76	46
Others Rest of the World	1547	904	6.8	7.4	13215	1199	228	122
Total	1638271	1221009	14.9	36.3	6015426	118264	110150	33673

TABLE IA.II: GREEN/ FUEL EFFICIENCY INNOVATION BY COUNTRY

The sample period is 2005-2022. In Panel A, we report the number of firm observations with at least one green, resepctively fuel efficiency, EPO patent by country for the full (public and private), public, private and Trucost sample. In Panel B, we report green patent counts in columns 1 and 2 and average green patent counts by firm conditional on green patenting in columns 3 and 4. Similarly, we report fuel efficiency patent counts in columns 5 and 6 and average fuel efficiency patent counts by firm conditional on fuel efficiency patenting in columns 7 and 8. The full sample is based on firms from Orbis and Compustat. Countries with less than 2000 firm-year observations in the full sample are aggregated by region under "Others" as in Table IA.I.

Panel A: Firm count	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	with at least one green patent				with at least one fuel efficiency patent			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
Australia	147	108	39	50	51	38	13	19
Austria	94	26	68	26	55	20	35	19
Belgium	188	31	157	29	67	16	51	13
Bermuda	16	14	2	12	12	11	1	11
Bosnia and Herzegovina	0	0	0	0	0	0	0	0
Brazil	33	16	17	14	16	9	7	7
Bulgaria	10	3	7	2	2	1	1	0
Canada	119	110	9	60	44	41	3	29
Cayman Islands	36	30	6	30	8	6	2	6
Chile	5	4	1	3	3	3	0	1
China	389	246	143	227	124	91	33	82
Croatia	2	1	1	0	2	0	2	0
Cyprus	2	0	2	0	2	0	2	0
Czechia	30	1	29	1	9	0	9	0
Denmark	238	27	211	26	67	10	57	9
Egypt	4	2	2	0	1	0	1	0
Estonia	9	0	9	0	1	0	1	0
Finland	179	39	140	30	74	21	53	17
France	473	147	326	126	189	69	120	61
Germany	698	178	520	140	339	96	243	82
Greece	7	4	3	2	3	2	1	2
Hong Kong	19	15	4	10	8	7	1	7
Hungary	10	1	9	1	7	1	6	2
Iceland	7	2	5	0	2	1	1	0
India	118	85	33	76	49	33	16	30
Indonesia	0	0	0	0	0	0	0	0
Iran (Islamic Republic of)	0	0	0	0	0	0	0	0
Ireland	36	17	19	22	20	10	10	14
Israel	50	44	6	26	16	13	3	9
Italy	537	59	478	51	247	39	208	34
Japan	947	764	183	650	468	402	66	369
Latvia	2	1	1	0	0	0	0	0
Lithuania	3	0	3	0	1	0	1	0
Luxembourg	86	9	77	4	44	7	37	5
Malaysia	18	12	6	10	10	6	4	6
Malta	4	0	4	0	0	0	0	0
Mauritius	0	0	0	0	0	0	0	0
Moldova, Republic of	0	0	0	0	0	0	0	0
Montenegro	0	0	0	0	0	0	0	0
Netherlands	168	41	127	41	87	28	59	30
New Zealand	14	9	5	4	1	1	0	0
North Macedonia	0	0	0	0	0	0	0	0
Norway	239	38	201	29	80	14	66	12
Pakistan	0	0	0	0	0	0	0	0
Peru	0	0	0	0	0	0	0	0
Philippines	3	2	1	2	1	0	1	0
Poland	60	21	39	10	23	9	14	4
Portugal	31	5	26	5	11	1	10	1
Republic of Korea	420	295	125	296	123	93	30	82
Romania	4	1	3	0	2	0	2	0
Russian Federation	40	10	30	5	14	4	10	3
Serbia	1	0	1	0	0	0	0	0
Singapore	43	20	23	12	21	13	8	12
Slovakia	5	0	5	0	1	1	0	0
Slovenia	11	3	8	2	5	0	5	0
South Africa	17	15	2	13	4	4	0	3
Spain	209	28	181	30	46	11	35	12
Sri Lanka	1	1	0	1	0	0	0	0
Sweden	350	111	239	87	113	49	64	45
Switzerland	100	83	17	81	38	35	3	34
Taiwan	195	186	9	130	36	33	3	24
Thailand	10	10	0	9	5	4	1	4
Turkey	23	17	6	14	12	10	2	10
Ukraine	0	0	0	0	0	0	0	0
United Kingdom	439	159	280	136	187	74	113	73
United States of America	1150	1022	128	777	406	363	43	317
Viet Nam	0	0	0	0	0	0	0	0
Others Asia	11	10	1	8	5	4	1	4
Others Europe	11	7	4	8	9	4	5	3
Others North America	6	6	0	4	3	3	0	2
Others Rest of the World	20	14	6	12	13	11	2	8
Total	8097	4110	3987	3344	3186	1722	1464	1517

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Patent count and firm average patent count for *green* and *fuel efficiency* patents								
	Green innnovation				Fuel efficiency innnovation			
	Patent count		Average number of patents conditional on patenting		Patent count		Average number of patents conditional on patenting	
	Full	Trucost	Full	Trucost	Full	Trucost	Full	Trucost
Australia	391	162	1.4	1.5	168	75	1.7	2.0
Austria	1284	707	3.9	6.0	476	119	3.0	1.8
Belgium	2491	972	3.7	6.1	1145	562	4.6	6.5
Bermuda	138	48	2.9	2.0	34	18	1.5	1.5
Bosnia and Herzegovina	0	.	.	.	0	.	.	.
Brazil	230	141	2.4	2.5	42	30	1.4	1.4
Bulgaria	16	1	1.0	1.0	2	0	1.0	.
Canada	1894	1262	4.6	6.0	374	243	2.8	2.7
Cayman Islands	480	318	4.2	4.4	199	45	8.0	4.1
Chile	220	114	5.5	5.2	11	5	1.0	1.0
China	4230	3071	4.5	6.2	601	267	2.2	1.9
Croatia	4	0	1.0	.	2	0	1.0	.
Cyprus	2	0	1.0	.	3	0	1.0	.
Czechia	50	8	1.2	2.7	9	0	1.0	.
Denmark	3669	2011	6.2	13.1	382	48	2.4	1.5
Egypt	43	0	3.1	.	22	0	7.3	.
Estonia	22	0	1.5	.	1	0	1.0	.
Finland	1448	881	2.9	4.5	778	525	3.4	6.0
France	13566	9910	7.2	13.4	5940	4423	7.9	12.0
Germany	22885	15855	8.7	19.4	11101	8351	9.2	18.7
Greece	9	1	1.3	1.0	3	1	1.0	1.0
Hong Kong	726	683	9.2	13.4	51	49	2.4	2.6
Hungary	15	4	1.1	1.3	21	1	2.6	1.0
Iceland	14	0	1.4	.	2	0	1.0	.
India	938	732	2.8	3.5	361	269	2.2	2.5
Indonesia	0	0	.	.	0	0	.	.
Iran (Islamic Republic of)	0	.	.	.	0	.	.	.
Ireland	1279	828	6.0	7.6	387	253	4.0	5.2
Israel	273	141	1.8	1.8	82	27	1.9	1.6
Italy	2523	938	2.0	4.9	1186	318	1.7	2.4
Japan	48661	44293	8.9	11.7	17282	15796	7.4	9.0
Latvia	4	.	1.0	.	0	.	.	.
Lithuania	14	0	1.4	.	5	0	1.2	.
Luxembourg	488	59	2.5	3.9	196	15	2.0	1.2
Malaysia	57	40	1.3	1.3	31	21	1.3	1.3
Malta	5	0	1.0	.	0	0	.	.
Mauritius	0	0	.	.	0	0	.	.
Moldova, Republic of	0	.	.	.	0	.	.	.
Montenegro	0	.	.	.	0	.	.	.
Netherlands	4700	3512	7.8	14.5	1548	936	5.3	7.1
New Zealand	90	5	3.8	1.0	2	0	1.0	.
North Macedonia	0	.	.	.	0	.	.	.
Norway	665	209	1.4	2.1	199	80	1.3	1.8
Pakistan	0	0	.	.	0	0	.	.
Peru	0	0	.	.	0	0	.	.
Philippines	13	7	1.2	1.2	1	0	1.0	.
Poland	331	126	2.6	4.8	376	184	6.2	7.7
Portugal	56	10	1.4	1.4	11	0	1.0	.
Republic of Korea	20205	19467	14.5	20.1	2092	1879	4.4	5.2
Romania	9	0	1.5	.	2	0	1.0	.
Russian Federation	211	52	2.3	4.7	17	5	1.1	1.2
Serbia	5	0	1.7	.	0	0	.	.
Singapore	272	161	2.1	2.6	90	60	1.7	1.9
Slovakia	6	.	1.0	.	1	.	1.0	.
Slovenia	16	2	1.1	1.0	6	0	1.0	.
South Africa	163	159	3.3	3.5	17	13	1.3	1.4
Spain	2341	1858	5.2	17.4	126	37	1.4	1.4
Sri Lanka	1	1	1.0	1.0	0	0	.	.
Sweden	3181	1851	3.1	5.7	2240	1632	5.5	7.9
Switzerland	4006	3615	7.0	8.2	451	377	2.5	2.4
Taiwan	1786	1503	3.3	4.0	122	95	1.7	1.9
Thailand	81	80	2.1	2.1	23	19	1.9	1.7
Turkey	118	80	1.9	2.1	58	50	1.5	1.6
Ukraine	0	0	.	.	0	0	.	.
United Kingdom	4216	2132	3.0	3.6	4130	1520	7.0	5.7
United States of America	26864	20636	5.3	6.2	16526	13274	10.0	10.8
Viet Nam	0	0	.	.	0	0	.	.
Others Asia	1033	781	29.5	43.4	515	403	20.6	31.0
Others Europe	191	46	3.6	2.6	262	4	13.8	1.0
Others North America	313	306	9.2	10.9	809	808	36.8	38.5
Others Rest of the World	125	84	1.9	1.9	39	19	1.3	1.1
Total	179067	139863	6.2	9.6	70560	52856	6.4	8.6

