The CO2 Question:

Technical Progress and the Climate Crisis[1]

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May 5, 2023

Abstract

We analyze green and brown R&D activity worldwide and its effects in reducing carbon emissions. Innovating companies with higher carbon emissions engage more in brown R&D and less in green R&D. Despite a steady rise in the share of green R&D, green innovation does not predict future reductions in carbon emissions of innovating firms, non-innovating firms in the same sector, firms in other sectors, and across countries, whether in the short term (one year after filing a green patent) or in the medium term (three or five years out). Rather, green innovation predicts *higher* indirect emissions in related industries.

JEL codes G12, G23, G30, D62, D83

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

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[1] We are grateful to Trucost for giving us access to their corporate carbon emissions data. We thank Rob Engle, Stefano Giglio, Po-Hsuan Hsu, Raj Iyer, Mirabelle Muuls, Ramana Nanda, 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 emissions. According to the latest IPCC (2021) report, to avoid an increase in average temperatures greater than 1.5° C, global net carbon emissions must be reduced to zero by 2050. To have any hope of attaining this goal, governments around the world have stepped up their policies to curb carbon emissions and accelerate the transition to renewable energy sources.

Yet nearly all analysts agree that a successful global decarbonization cannot be founded only on 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 to 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 brown 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 2020. All in all, our data covers more than 136 million patents held by 2.3 million firms. Based on a patent's Cooperative Patent Classification (CPC), we can sort patents into three broad categories, *green patents* (which concern technological improvements in environmental impacts of economic activities), *brown efficiency-improving patents* (which achieve advances in fossil energy efficiency), and other patents that are not directly related to the environment or to energy. For each firm we can determine the intensity of their green or brown innovation activities by calculating the ratio of the number of their green (respectively brown efficiency) patents to the total number of patents they have filed. We calculate these ratios based on either worldwide patent filings or on filings with the European patent office, which are known to be more reliable. We can also weigh the importance of each patent based on the number of citations.

We begin our analysis by exploring how these measures of corporate green (or brown) innovation activity are associated with firm characteristics (our analysis covers corporate innovative activity around the world, which allows us to control for country, sector, and firm characteristics). 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 22.3% of publicly listed companies engage in innovation, while only 1.6% of private companies file patents in a given 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 0.080 in 2005 to 0.130 in 2020.

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 the technologies they use better, 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 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 (as measured by the stock of brown efficiency patents they already own) are less likely to engage in green innovation and companies with greater experience with green technologies (as measured by the stock of green patents they already own) are less likely to engage in brown efficiency innovation.[1] Furthermore, we find that that brown companies (with higher emissions and that are older) do not tend to engage in green R&D. This is true in particular for companies with higher indirect (scope 3) emissions, which suggests that there is a broader replacement effect at work than the one identified by Arrow: brown companies appear to be locked into fossil-fuel dependent technologies through their production networks. If input suppliers or downstream firms/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, in order to induce firms to transition from brown to

[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.II that most of Halliburton's innovation activity in recent years has been in brown innovation, which has steadily increased over time.

green technologies, industrial policy may be necessary to coordinate this transition across all firms linked through the supply chain.

Our findings that green R&D is more likely to be undertaken by new entrants and brown efficiency R&D is more likely for established companies with operations that are based on fossil fuel energy are consistent with earlier studies 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 brown) technologies is self-reinforcing. Our study extends this evidence in support of the path-dependency view of innovation to all sectors, across countries, not just the automobile sector.

Even if innovation is path dependent, and even if brown firms are less likely to undertake green R&D, we find that there has been a steady rise in the number of green patent filings (as shown in Figure 2). It is therefore possible that the promise of a *sustainability revolution* could be fulfilled. 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 green innovation on corporate outcomes is that there has been no significant impact on future carbon emissions reductions. Whether in the short run (one year), or medium run (three & five years ahead), we do not find any significant effect of green innovation on direct and indirect corporate carbon emissions of the innovating firms. Consistent with the Jevons paradox, we find that brown efficiency innovation does result in lower future carbon intensity, but this benefit is undone by higher sales, which overall result in higher future emissions.