TABLE IA.III: DISTRIBUTIONS OF PATENT RATIOS

The sample period is 2005-2022. We report average patent ratios for the full (public and private), public, private and Trucost sample by country in Panel A, by GICS 6-Industry in Panel B, and by year in Panel C. Countries with less than 2000 firm-year observations in the full sample are aggregated by region under "Others" as in Table IA.I. We report the average *GREENRATIO* in columns 1 to 4 and the average *EFFRATIO* in columns 5 to 8. *GREENRATIO* is the number of green patents over the total number of patents granted or purchased at the firm and year level. *EFFRATIO* similarly is the number of fuel efficiency patents over the total number of patents.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Patent ratio by country								
	GREENRATIO (in %)				EFFRATIO (in %)			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
Australia	13.846	13.397	15.350	10.937	4.213	4.370	3.683	4.852
Austria	9.421	10.573	8.854	10.770	4.095	3.882	4.200	3.819
Belgium	10.788	13.083	10.160	14.590	2.814	4.638	2.315	5.724
Bermuda	7.507	7.713	5.780	7.551	4.628	5.124	0.478	4.496
Bosnia and Herzegovina	0.000		0.000		0.000		0.000	
Brazil	14.859	14.811	14.941	20.311	2.222	2.029	2.552	2.827
Bulgaria	21.324	31.818	19.298	33.333	2.206	4.545	1.754	0.000
Canada	14.623	14.097	19.236	16.408	3.354	3.439	2.612	3.917
Cayman Islands	14.976	17.731	4.156	17.137	1.359	1.397	1.208	1.289
Chile	10.174	9.760	12.500	13.192	2.105	2.479	0.000	0.259
China	13.065	12.600	14.075	14.398	2.613	2.683	2.462	2.436
Croatia	21.053	23.077	16.667		10.526	0.000	33.333	
Cyprus	4.040	0.000	4.167		7.576	0.000	7.812	
Czechia	10.654	18.452	10.360	22.143	2.222	0.000	2.306	0.000
Denmark	15.716	14.816	15.970	16.393	3.457	1.315	4.062	1.616
Egypt	18.334	16.635	23.432	0.000	1.769	0.000	7.074	0.000
Estonia	22.656		22.656		1.562		1.562	
Finland	11.387	11.454	11.359	13.098	5.078	5.712	4.809	6.414
France	9.211	10.298	8.687	11.371	2.349	2.607	2.225	2.762
Germany	9.078	12.261	8.060	15.110	3.276	3.882	3.082	4.620
Greece	8.537	7.407	10.714	7.143	3.659	3.704	3.571	7.143
Hong Kong	10.022	8.524	25.851	8.176	1.904	1.947	1.449	3.290
Hungary	10.399	7.143	11.961	11.364	6.399	1.429	8.782	2.273
Iceland	5.100	0.699	8.314	0.000	0.956	0.091	1.587	0.000
India	11.031	11.350	10.258	13.684	4.664	4.037	6.187	5.128
Indonesia	0.000	0.000		0.000	0.000	0.000		0.000
Ireland	8.351	8.282	8.415	8.709	2.596	2.729	2.473	2.077
Israel	9.121	8.922	11.105	8.655	2.037	1.967	2.736	1.638
Italy	8.334	11.736	7.917	12.604	4.182	6.393	3.912	7.357
Japan	11.880	11.896	11.793	13.167	3.866	3.883	3.776	4.284
Latvia	6.994	7.986	6.250		0.000	0.000	0.000	
Lithuania	15.352	0.000	16.376		5.208	0.000	5.556	
Luxembourg	9.091	10.497	8.857	5.026	4.302	2.312	4.633	2.442
Malaysia	11.328	12.126	9.710	15.992	4.542	5.532	2.535	6.791
Malta	9.259	0.000	9.434		0.000	0.000	0.000	
Mauritius	0.000	0.000	0.000		0.000	0.000	0.000	
Netherlands	12.828	13.009	12.740	13.782	4.308	3.895	4.507	4.316
New Zealand	11.137	6.415	24.724	7.139	0.839	1.130	0.000	0.000
North Macedonia	0.000		0.000		0.000		0.000	
Norway	18.299	14.037	19.586	14.090	5.291	3.573	5.810	4.085
Pakistan	0.000		0.000		0.000		0.000	
Peru	0.000	0.000		0.000	0.000	0.000		0.000
Philippines	14.516	16.176	12.500	16.667	0.323	0.000	0.714	0.000
Poland	10.724	8.313	12.164	6.496	3.910	4.235	3.716	5.270
Portugal	10.994	12.585	10.685	22.024	3.654	2.041	3.968	0.000
Republic of Korea	16.060	17.625	11.472	18.882	3.019	3.069	2.872	2.974
Romania	18.590	50.000	12.879		7.692	0.000	9.091	
Russian Federation	19.187	17.986	19.614	13.999	2.581	1.322	3.028	1.504
Serbia	1.109	0.000	1.188		0.000	0.000	0.000	
Singapore	16.655	17.105	15.902	20.621	6.753	7.645	5.257	9.042
Slovakia	8.696	0.000	10.000		1.449	11.111	0.000	
Slovenia	5.484	4.898	5.631	2.315	2.072	0.000	2.590	0.000
South Africa	15.979	15.975	16.071	17.863	3.224	3.366	0.000	1.413
Spain	13.226	19.376	11.922	24.223	1.905	1.513	1.988	2.111
Sri Lanka	50.000	50.000		100.000	0.000	0.000		0.000
Sweden	11.176	8.983	12.407	8.125	2.971	3.487	2.681	4.951
Switzerland	11.483	10.572	16.010	11.167	1.399	1.593	0.436	1.771
Taiwan	12.126	12.356	9.116	12.791	1.032	0.971	1.834	0.960
Thailand	13.312	16.080	0.000	20.322	2.202	2.165	2.381	2.915
Turkey	4.538	4.256	5.092	4.530	1.937	2.402	1.023	3.538
United Kingdom	11.068	11.177	10.991	11.479	3.806	3.545	3.990	4.245
United States of America	10.688	10.701	10.580	10.664	2.555	2.644	1.836	3.035
Viet Nam	0.000	0.000	0.000		0.000	0.000	0.000	
Others Asia	16.988	17.439	13.685	18.755	4.307	3.231	12.201	4.571
Others Europe	8.278	11.284	4.714	10.932	5.524	3.052	8.454	3.423
Others North America	13.157	13.698	0.000	15.488	9.657	10.054	0.000	15.644
Others Rest of the World	15.802	11.978	34.333	15.837	5.176	6.010	1.134	6.578
Total	11.232	11.895	10.487	12.854	3.257	3.209	3.312	3.564