We also analyse how aggregate sectoral changes in emissions are associated with green R&D on the presupposition that innovation could be of use not just for the innovator but also for other firms operating in the same sector. However, we do not find any significant spillover effects of green innovation on the carbon emissions of either innovating or non-innovating firms in the same (GICS-6) sector. Yet, consistent with the displacement effect and the greater reliance on brown electricity, we do find that green innovation is associated with subsequent increases in scope 2 emissions of the same sector. In contrast, brown efficiency innovation does not predict future emission changes of other innovating firms in the same sector. However, it does benefit non-innovating firms whose direct and indirect emissions go down. But this decrease is mostly a consequence of lower sales for this group of firms.

We also find that the association of innovation activity by publicly listed companies and their future emissions is not strongly correlated with the same association of innovation and future emissions by privately held firms. That is, innovation by publicly listed companies has a stronger positive effect on their future scope 2 emissions than the innovation by privately held firms on their future scope 2 emissions. Furthermore, we do not find any spillover effects broadly speaking across sectors or across countries. The one notable exception is our finding that an increase in green innovation predicts subsequent reductions in scope 3 downstream emissions of *broadly* related industries.

Another indirect channel through which innovation can affect future emissions of non-innovating firms is through changes in the market shares of innovating firms. We find that firms with higher green patent ratios tend to lose market share to other firms that have higher emissions, a form of displacement effect. Finally, our third main finding on the effects of green innovation on future corporate carbon emissions is that to a large extent green innovation has little to contribute to decarbonization. Where we see significant reductions in corporate carbon emissions, we find that these reductions are for the most part not due to green innovation. Overall, green innovation contributes only 1% to corporate carbon emission reductions. In sum, green innovation may be necessary for the sustainability revolution, but it is far from sufficient. The overwhelming conclusion of our analysis is that the green industrial revolution has not materialized over our sample period and the promise that green innovation will set the global economy on a sustainable path to net zero has not yet borne fruit.

Our paper 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 specific differences are that we extend our sample to firms that also file for patents outside the USPTO, and to firms that are located outside the U.S. We further distinguish between green and brown efficiency patents, which allows us to evaluate the path-dependency hypothesis more explicitly. In this regard, we note that the classification of green patents used in their study tends to nest what we define as brown efficiency patents. Finally, their study takes ESG scores as a metric of environmental performance, which they motivate by the fact that asset managers tend to focus on such scores in their divestment screens. Our focus instead is on carbon emission outcomes.

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, 2022a) 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. (2022) 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.

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.

[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.

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 drivers of green innovation. Section 5 provides the results on the impact of innovation on future emissions and other corporate decisions. Section 6 concludes.

2. Conceptual Framework

We begin with a conceptual discussion of green innovation and the transition to a net-zero economy. There are three key guiding concepts 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 a rebound effect if a brown efficiency innovation subsequently improves the carbon intensity of operations, but overall carbon emissions are not significantly affected or are higher. A general reason why one should expect a positive effect on operations and sales from a brown 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

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

fully offset by lower scope 1 emissions than a combustion engine vehicle only after the EV has clocked up many thousands of miles.

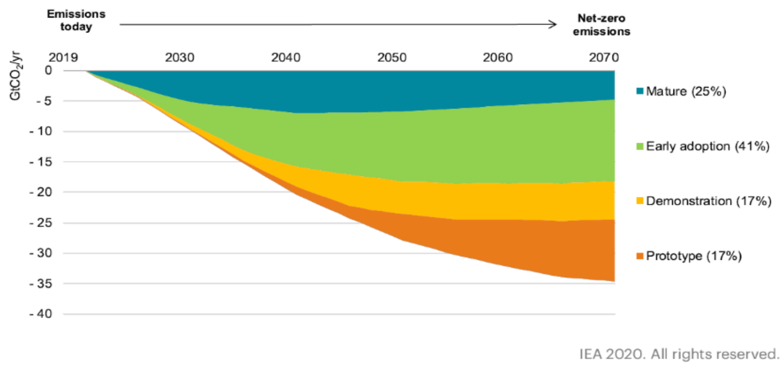
Other rebound effects operate through product market competition. If green innovation involves higher costs than brown efficiency innovation (or no innovation), then the green innovating firm will be at a cost disadvantage relative to its industry peers. It may as a result lose market share. This would 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 with 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-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 master 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 engage in green innovation, a new technology they are less familiar with, and less likely to replace their brown operations with green operations. A related general prediction is that innovation is likely to be path dependent: a company that has already been actively researching brown efficiency innovations is more likely to continue to do brown R&D. Green innovation, therefore is most likely to be undertaken by companies that are 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 brown 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. Thus, the more dependent upstream and downstream industries are on fossil fuels, the less likely it is that an individual firm in one sector 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 due to the time it takes to go from a working prototype to a mature technology. According to the latest research by the IEA (2021), many new green technologies in the energy sector are still at the prototype stage. Their impact on future carbon emission reductions is therefore likely to be small in the immediate future (see the IEA figure below).

Figure 3.1 Global energy sector CO_2 emissions reductions by current technology readiness category in the Sustainable Development Scenario relative to the Stated Policies Scenario



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 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, which according to the latest climate research is less than 300 gigatons (Gt) of CO2 as of 2020 if temperature rise is to be limited to less than 1.5^{0}C with an 83% probability (IPCC 2021). 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 starts with all global firms, both publicly listed and private, identified between 2005 and 2020 in the following data bases: Orbis Intellectual Property Financial, Orbis, Factset, and Worldscope for financial information (balance sheets and income statements). The financial data for public firms is based on all four. The financial data for private firms is based solely on Orbis IP Financial and Orbis. The latter data sets only cover the ten most recent years. The overall dataset is termed "full sample". We merge these datasets with the Orbis Intellectual Property 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. Henceforth, we refer to this dataset as the "patenting sample".

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 CO_2 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 788,983, of which 54,009 are publicly listed companies and 734,974 are privately held firms. There are 18,819 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. Throughout our main analysis, we focus on patents registered with the European Patent Office (EUPO). As is well known, the filing process is most rigorous at the EUPO, so that these filings reflect more significant and enduring innovations. In the Appendix, we provide additional robustness results using patents registered with any patent office worldwide. 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 about the same fraction of the sample with patents as privately held patenting firms. 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 across countries. Most patents came from publicly listed companies, which provides further evidence that innovation is typically produced within large companies. Notably, the fraction of patents registered by companies that are part of the Trucost data is over 75%. 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. The next three countries are Germany, France, and South Korea, each with more than 100,000 patents. In columns 5-8, we show the average number of patents per firm, for companies that do engage in patenting activity. An average company in our sample registered more than 17 patents over the sample period. The fraction is significantly larger for public firms, which register more than 24 patents per firm in contrast to private firms where this number is 5.7.

Table IA.II further shows 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 3,700,000 firm-year observations due to this restriction. In addition, we require public firms to have records for capex, previous year's December return, volatility, and market capitalization. This leads to another 200,000 firm-year observations being lost. In the paper, we refer to this filtered dataset with 5.3 million firm-year observations as the "full sample". Columns 1-4 present the numbers for the full set of public and private companies. The number of observations in the full sample is 5,318,818, of which 390,985 are observations from public firms and 4,927,833 are observations from private firms. In columns

5-8, we restrict the sample to companies with at least one listed patent. That sample includes 88,727 observations, 63% of which are from publicly listed companies.

3.2 Green and brown innovation

We make a key distinction between *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 *brown innovation*, which targets improvements in fossil-fuel based technologies. For this patent classification we rely on the description of the patent and 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)[4], the International Patent Classification (IPC) Green Inventory[5], 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. We classify patents into three broad categories[6]: i) green patents for environmental technologies; ii) general efficiency improvement patents that deal with technologies that improve process efficiency and therefore could reduce emission intensity; iii) brown patents that deal with technological innovation for fossil fuel-based technologies. For robustness, we also consider the OECD classification of green patents, which includes technologies related to environmental applications, such as climate mitigation, biodiversity, and wastewater management, as well as green and general efficiency improvements patents.