Panel B: Patent ratio by GICS-6 industry	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GREENRATIO (in %)				EFFRATIO (in %)			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
Aerospace & Defense	9.584	9.266	10.161	8.392	5.775	6.623	4.240	5.938
Air Freight & Logistics	8.706	6.727	8.952	6.947	3.720	0.164	4.161	0.214
Airlines	2.530	2.588	2.222	2.447	0.740	0.879	0.000	0.991
Auto Components	8.121	7.995	8.461	8.540	8.779	8.642	9.151	6.808
Automobiles	24.940	27.431	19.702	26.734	10.834	12.907	6.476	14.050
Banks	9.299	9.820	9.291	9.369	3.242	2.568	3.254	2.767
Beverages	10.718	10.731	10.667	11.925	0.607	0.679	0.333	0.578
Biotechnology	16.397	16.536	15.720	19.100	0.042	0.048	0.014	0.041
Building Products	9.738	13.539	4.524	13.319	4.745	6.144	2.826	4.584
Capital Markets	9.194	9.358	8.835	10.111	2.019	2.041	1.969	2.366
Chemicals	12.780	14.182	9.764	15.352	3.006	3.224	2.536	3.390
Commercial Services & Supplies	11.511	10.438	12.237	11.285	2.957	3.241	2.765	3.424
Communications Equipment	3.861	4.060	3.245	4.360	0.220	0.139	0.471	0.264
Construction Materials	19.526	21.764	16.479	24.267	8.022	9.530	5.968	9.420
Construction & Engineering	21.592	21.718	21.514	25.323	8.154	8.523	7.928	9.007
Consumer Finance	9.606	0.000	12.123	0.000	4.772	0.000	6.022	0.000
Containers & Packaging	3.419	3.837	2.831	5.123	0.876	0.411	1.529	0.237
Distributors	10.210	11.531	10.017	19.236	2.207	1.344	2.333	0.725
Diversified Consumer Services	14.609	2.273	15.733	5.263	2.526	0.000	2.756	0.000
Diversified Financial Services	10.224	9.523	10.303	9.153	3.904	5.925	3.675	8.507
Diversified Telecommunication Services	2.151	2.312	1.587	2.088	0.056	0.072	0.000	0.017
Electric Utilities	50.896	47.625	57.018	46.724	12.065	13.721	8.966	14.208
Electrical Equipment	34.186	35.750	30.398	34.887	3.166	2.714	4.261	3.060
Electronic Equipment, Instruments & Components	11.740	11.956	10.867	12.852	1.689	1.489	2.499	1.273
Energy Equipment & Services	16.979	16.898	17.275	17.751	19.291	19.319	19.189	19.906
Entertainment	2.682	2.656	2.787	2.200	1.189	0.871	2.509	0.544
Equity Real Estate Investment Trusts (REITs)	12.209	14.052	0.000	15.385	0.000	0.000	0.000	0.000
Food Products	13.458	13.665	13.056	14.131	0.685	0.583	0.883	0.724
Food & Staples Retailing	8.613	6.408	9.823	7.120	2.922	1.681	3.603	1.266
Gas Utilities	35.981	37.153	25.000	39.806	9.025	7.321	25.000	7.844
Health Care Equipment & Supplies	4.130	4.119	4.161	4.227	0.291	0.303	0.259	0.366
Health Care Providers & Services	8.174	11.022	6.188	7.955	0.692	1.039	0.450	0.087
Health Care Technology	6.742	7.706	2.500	5.346	0.472	0.579	0.000	1.544
Hotels, Restaurants & Leisure	4.664	3.382	7.778	4.730	4.907	3.529	8.254	3.041
Household Durables	6.485	5.223	8.856	5.997	3.271	2.532	4.657	3.570
Household Products	6.740	6.276	7.215	5.377	0.891	0.832	0.952	0.707
IT Services	5.837	3.921	7.415	3.466	1.161	1.613	0.789	1.158
Independent Power and Renewable Electricity Producers	57.199	51.834	67.816	51.317	11.380	16.895	0.463	18.189
Industrial Conglomerates	14.931	14.499	21.402	16.039	3.858	3.888	3.400	4.393
Insurance	9.722	7.807	10.347	6.187	1.856	5.431	0.689	4.590
Interactive Media & Services	2.607	3.018	0.663	3.437	0.823	0.989	0.039	0.200
Internet Software & Services	1.351	0.000	7.143	0.000	1.351	1.667	0.000	0.000
Internet & Direct Marketing Retail	3.145	0.630	5.051	1.051	1.724	0.000	3.030	0.000
Leisure Products	11.056	12.310	7.232	14.791	1.017	1.350	0.000	1.499
Life Sciences Tools & Services	11.898	11.321	16.117	10.883	0.600	0.659	0.163	0.864
Machinery	7.790	8.110	7.335	9.525	6.204	6.710	5.483	7.836
Marine	16.680	19.190	14.762	21.989	11.084	14.078	8.796	16.131
Media	5.269	4.837	5.773	6.092	1.192	1.011	1.403	0.697
Metals & Mining	11.758	12.935	10.580	12.479	6.380	7.851	4.906	6.867
Mortgage Real Estate Investment Trusts (REITs)	0.000		0.000		0.000		0.000	
Multi-Utilities	38.646	35.736	69.314	35.707	12.418	12.855	7.809	12.993
Multiline Retail	4.288	4.246	4.545	2.719	0.629	0.000	4.545	0.000
Oil, Gas & Consumable Fuels	37.943	37.987	37.800	36.178	8.436	9.196	5.916	9.926
Paper & Forest Products	13.546	13.956	12.648	14.435	0.443	0.637	0.019	0.260
Personal Products	3.684	3.865	2.913	2.992	0.079	0.097	0.000	0.136
Pharmaceuticals	5.889	5.955	5.695	6.741	0.117	0.084	0.217	0.051
Professional Services	14.287	13.812	14.329	10.003	2.594	4.890	2.390	6.511
Real Estate Management & Development	9.711	16.206	9.307	10.976	3.447	0.551	3.627	0.000
Road & Rail	16.798	17.277	16.428	11.073	2.447	0.000	4.338	0.000
Semiconductors & Semiconductor Equipment	20.435	20.857	15.648	21.527	0.767	0.815	0.223	0.614
Software	2.360	2.612	1.100	2.322	0.481	0.485	0.460	0.498
Specialty Retail	9.134	6.555	11.675	7.219	0.440	0.804	0.081	0.488
Technology Hardware, Storage & Peripherals	4.337	4.194	5.127	4.771	0.550	0.415	1.297	0.510
Textiles, Apparel & Luxury Goods	3.756	4.526	2.481	3.727	0.717	0.589	0.928	0.240
Thrifts & Mortgage Finance	1.668	1.508	2.415	1.885	0.000	0.000	0.000	0.000
Tobacco	11.588	12.133	7.143	11.162	2.580	2.499	3.242	2.688
Trading Companies & Distributors	10.465	10.340	10.504	12.578	3.069	3.589	2.904	4.053
Transportation Infrastructure	8.133	5.823	12.698	5.291	1.600	1.205	2.381	1.587
Water Utilities	16.948	19.118	15.103	33.333	4.247	2.941	5.357	0.000
Wireless Telecommunication Services	1.889	1.876	1.975	1.975	0.100	0.003	0.741	0.003
Total	11.232	11.895	10.487	12.854	3.257	3.209	3.312	3.564

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel C: Patent ratio by year								
	GREENRATIO (in %)				EFFRATIO (in %)			
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
2005	8.098	8.482	7.381	9.414	3.103	2.978	3.337	3.386
2006	8.103	8.838	6.794	9.480	3.202	3.078	3.424	4.008
2007	8.493	9.502	6.729	9.507	3.061	3.289	2.663	3.636
2008	8.267	9.260	6.714	10.169	3.132	3.244	2.956	4.353
2009	9.544	10.466	8.206	10.500	2.756	3.035	2.351	3.708
2010	9.311	10.794	7.286	11.010	3.162	3.368	2.881	4.137
2011	10.272	10.960	9.488	11.527	2.998	3.112	2.868	3.761
2012	10.595	11.353	9.819	12.831	3.013	3.199	2.823	3.717
2013	11.277	11.502	11.062	12.514	2.853	2.866	2.840	3.637
2014	11.802	12.394	11.163	13.429	3.444	3.559	3.321	4.341
2015	11.644	12.437	10.836	13.606	3.425	3.385	3.467	4.285
2016	12.306	13.580	11.175	13.627	3.232	3.331	3.144	3.602
2017	12.400	12.964	11.911	13.216	3.625	3.277	3.926	3.183
2018	12.469	12.645	12.321	12.928	3.721	3.549	3.865	3.486
2019	12.532	13.531	11.699	13.458	3.572	3.508	3.625	3.650
2020	12.510	13.794	11.436	14.085	3.354	3.077	3.586	3.130
2021	13.130	13.910	12.397	14.509	3.215	2.710	3.690	3.022
2022	15.256	15.078	17.722	15.322	3.082	3.012	4.053	2.990
Total	11.232	11.895	10.487	12.854	3.257	3.209	3.312	3.564