Prior research (e.g., Cohen et al., 2022; Aghion et al., 2016) has relied on the OECD classification of green patents only. But the OECD classification does not always distinguish between patents on renewable energy technologies and brown efficiency improvement patents. Some green patents within the OECD classification are brown efficiency patents. To illustrate this point, 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 the OECD classification, searching for the dominant words and stripping out the common words from our classification. We present the resulting clouds in Figure 1.

In the left figure, we show the words that are uniquely dominant to our classification. Words, such as mri, magnetoresistive, or magnetometer are very common to fusion reactions and underlie the green nature of the patent. In the right figure, we start with the OECD words and

[4] https://www.oecd.org/env/indicators-modelling-outlooks/green-patents.htm
[5] https://www.wipo.int/classifications/ipc/green-inventory/home
[6] We provide a detailed description of our approach and the underlying IPC/ CPC classes in the following online document: https://wiedemannm.github.io/documents/DescriptionPatentClassification.pdf

filter out common words from our classification. The dominant words of this process include exhaust gas, internal combustion, or abradable, all three likely attributed to efficiency gains of brown technology. Overall, this analysis suggests that our classification is more accurate in identifying purely green patents. The OECD classification misclassifies some patents as green when they are more likely to be brown patents. For the rest of the analysis, we will thus rely on our classification, but we also check the robustness of our findings to using the OECD classification.

In Table IA.III, we report the distribution of firms and patents conditional on a firm filing a green or brown 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 brown patent. Only about 1% (0.4%) of all firms have at least one green (brown) patent. In the cross-section, the U.S., Japan, and Germany (the U.S., Japan, and China) have the largest number of firms with green (brown) patents, each of them representing 7%-20% (7%-28%) of the total number of patenting firms. The distribution of countries contributing at least one green (brown) patent is skewed, with the top 10 countries contributing most green (brown) patents. Publicly listed companies account for 63% (66%) of firms with green (brown) patents. The fraction of firms with at least one green (brown) patent that is covered by Trucost is roughly 42% (48%).

In Panel B, we provide a similar breakdown for the total and average (per firm) number of green patents. In the full sample, over the period 2005-2020, companies have filed 162,039 green patents. In this group, a large number (144,614) of green patents is registered with publicly listed companies, and only 17,368 patents are registered with private companies. More than 131,000 of green patents have been filed by companies with emission data in Trucost. The highest number of green patents by firm comes from Saudi Arabia, South Korea, and Germany, each of them having more than 10 patents per firm. In Panel C, we provide a similar breakdown for brown patents. In the full sample, we observe 63,689 brown patents in total; 56,556 of those patents have been filed by publicly listed companies and the remaining 7131 are those filed by private companies. Saudi Arabia, Germany, and the United Kingdom are the three countries with the highest number of brown patents per firm.

In Figure 2, Panel A we show the year-by-year distribution of patenting activity, measured by green and brown patent counts, based on the sample of all firms with patent data. We observe a steady increase in patenting activity over time at least until 2018, 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 brown patents are Asia and Europe. At the peak of 2018, each region contributed almost 10,000 patents each. The equivalent number for North America is significantly less and accounts for about 5,000 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. This can be better observed in Panel C, in which 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 *Innovation Capacity: scale & scope*

The summary statistics in Section 3.1 suggest that the probability of a firm filing a patent is skewed towards larger firms. This result is not entirely surprising. To be able to innovate firms need to build research teams, laboratories, and other facilities. It is to be expected that bigger firms can build bigger research facilities, and therefore can produce more patents. What is more, firms are more likely to continue incurring these fixed costs if their innovative activities have been successful. And so, a plausible hypothesis is that the past stock of patents along with the size of the firm predict future patenting activity. If firms' innovation capacities are limited by their size, one would also expect to see some substitution between different R&D directions. Not all promising research and development projects can be pursued at the same time. Firms choose the projects that show the greatest promise given their state of knowledge and know-how. Thus, another plausible hypothesis is that firms specialize in the R&D they become good at.