TABLE IA.IV: ESTIMATES OF KPSS PATENT VALUE: ALL PATENTS

The table replicates Table 1 from Kogan et al. (2017) for our sample. Our sample is based on patents granted or purchased by the United States Patent Offices (USPTO) in Panel A and the European Patent Office (EPO) in Panel B between 2005 and 2022. We cover all public coporations regardless of emission data. This leads to 4,268,399 USPTO patents, of which about 75% were granted and 25% purchased, and 1,484,841 EPO patents, of which about 94% were granted and 6% purchased. We report the distribution of the following variables across the patents in our sample: the number of future citations till the end of our sample period C, the number of citations scaled by the mean number of cites to patents issued in the same year $\bar{C}$, the market-adjusted firm returns R_f on the three-day window following the patent issue date; the filtered component of returns $E[v|R_f]$ related to the value of innovation using Kogan et al. (2017)'s equation 4; and the filtered dollar value of innovation ζ using Kogan et al. (2017)'s equation 3 deflated to 1982 (million) dollars using the CPI. Market adjusted returns are computed as the difference between the firm return (Compustat) minus the return of the country-specific market index. We restrict attention to the patents for which we have nonmissing data on three-day announcement return, market capitalization, and return volatilities - inputs needed to compute the economic value.

Moment	C	$\frac{C}{\bar{C}}$	$R_f(\%)$	$E[v\|R_f](\%)$	ζ
Panel A: USPTO patents					
Mean	43.40	1.00	0.04	0.35	21.98
Std. dev.	477.70	8.49	3.69	0.17	80.75
Percentiles					
p1	0.00	0.00	-9.34	0.13	0.00
p5	0.00	0.00	-5.14	0.16	0.04
p10	1.00	0.04	-3.44	0.19	0.20
p25	5.00	0.13	-1.54	0.24	1.38
p50	14.00	0.35	-0.08	0.31	4.81
p75	36.00	0.83	1.46	0.42	15.53
p90	84.00	1.89	3.51	0.55	46.70
p95	144.00	3.24	5.35	0.67	91.46
p99	440.00	10.19	10.96	0.96	285.33
Panel B: EPO patents					
Mean	46.62	1.00	0.03	0.39	48.88
Std. dev.	773.11	11.76	3.53	0.18	135.14
Percentiles					
p1	0.00	0.00	-9.89	0.14	0.11
p5	0.00	0.00	-5.11	0.17	0.69
p10	1.00	0.02	-3.44	0.20	1.56
p25	4.00	0.12	-1.56	0.27	5.43
p50	13.00	0.34	-0.05	0.35	15.75
p75	36.00	0.80	1.52	0.47	43.05
p90	83.00	1.79	3.57	0.62	110.35
p95	143.00	3.00	5.40	0.74	195.20
p99	462.00	9.34	10.74	0.98	517.82

TABLE IA.V: TOTAL ESTIMATES OF KPSS PATENT VALUES

We report total patent values across all public coporations regardless of emission data. We include patents granted or purchased by the European Patent Office (EPO) between 2005 and 2022 and report the value of innovation estimated following Kogan et al. (2017). Column 1 reports the total patent values deflated to 1982 (million) dollars using the CPI based on all patents, column 2 based on green patents only and column 3 based on fuel efficiency patents only. In column 4, we report global GDP collected from Worldbank also deflated to 1982 (million) dollars using the CPI.

	(1)	(2)	(3)	(4)
	KPSS patent values			
Year	All patents	Green patents	Fuel efficiency patents	Global GDP
2005	1,940	152	87	23,036
2006	2,382	201	110	24,060
2007	2,694	234	132	25,112
2008	3,843	318	188	25,630
2009	3,081	283	132	25,282
2010	2,714	267	116	26,427
2011	3,028	305	115	27,307
2012	2,759	310	115	28,046
2013	3,007	331	124	28,851
2014	2,997	335	132	29,752
2015	3,479	396	163	30,682
2016	3,232	377	153	31,548
2017	2,908	365	129	32,639
2018	3,897	461	150	33,712
2019	3,637	416	131	34,603
2020	6,848	789	259	33,588
2021	5,706	731	180	35,691
2022	5,283	656	169	36,793
Total	63,436	6,924	2,584	532,759

We replicate Kogan et al.'s (2017) patent value measure for our sample of publicly listed firms from 2005 to 2022. We generally follow their procedure, but given that we have an international sample instead of a USA-only sample take four additional steps. First, we include both granted and purchased patents in our sample. Next, we match monthly foreign exchange rates to translate all firm and thus patent market values to USD. We also use country-specific indexes to calculate market-adjusted returns, while they use the CRSP-weighted index for the USA-only sample. While Kogan et al. (2017) estimate a signal to noise ratio of 0.0145, our estimate is similar with 0.0195. Finally, we also replicate KPSS (2017) Table 2 in undocumented results. To do so, we need to add patent classification fixed effects. We use the cooperative patent classification (CPC) sections, the highest level of the classification system, and identify up to three CPC sections per patent. In line with Kogan et al. (2017) we find a positive association between citations and patent values for USPTO granted patents. For EPO granted and purchased patents this association is weaker.