We begin our analysis by formally exploring these two hypotheses. First, we associate a firm's number of new patent filings at the European patent office in year *t* (ANYCOUNTEP) with its stock of European patents up to year *t* (PASTSTOCKANYEP), its size, number of employees, assets, and its age, using a Poisson pseudo-maximum likelihood model (which allows for non-trivial numbers of zeros in dependent variables). We report our findings in Table 1, Panel A. In columns 1 to 3, we look at the extensive margin by including all firms, whether they have any patents or not. In columns 4 to 6, we look at the intensive margin, by including only firms that have engaged in innovation activities in the past and own some patents. Specifications 1 and 4 include country and year fixed effects, specifications 2 and 5 additionally include industry-year fixed effects, and specifications 3 and 6 use firm fixed effects instead of industry-year fixed effects.

In all models, we double cluster standard errors at the firm and year dimensions to allow for cross-correlation and serial correlation of residuals.

Consistent with our first hypothesis, we find that the stock of patents already owned prior to year *t* (PATSTOCKANYEP), the age of the company, and the three measures of firm size (market cap, number of employees and total assets), all positively predict future patenting activity when we add industry-year fixed effects. This is true both at the extensive and intensive margins. In other words, innovative activities of firms are constrained by their innovative capacity, which is greater for larger firms and for firms that have greater R&D experience (as reflected in the patent stock and firm age variables). As others have pointed out (e.g., Acs and Audretsch 1988, 1991), much innovation activity takes place at large companies. Our findings confirm these observations (albeit based on broader and more recent data). These results provide important context for our other findings below on the path-dependency of R&D activity.

In Panel B of Table 1 we turn to our second hypothesis, specialization through learning-by-doing. Here we distinguish between the number of green patents a firm files in year *t* (GREENCOUNTEP) in columns 1 to 3, and the number of brown patents (BROWNEFFCOUNTEP) it files, in columns 4 to 6. We also break down the patent stock variable into the stock of green patents (PATSTOCKGREENEP) the firm holds up to year *t*, and the stock of brown patents (PATSTOCKBROWNEFFEP). Consistent with our hypothesis, we find strong evidence of specialization, with a higher stock of green patents (resp. brown patents) positively predicting future green innovation activity (resp. brown innovation activity). Moreover, a higher stock of green patents (resp. brown patents) negatively predicts future brown innovation activity (resp. green innovation activity). This latter finding in particular reveals both the presence of scope constraints for innovation and the effects of learning-by-doing. Overall, this latter finding uncovers strong path-dependency for innovation: greater experience with brown technology reduces the likelihood of future green innovation activity; similarly, greater experience with green technology reduces the likelihood of future brown efficiency innovation. This evidence is consistent with the path-dependency findings of Aghion et al. (2016) for the auto industry. Path dependency is not just a feature of that industry. It extends across industries and around the world.

3.4 *Green and brown innovation ratios*

As we have shown, patenting activity in any given year is significantly driven by a firm's innovation capacity. Moreover, the different directions in which a firm can pursue R&D are constrained by the firm's innovation capacity, so that there is some substitution between different R&D directions. Accordingly, new patent filings must be related to the firm's innovation capacity to get a more accurate picture of the intensive margin of innovation activity. For that reason, we normalize the number of green (respectively brown) patent filings by the total number of patent filings and define the following two variables: GREENRATIOEP is the ratio of green patents filed at EUPO over the total number of patent filings in that year; BROWNEFFRATIOEP is the ratio of brown patents filed at EUPO over the total number of patent filings in that year.