TABLE IA.VI: SUMMARY STATISTICS OF QUANTITATIVE VARIABLES

The table reports sample averages, medians, and standard deviations of various firm-level characteristics for the period 2005 to 2022. Panel A reports summary statistics for the entire sample (public and private) firms, while summary statistics in Panel B are based on the Trucost sample. Column 1 to 3 aggregate all firm-years with at least one patent at the EPO. Column 4 to 6 aggregate firm-years without any. Column 7 to 9 aggregate firm-years in the bottom decile based on a firm's average *GREENRATIO* across the whole period. This covers only firms with 0 green patents and represents about about 35% of firm-year observations in Panel B. Column 10 to 12 aggregate firm-years in the top decile based on a firm's average *GREENRATIO* across the whole period. The variables are defined in Table 2, Table 3; Table 6 and Table 7. The summary statistics are based on annual data rather than any long cumulative versions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All public and private firms												
	Patenting Sample			Sample w/o patents			Bottom decile green ratio			Top decile green ratio		
	mean	*p*50	*sd*	*mean*	*p*50	*sd*	*mean*	*p*50	*sd*	*mean*	*p*50	*sd*
GREENRATIO (in %)	11.232	0.000	26.814	.	.	.	0.000	0.000	0.000	83.364	100.000	30.876
EFFRATIO (in %)	3.257	0.000	14.638	.	.	.	2.699	0.000	15.391	1.799	0.000	10.539
LOGASSETS	5.790	5.803	2.661	1.729	1.142	1.786	4.032	3.894	2.330	4.388	4.213	2.732
LOGPPE	3.944	3.970	2.783	0.782	0.080	1.391	2.390	1.981	2.222	2.882	2.330	2.758
LEVERAGE	16.037	11.547	16.795	10.493	0.000	18.489	13.500	6.666	16.896	15.042	8.228	17.784
ROE	6.324	7.540	26.474	13.277	6.540	32.788	7.426	7.120	27.889	4.891	5.670	30.320
INVEST/A	4.448	2.980	5.085	3.719	0.320	6.999	4.662	2.520	6.104	5.172	2.834	6.529
LOGAGE	3.257	3.258	0.942	2.499	2.639	0.905	2.987	3.045	0.914	2.878	2.890	0.948
Panel B: Public firms with emission data												
	Patenting Sample			Sample w/o patents			Bottom decile green ratio			Top decile green ratio		
	mean	*p*50	*sd*	*mean*	*p*50	*sd*	*mean*	*p*50	*sd*	*mean*	*p*50	*sd*
GREENRATIO (in %)	12.854	0.000	24.976	.	.	.	0.000	0.000	0.000	70.788	87.500	34.629
EFFRATIO (in %)	3.564	0.000	13.025	.	.	.	2.466	0.000	14.281	3.312	0.000	12.935
GREENKPSSRATIO (in %)	12.908	0.000	25.055	.	.	.	0.000	0.000	0.000	70.549	87.661	35.013
EFFKPSSRATIO (in %)	3.593	0.000	13.142	.	.	.	2.472	0.000	14.374	3.373	0.000	13.155
GREENBBRATIO (in %)	6.306	0.000	17.721	.	.	.	0.071	0.000	2.468	34.884	20.000	37.765
EFFBBRATIO (in %)	1.968	0.000	9.891	.	.	.	1.906	0.000	12.230	2.208	0.000	10.608
LOGS1TOT	10.837	10.744	2.834	9.885	9.670	2.939	9.827	9.648	2.817	11.127	10.877	3.571
LOGS2TOT	10.860	10.972	2.388	9.606	9.661	2.208	9.780	9.839	2.281	10.326	10.555	2.691
LOGS3UPTOT	12.841	13.065	2.367	11.319	11.414	2.115	11.653	11.841	2.236	12.278	12.642	2.709
LOGS3DOWNTOT	11.831	12.475	4.043	10.688	11.052	3.456	10.544	11.136	3.716	11.618	12.239	4.402
S1INT	1.314	0.186	4.010	2.428	0.207	6.392	1.550	0.169	4.898	3.124	0.388	6.694
S2INT	0.419	0.223	0.551	0.433	0.218	0.587	0.365	0.184	0.526	0.521	0.254	0.670
S3UPINT	2.218	1.818	1.605	1.792	1.126	1.764	1.829	1.240	1.673	2.334	1.860	1.668
S3DOWNINT	8.147	1.619	15.413	7.373	1.256	15.791	6.240	1.005	13.538	13.079	2.817	20.674
LOGSIZE	8.041	8.044	1.753	6.923	6.942	1.607	7.237	7.235	1.678	7.509	7.564	1.819
LOGASSETS	8.178	8.136	1.892	7.202	7.112	1.732	7.348	7.245	1.844	7.751	7.742	2.012
LOGPPE	6.407	6.434	2.146	5.345	5.375	2.200	5.448	5.428	2.129	6.314	6.218	2.490
LEVERAGE	21.464	20.568	15.274	22.765	20.598	18.187	21.000	18.807	17.157	22.369	21.141	16.010
ROE	7.843	9.072	20.531	7.866	8.685	19.593	6.902	8.781	21.923	4.134	7.663	23.202
M/B	3.161	1.966	3.619	2.929	1.731	3.565	3.356	2.034	3.886	2.928	1.729	3.498
INVEST/A	4.084	3.225	3.491	4.414	2.819	4.999	3.992	2.837	3.974	5.499	4.128	5.099
LOGAGE	3.674	3.714	0.764	3.393	3.332	0.678	3.475	3.434	0.701	3.382	3.332	0.758
BETA	0.908	0.848	0.585	0.704	0.618	1.364	0.805	0.717	0.614	0.890	0.776	0.724
VOLAT	0.101	0.087	0.067	0.110	0.093	0.077	0.108	0.091	0.073	0.120	0.100	0.084
MSCI	0.444	0.000	0.497	0.209	0.000	0.407	0.277	0.000	0.447	0.369	0.000	0.483

TABLE IA.VII: ALTERNATIVE PATENT RATIOS AND TOTAL EMISSIONS (FIRM-LEVEL ANALYSIS)

The unit of observation is firm(f)-year(t). The sample period is 2005 to 2022. The dependent variables are $LOGS1TOT$, $LOGS2TOT$, $LOGS3UPTOT$, and $LOGS3DOWNTOT$ as defined in Table 2. In Panel A, the key independent variables are $GREENBBRATIO$ and $EFFBBRATIO$, which is a 3-year cumulative sum of green, respectively efficiency, blockbuster patents over total number of patents from *t-3 to t-1*. We define Blockbuster patents as patents that are above the 95th percentile based on the number of forward citations in a given year and classification (green, respectively efficiency). In Panel B, the key independent variables are $GREENATRATIO$ and $EFFATRATIO$, which are 3-year cumulative sum of green, respectively efficiency, patent counts over total assets from *t-3 to t-1*. In Panel C, the key independent variables are $APGREENRATIO$ and $APEFFRATIO$, which are 3-year cumulative sum of green, respectively efficiency, patent counts over total patent counts from *t-4 to t-2*. In contrast $GREENRATIO$ and $EFFRATIO$, the patent counts are based on the application date conditional on the patent being granted, rather than on granted dates. Given the greater distance to production based on application dates, we lag these ratios by one additional year. Controls include: $LOGSIZE$, $LOGASSETS$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $LOGAGE$, $BETA$, $VOLAT$, $MSCI$. All control variables are defined in Table 2 and are lagged by one year. The model is estimated using pooled regression model. All regressions include GICS-6 industry-year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) $LOGS1-TOT_{j,t:t+2}$	(2) $LOGS2-TOT_{j,t:t+2}$	(3) $LOGS3-UPTOT_{j,t:t+2}$	(4) $LOGS3-DOWNTOT_{j,t:t+2}$	(5) $LOGS1-TOT_{j,t:t+2}$	(6) $LOGS2-TOT_{j,t:t+2}$	(7) $LOGS3-UPTOT_{j,t:t+2}$	(8) $LOGS3-DOWNTOT_{j,t:t+2}$
Panel A: Blockbuster ratios								
$GREENBBRATIO_{f,t-3:t-1}$	0.072**	−0.002	0.040**	−0.030				
	(0.033)	(0.038)	(0.019)	(0.107)				
$EFFBBRATIO_{f,t-3:t-1}$					0.079	−0.042	0.011	0.135
					(0.063)	(0.068)	(0.031)	(0.142)
R2	0.968	0.967	0.985	0.953	0.968	0.967	0.985	0.953
Observations	39450	39450	39450	21751	39450	39450	39450	21751
Panel B: Asset ratios								
$GREENATRATIO_{f,t-3:t-1}$	2.633	2.163	1.060	−4.135				
	(4.505)	(4.305)	(3.705)	(3.904)				
$EFFATRATIO_{f,t-3:t-1}$					11.678	10.383	−1.145	71.114
					(19.959)	(12.396)	(10.466)	(59.280)
R2	0.968	0.967	0.985	0.953	0.968	0.967	0.985	0.953
Observations	39450	39450	39450	21751	39450	39450	39450	21751
Panel C: Patent ratios based on application dates conditional on being granted								
$APGREENRATIO_{f,t-4:t-2}$	−0.040	0.019	0.012	0.170				
	(0.038)	(0.037)	(0.025)	(0.094)				
$APEFFRATIO_{f,t-4:t-2}$					0.138	−0.078	0.000	−0.056
					(0.084)	(0.080)	(0.034)	(0.171)
R2	0.969	0.969	0.986	0.955	0.969	0.969	0.986	0.955
Observations	37605	37605	37605	21180	37605	37605	37605	21180
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes

TABLE IA.VIII: ALTERNATIVE PATENT RATIOS AND EMISSION FACTORS (FIRM-LEVEL ANALYSIS)

The unit of observation is firm(f)-year(t). The sample period is 2005 to 2022. The dependent variables are $S1INT$, $S2INT$, $S3UPINT$, $S3DOWNINT$, $LOGSALES$, and $LOGCAPEX$ as defined in Table 3. The key independent variables are $GREENBBRATIO$ and $EFFBBRATIO$ in Panel A, $GREENATRATIO$ and $EFFATRATIO$ in Panel B as well as $APGREENRATIO$ and $APEFFRATIO$ in Panel C. All patent variables are defined in Appendix Table IA.VII. Controls include: $LOGSIZE$, $LOGASSETS$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $LOGAGE$, $BETA$, $VOLAT$, $MSCI$. All control variables are defined in Table 2 and are lagged by one year. The model is estimated using pooled regression model. All regressions include GICS-6 industry-year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