Table IA.IV, Panel A provides information on the ratios of green or brown 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 listed and private companies, with the former having an average ratio of 11.4% and the latter 10.3%. 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 300 public or private companies, some of the ones with the highest ratios of green to total number of patents are: Norway with a ratio of 16.4%, Canada with a ratio of 15%, and Denmark with a ratio of 14.5%. In comparison China has a ratio of 12.9%, and the U.S. an even lower ratio of 10%. Notably, Saudi Arabia reports a large fraction of green patents 14.9%, and the UAE an even higher ratio of 23.5%, which is interesting given their strong reliance on oil production. In columns 5-8 we provide respective summary statistics for brown patents. On average, brown patent ratios are significantly smaller. The average number for the EUPO patents equals 3.33%. The unconditional numbers do not deviate much from those based on the Trucost sample. Notable countries for significant brown patenting activity include Malaysia, Australia, India, Greece, Singapore, and the U.K. The numbers for the U.S. and China are about the same 2.61%.

Panel B breaks patent activity down by sector (GICS6-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 EUPO, with 53.78%, followed by Electric Utilities, Multi-Utilities, and Gas Utilities. These results are broadly consistent with those in Cohen, Gurun, and Nguyen (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 brown 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 19.95%, followed by Automobiles at 14.38%, and Independent Power and Renewable Electricity Producers at 12.5%.

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 brown 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 2020 with a ratio of 12.9%. 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 brown patent filings, we see the opposite trend and a decline in R&D activity over time for brown technologies, but the rate of reduction is very small. In Figure 3 we display the patent ratios across time by region and find broadly similar patterns.

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 that can be 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. Besides the variables measuring general innovation activity and respectively green innovation, and brown efficiency improvements that we defined above, we also include variables measuring the impact of patents by how widely cited they are. GREENRATIOEP2 is defined as the number of granted or purchased "green" or "general efficiency" patents over the total number of granted or purchased patents; OECDRATIOEP is a patent ratio based on OECD green Env-tech classification, calculated as the number of granted or purchased OECD patents over the total number of granted or purchased patents; GREENCITMAXEP (BROWNEFFCITMAXEP) is the maximum number of forward citations any green (brown) patent of a firm received; GREENBBCOUNTEP (BROWNEFFBBCOUNTEP) is the number of green (brown) blockbuster patents patent per firm, where blockbuster patents are defined as patents in the 95th percentile based on the number of forward citations in a given grant year and classification.[7]

[7] Measuring the importance of patent value is generally a challenging question and, in this paper, we rely on the most basic measure of citation, particularly because of our global focus in the paper. Kogan et al. (2017) is an excellent study providing a more detailed discussion of these issues.

In our second category we include variables measuring corporate carbon emissions (direct and indirect) when available, and standard variables capturing key corporate characteristics.[8] Thus, LOGS1TOT, LOGS2TOT, LOGS3TOT, LOGS3UPTOT, and LOGS3DOWNTOT respectively stand for the natural logarithm of firm-level scope 1, 2, and 3 (also upstream and downstream) total carbon emissions, and S1INT, S2INT, S3INT, 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) LOGPPE is given by the natural logarithm, of the firm's property, plant, and equipment (in $ million); iii) LEVERAGE is the ratio of debt to book value of assets; iv) ROE is given by the ratio of firm *i*'s net yearly income divided by the value of its equity; v) M/B is the end of year market cap divided by the firm's book value; vi) BETA is the market beta of individual companies calculated over the preceding 12-month period; vii) VOLAT is the standard deviation of returns based on the past 12 monthly returns; viii) momentum, MOM is given by the average of the most recent 12 months' returns on stock *i*, leading up to and including month *t-1*; ix) short-term reversal, RET is the past year's December return on stock *i*; x) capital expenditure INVEST/A is the firm's capital expenditures divided by the book value of its assets; 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; xii) LOGCAPEX is the natural logarithm of firm-level capital expenditures; and xiii) LOGCASH is the natural logarithm of firm-level cash positions. To mitigate the impact of outliers we winsorize M/B, LEVERAGE, INVEST/A, and ROE at the 2.5% level, and MOM and VOLAT at the 0.5% level.