	(1) $S1INT_{j,p,t:t+2}$	(2) $S2INT_{j,p,t:t+2}$	(3) $S3UPINT_{j,p,t:t+2}$	(4) $S3DOWNINT_{j,p,t:t+2}$	(5) $LOGSALES_{j,p,t:t+2}$	(6) $LOGCAPEX_{j,p,t:t+2}$
Panel A: Blockbuster ratios						
Panel A.1: Green innovation						
$GREENBBRATIO_{f,t-3:t-1}$	0.293	0.008	0.039	0.328	0.018	0.013
	(0.178)	(0.022)	(0.042)	(0.531)	(0.017)	(0.034)
Observations	39450	39450	39450	21751	39450	39359
R2	0.940	0.864	0.938	0.903	0.985	0.955
Panel A.2: Efficiency innovation						
$EFFBBRATIO_{f,t-3:t-1}$	−0.052	−0.069**	−0.149***	−0.537	0.071***	0.191**
	(0.303)	(0.027)	(0.050)	(1.450)	(0.023)	(0.071)
Observations	39450	39450	39450	21751	39450	39359
R2	0.940	0.864	0.938	0.903	0.985	0.955
Panel B: Asset ratios						
Panel B.1: Green innovation						
$GREENATRATIO_{f,t-3:t-1}$	−1.026	1.697	1.728	33.822	1.474	0.603
	(7.777)	(1.936)	(1.982)	(37.768)	(3.271)	(3.201)
Observations	39450	39450	39450	21751	39450	39359
R2	0.940	0.864	0.938	0.903	0.985	0.955
Panel B.2: Efficiency innovation						
$EFFATRATIO_{f,t-3:t-1}$	1.784	−0.618	−36.780***	−23.285	23.203*	28.355*
	(22.854)	(7.706)	(11.849)	(268.511)	(11.314)	(15.540)
Observations	39450	39450	39450	21751	39450	39359
R2	0.940	0.864	0.938	0.903	0.985	0.955
Panel C: Patent ratios based on application dates conditional on being granted						
Panel C.1: Green innovation						
$APGREENRATIO_{f,t-4:t-2}$	−0.059	−0.014	0.005	0.224	0.008	0.026
	(0.112)	(0.019)	(0.033)	(0.498)	(0.020)	(0.034)
Observations	37605	37605	37605	21180	37605	37524
R2	0.941	0.869	0.941	0.903	0.986	0.955
Panel C.2: Efficiency innovation						
$APEFFRATIO_{f,t-4:t-2}$	0.511	−0.017	−0.128*	−0.384	0.030	0.092
	(0.310)	(0.036)	(0.069)	(1.496)	(0.024)	(0.062)
Observations	37605	37605	37605	21180	37605	37524
R2	0.941	0.869	0.941	0.903	0.986	0.955
Controls	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes

TABLE IA.IX: JOINT PATENT RATIOS AND EMISSIONS (FIRM-LEVEL ANALYSIS)

The unit of observation is firm(f)-year(t). The sample period is 2005 to 2022. In Panel A, the dependent variables are *LOGS1TOT*, *LOGS2TOT*, *LOGS3UPTOT*, and *LOGS3DOWNTOT* as defined in Table 2. In Panel B, the dependent variables are *LOGS1INT*, *LOGS2INT*, *LOGS3UPINT*, *LOGS3DOWNINT*, *LOGSALES*, and *LOGCAPEX* as defined in Table 3. The key independent variables are *JOINTRATIO* in Panel A.1 and B.1, which is the sum of green and brown patent counts relative to total patent counts, *JOINTKPSSRATIO* in Panel A.2 and B.2, which is the sum of green and brown patent dollar values relative to total dollar values, and *JOINTBBRATIO* in Panel A.3 and B.3, which is the sum of green and brown blockbuster patents relative to total patent counts. Controls include: *LOGSIZE*, *LOGASSETS*, *LOGPPE*, *LEVERAGE*, *ROE*, *M/B*, *INVEST/A*, *LOGAGE*, *BETA*, *VOLAT*, *MSCI*. All control variables are defined in Table 2 and are similarly lagged by one year. The model is estimated using pooled regression model. All regressions include GICS-6 industry×year and firm fixed effects. We double cluster standard errors at the firm and year dimension. *** 1% significance, ** 5% significance * 10% significance.

Panel A: Total Emissions	(1) $LOGS1TOT_{f,t:t+2}$	(2) $LOGS2TOT_{f,t:t+2}$	(3) $LOGS3UPTOT_{f,t:t+2}$	(4) $LOGS3DOWNTOT_{f,t:t+2}$
Panel A.1: Count-based ratios				
$JOINTRATIO_{f,t-3:t-1}$	0.039	0.016	0.026	0.027
	(0.031)	(0.028)	(0.016)	(0.069)
R2	0.968	0.967	0.985	0.953
Observations	39450	39450	39450	21751
Panel A.2: KPSS ratios				
$JOINTKPSSRATIO_{f,t-3:t-1}$	0.054	0.005	0.023	0.009
	(0.031)	(0.027)	(0.015)	(0.075)
R2	0.967	0.967	0.986	0.953
Observations	38568	38568	38568	21175
Panel A.3: Blockbuster ratios				
$JOINTBBRATIO_{f,t-3:t-1}$	0.079**	−0.013	0.036*	0.002
	(0.031)	(0.033)	(0.017)	(0.091)
R2	0.968	0.967	0.985	0.953
Observations	39450	39450	39450	21751
Controls	yes	yes	yes	yes
Industry×Year F.E.	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes

Panel B: Emission Factors	(1) $LOGS1INT_{f,t:t+2}$	(2) $LOGS2INT_{f,t:t+2}$	(3) $LOGS3UPINT_{f,t:t+2}$	(4) $LOGS3DOWNINT_{f,t:t+2}$	(5) $LOGSALES_{f,t:t+2}$	(6) $LOGCAPEX_{f,t:t+2}$
Panel B.1: Count-based ratios						
$JOINTRATIO_{f,t-3:t-1}$	−0.004	−0.006	−0.010	−0.020	0.026*	0.028
	(0.019)	(0.018)	(0.019)	(0.036)	(0.014)	(0.030)
Observations	39450	39450	39450	21751	39450	39359
R2	0.914	0.737	0.842	0.927	0.985	0.955
Panel B.2: KPSS ratios						
$JOINTKPSSRATIO_{f,t-3:t-1}$	−0.002	−0.010	−0.018	−0.011	0.029*	0.032
	(0.020)	(0.020)	(0.021)	(0.036)	(0.013)	(0.030)
Observations	38568	38568	38568	21175	38568	38478
R2	0.913	0.736	0.840	0.926	0.985	0.954
Panel B.3: Blockbuster ratios						
$JOINTBBRATIO_{f,t-3:t-1}$	0.021	−0.003	0.006	−0.011	0.033**	0.060
	(0.019)	(0.017)	(0.016)	(0.031)	(0.015)	(0.036)
Observations	39450	39450	39450	21751	39450	39359
R2	0.914	0.737	0.842	0.927	0.985	0.955
Controls	yes	yes	yes	yes	yes	yes
Industry×Year F.E.	yes	yes	yes	yes	yes	yes
Firm F.E.	yes	yes	yes	yes	yes	yes

TABLE IA.X: BALANCE TABLE FOR INNOVATORS VS NEVER-INNOVATORS

We unit of observation is firm-year. We report the balance test for the innovator and never-innovator observations, as defined in Table 9. We restrict the sample to the emission sample and claculate the market capitalization weighted average, standard deviation and median for market to book ratio, emission intensities (scope 1, 2, upstream 3 and downstream 3) and 5-year change in market capitalization. In Panel A we split between ever green innovators and never green innovators, and in Panel B between ever fuel efficiency innovators and never fuel efficiency innovators.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Innovator sample				Never-Innovator sample				Difference	
	Mean	Std. Dev.	Median	Count	Mean	Std. Dev.	Median	Count	Difference	p-value
Panel A: Green ever-innovators vs. never-innovators										
M/B	4.661	4.855	2.817	41173	4.100	4.618	2.334	115756	0.561	0.000
S1INT	173.658	495.848	13.060	42046	212.850	646.279	9.203	120861	−39.191	0.000
S2INT	36.735	56.876	18.531	42048	38.577	63.760	14.517	120864	−1.843	0.022
S3UPINT	196.288	177.180	142.316	42048	136.075	182.633	62.272	120864	60.212	0.000
S3DOWNINT	894.958	1845.961	88.754	19670	528.166	1359.090	76.718	75093	366.792	0.000
5YR-PC MKTCAP	0.323	1.056	0.104	23844	0.244	1.034	0.045	49792	0.079	0.000
Panel B: Fuel efficiency ever-innovators vs. never-innovators										
M/B	4.316	4.485	2.661	22143	4.491	4.931	2.526	134786	−0.174	0.384
S1INT	206.184	534.928	15.199	22506	181.018	583.999	9.025	140401	25.166	0.002
S2INT	37.628	58.650	19.948	22508	37.469	60.731	14.880	140404	0.158	0.862
S3UPINT	220.769	176.824	177.927	22508	139.455	178.209	70.247	140404	81.314	0.000
S3DOWNINT	1125.805	2023.961	169.333	9301	517.495	1371.179	63.437	85462	608.310	0.000
5YR-PC MKTCAP	0.274	0.977	0.081	13990	0.302	1.094	0.074	59646	−0.027	0.233

TABLE IA.XI: LONG-TERM PATENT RATIOS AND EMISSIONS

In Panel A, firms (f) are the unit of observation. The dependent variables are $PCS1TOT$, $PCS2TOT$, and $PCS3UPTOT$ in Panel A.1 and $PCS1INT$, $PCS2INT$, and $PCS3UPINT$ in Panel A.2. The dependent variables are percentage changes between the *2015 to 2022* average and the *2005 to 2014* average for scope 1 (2 and upstream 3) emissions, respectively emission intensities. We winsorize all percentage changes at the 2.5% and 97.5% level. The key independent variables, $GREENRATIO$ and $EFFRATIO$, are long cumulative green, respectively brown, patent ratios from *1990 to 2004*. Control variables include $PCSALES$, $LOGSIZE$, $LOGASSETS$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $BETA$, $VOLAT$, MOM, RET, $MSCI$ and are based on 2004 except for $PCSALES$ which follows the same calculation as the emission variables. The model is estimated using pooled regression model. All regression include country and GICS6 industry fixed effects. We cluster standard errors at the GICS6 industry dimension. In Panel B, the unit of observation is GICS6 (j) industry level, but we follow a similar approach otherwise. The dependent variables are GICS6 industry level $PCS1TOT$, $PCS2TOT$, and $PCS3UPTOT$ in Panel B.1 and $PCS1INT$, $PCS2INT$, and $PCS3UPINT$ in Panel B.2. The dependent variables are percentage changes between the *2015 to 2022* GICS6 industry average and the *2005 to 2014* GICS6 industry average for scope 1 (2 and upstream 3) emissions, respectively emission intensities. We again winsorize all percentage changes at the 2.5% and 97.5% level. The key independent variable is a long GICS6 industry level cumulative green, respectively brown, patent ratio from *1990 to 2004*. Control variables include industry level $PCSALES$, $LOGSIZE$, $LOGPPE$, $LEVERAGE$, ROE, M/B, $INVEST/A$, $BETA$, $VOLAT$, MOM, RET, $MSCI$ and are based on *2004* except for $PCSALES$ which follows the same calculation as the emission variables. The model is estimated using pooled regression model. We use robust standard errors. *** 1% significance, ** 5% significance * 10% significance.

Panel A: Firm-level	(1) $PCS1TOT_f$	(2) $PCS2TOT_f$	(3) $PCS3UPTOT_f$	(4) $PCS1TOT_f$	(5) $PCS2TOT_f$	(6) $PCS3UPTOT_f$
$GREENKPSSRATIO_{f,90:04}$	0.091	0.317	−0.044			
	(0.149)	(0.326)	(0.049)			
$EFFKPSSRATIO_{f,90:04}$				0.449	−0.239	−0.182***
				(0.290)	(0.340)	(0.059)
Observations	1681	1681	1681	1681	1681	1681
R2	0.297	0.354	0.755	0.298	0.353	0.756
Controls	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes
Panel B: Industry-level	$PCS1TOT_j$	$PCS2TOT_j$	$PCS3UPTOT_j$	$PCS1TOT_j$	$PCS2TOT_j$	$PCS3UPTOT_j$
$GREENKPSSRATIO_{j,90:04}$	1.148	2.753*	−0.972**			
	(1.463)	(1.590)	(0.425)			
$BROWNKPSSRATIO_{j,90:04}$				3.110***	−0.534	−0.113
				(1.154)	(0.594)	(0.241)
Observations	70	70	70	70	70	70
R2	0.406	0.673	0.919	0.503	0.643	0.913
Controls	yes	yes	yes	yes	yes	yes

TABLE IA.XII: BALANCE TABLE FOR THE ATOMAUSSTIEG EXPERIMENT

The unit of observation is GICS-8 industry-country-year. We report the balance test for treated (German) industry observations and control observations, as defined in Table 10 for the year 2010, the year before the Atomausstieg. Private/public sample controls are defined in Table 7, public sample controls are defined in Table 2, emissions variables are defined in Table 3 and patent variables are defined in Table 10.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Treat sample				Control sample				Difference	
	Mean	Std. Dev.	Median	Count	Mean	Std. Dev.	Median	Count	Difference	p-value
Panel A: Private/ public sample controls										
LOGASSETS(pub/pri)	10.310	1.490	10.287	47	10.023	1.814	10.091	168	0.287	0.266
LOGPPE(pub/pri)	8.594	1.671	8.687	47	7.913	1.871	7.896	168	0.680	0.017
LEVERAGE(pub/pri)	22.218	11.740	20.154	47	21.979	12.334	19.528	168	0.239	0.903
ROE(pub/pri)	11.436	6.773	12.251	47	12.211	12.227	10.266	168	−0.776	0.570
INVEST/A (pub/pri)	4.215	2.450	3.508	47	3.874	3.238	3.161	168	0.340	0.434
PUBLIC	0.771	0.256	0.902	47	0.804	0.278	0.938	168	−0.033	0.440
LOGAGE(pub/pri)	4.127	0.698	4.372	47	3.705	0.709	3.795	168	0.423	0.000
Panel B: Public sample controls										
LOGSIZE	9.383	1.209	9.444	47	9.192	1.559	9.254	168	0.191	0.371
LOGASSETS	9.931	1.599	9.754	47	9.695	1.935	9.491	168	0.236	0.394
LOGPPE	8.082	1.757	8.160	47	7.656	1.970	7.615	168	0.426	0.152
LEVERAGE	20.559	11.487	19.619	47	21.727	11.894	20.614	168	−1.168	0.540
ROE	12.992	6.805	12.251	47	13.226	14.310	11.761	168	−0.234	0.875
INVEST/A	4.023	2.419	3.284	46	4.231	3.658	3.129	163	−0.208	0.650
M/B	2.368	1.142	2.136	47	2.761	2.475	2.128	168	−0.394	0.121
BETA	0.911	0.383	0.942	47	0.905	0.426	0.865	167	0.006	0.921
MSCI	0.558	0.446	0.742	47	0.433	0.439	0.314	168	0.125	0.088
VOLAT	0.081	0.026	0.080	47	0.094	0.055	0.087	168	−0.013	0.022
LOGAGE	4.102	0.815	4.436	47	3.673	0.783	3.820	166	0.429	0.001
Panel C: Emissions										
S3UPINT	2.066	1.404	1.898	47	1.923	1.589	1.425	168	0.143	0.549
S2INT	0.428	0.555	0.190	47	0.377	0.529	0.171	168	0.051	0.574
S3UPINT	2.066	1.404	1.898	47	1.923	1.589	1.425	168	0.143	0.549
Panel D: Patents										
GREENRATIO ex NUCLEAR (pub/pri)	0.084	0.166	0.028	47	0.097	0.175	0.027	168	−0.013	0.642
GREENRATIO ex NUCLEAR (public)	0.127	0.255	0.026	42	0.101	0.192	0.023	139	0.025	0.550
GREENKPSSRATIO ex NUCLEAR(public)	0.134	0.253	0.034	42	0.088	0.169	0.017	136	0.046	0.273
GREENBBRATIO ex NUCLEAR(public)	0.052	0.158	0.006	42	0.043	0.109	0.003	139	0.009	0.726
BROWNRATIO(public)	0.055	0.083	0.004	42	0.033	0.080	0.000	139	0.022	0.127

IA.2 Internet Appendix; Figures

FIGURE IA.I: PATENT RATIOS FOR HALLIBURTON COMPANY

We report GREENRATIO and EFFRATIO for Halliburton Company per year between 2005 and 2022. The variables are defined in Table 2.

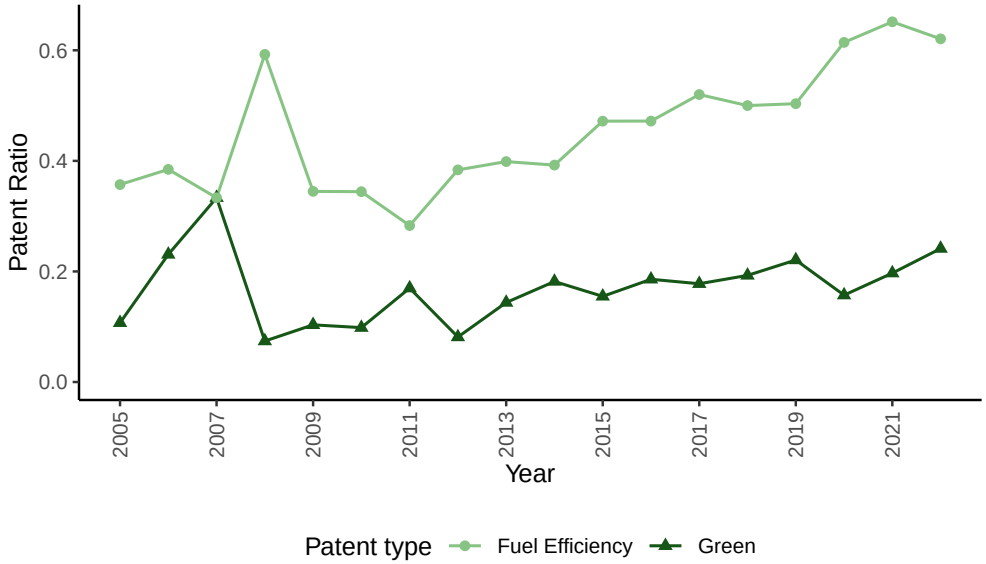
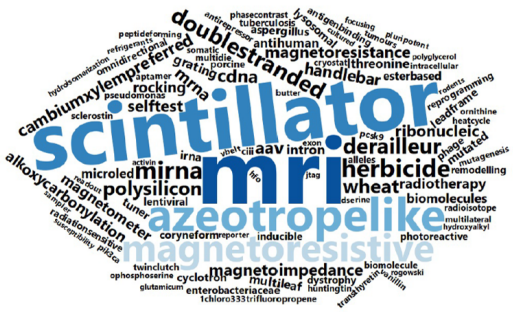


FIGURE IA.II: COMPARING GREEN AND OECD TITLES

The sample is all patents granted by the EPO from 2005 to 2022 that belong to the Trucost sample. Wordclouds display the top 100 words (unigrams) based on the TF-IDF comparing patent titles of green patents to OECD env-tech patents, respectively fuel-efficiency patents to OECD env-tech patents.

(A) "GREEN" AGAINST "OECD"



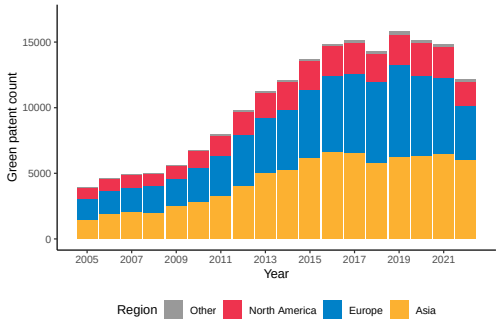
(B) "FUEL-EFFICIENCY" AGAINST "OECD"



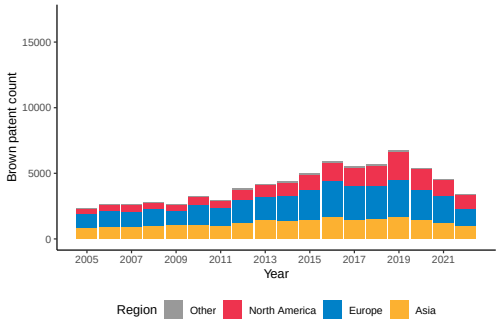
FIGURE IA.III: GREEN AND FUEL-EFFICIENCY PATENT COUNTS ACROSS REGIONS

The sample period is 2005 to 2022. We report the total number of granted or purchased green and fuel-efficiency EPO patents for the regions North America, Europe and Asia and rest of the world (other) per year. In Panel A the sample covers the full sample, i.e all public and private firms and in Panel B the sample covers only public firms with emission data from Trucost.

(A) FULL (PUBLIC/PRIVATE) SAMPLE

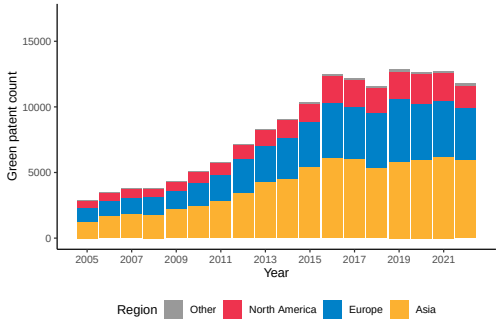


(A.1) GREEN PATENTS

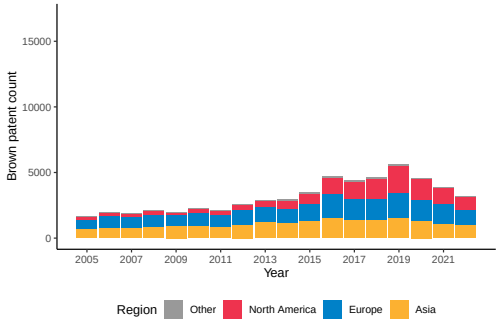


(A.2) FUEL-EFFICIENCY PATENTS

(B) TRUCOST SAMPLE



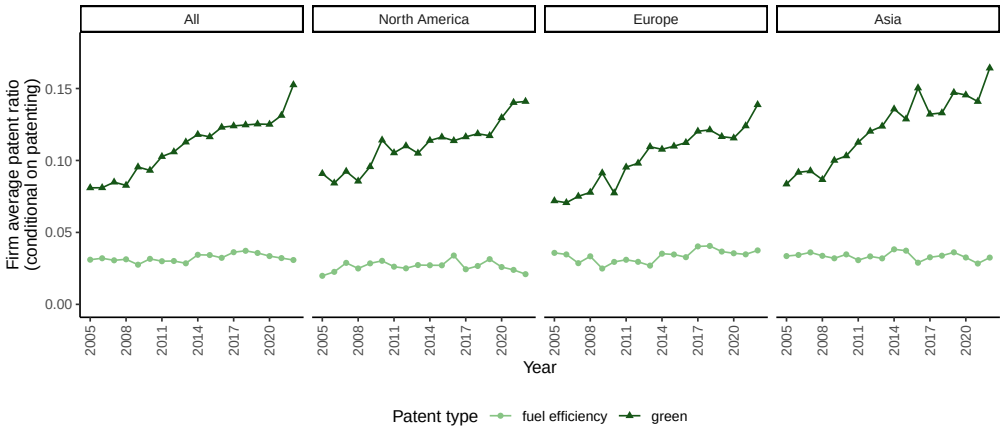
(B.1) GREEN PATENTS



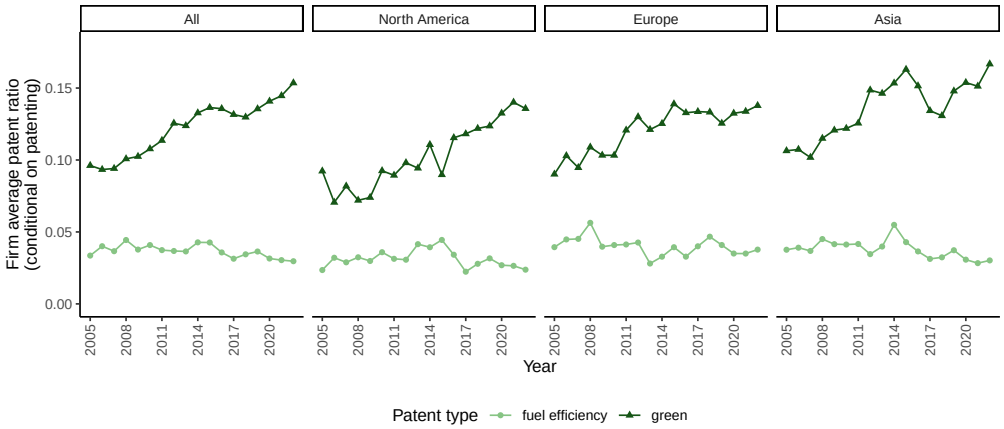
(B.2) FUEL-EFFICIENCY PATENTS

FIGURE IA.IV: GREEN AND BROWN PATENT RATIOS ACROSS REGIONS

The sample period is 2005 to 2022. We report the average GREENRATIO and EFFRATIO across all regions and by region, namely North America, Europe and Asia per year. Green and fuel-efficiency patent ratios are annual observations and are defined in Table 2. In Panel A the sample covers the full sample, i.e all public and private firms. In Panel B the sample covers only public firms with emission data from Trucost.



(A) FULL (PUBLIC/PRIVATE) SAMPLE



(B) TRUCOST SAMPLE