In Table IA.V 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 GREENRATIOEP 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 GREENRATIOEP 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 GREENRATIOEP of 26.08% and the standard deviation of GREENCITMAXEP of 155.89.

[8] Note that we do not have a complete coverage of all corporate emissions. The Trucost data covers around 85% of listed companies worldwide, and almost no privately held companies. The numbers we report are therefore an underestimate of total corporate emissions, and since a growing fraction of high emitting companies (or their affiliates) have delisted over the period we cover, this underestimate is likely to be larger in later years.

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 6.13 for innovating firms but only 4.85 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 7.86 for innovating firms versus 6.93 for non-innovating firms). Patenting firms have also greater values of LOGPPE, LOGCAPEX, and LOGCASH, 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 BETA, VOLAT, MOM, and INVEST/A. Notably, we observe similar relationships for variables that are observed for the full and restricted samples, which suggests that the relationships we identify based on our restricted samples are not less likely driven by specific selections along different observables.

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."[9] 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 *brown efficiency improvements*. Indeed, this innovative activity plays into the strengths of the incumbent firm, its expertise with brown 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 brown efficiency innovations are central to the drive to decarbonize the economy. But, as Jevons (1865) has pointed out, brown 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 how green innovation activity is shaped by Arrow's replacement effect. In the following section we turn to Jevons' paradox and the displacement

[9] Kenneth Arrow "Economic Welfare and the Allocation of Resources for Invention," page 620, in *The Rate and Direction of Inventive Activity: Economic and Social Factors*, NBER.

effect to explore the link between green innovation and the future decarbonization of the economy.

4. Green Innovation Activity: Arrow's replacement effect and path-dependent innovation

Basic economic analysis would suggest that firms engage in green R&D if it is more profitable than both no R&D and other R&D. Another consideration is comparative advantage—some firms, such as renewable energy companies, may be both better equipped and benefit more from green R&D. Brown companies that rely on fossil fuel energy may be better at squeezing out efficiency gains in brown technologies. Alternatively, "khaki" R&D, that is, green innovation by brown companies, may be most profitable if fossil fuel energy is increasingly regulated and expected to become obsolete. We explore these hypotheses in this section and point to some key factors driving green R&D across sectors and around the world. Overall, the picture that emerges is the importance of path-dependency in understanding green innovation activity at the firm level. As we will show, green firms (that are already familiar with green technologies) are more likely to produce green patents, whereas brown firms (which have expertise in fossil fuel-dependent technologies) are more likely to produce brown patents. Similarly, older companies (the industry incumbents) are more likely to engage in brown efficiency innovation, while younger companies (the new entrants) are more likely to engage in green innovation. We also find that a key predictor of patenting activity is the stock of past patents that a company holds. Companies that have been successful innovators in the past have capacities that allow them to continue to innovate. However, as we have shown, innovation capacities are limited. Companies cannot innovate in all promising directions. If their past innovative activities tended to be specialized in brown efficiency innovations, they will continue to innovate in that direction. In sum, innovation activity is characterized by path-dependence consistent with the findings of (Popp, 2002) and Aghion et al., 2016).

4.1 *Green vs Brown Innovation: Firm type and Path-dependency*

The sustainable energy technological revolution necessarily involves 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)? This is the question we explore in this section.

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. As the histograms in Figure 4 show, our green vs brown firm type classification is broadly descriptive of our universe of companies. Each panel shows the distribution of scope 1 emissions for companies in the lowest and the highest quintile of the distribution that is conditional on three different characteristics. In Panel A we show how younger firms (in the bottom quintile) have a distribution of scope 1 emissions that is skewed towards lower levels than the distribution for older firms (in the top quintile). Similarly, in Panels B and C we show that firms with respectively larger asset size and larger M/B ratios have also lower means and medians of their emissions.

Our question, rephrased with reference to these two firm types, then will be the extent to which 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. brown efficiency) R&D in terms of the ratio of green-to-total patent filings (resp. brown efficiency-to-total patent filings).

How are green (resp. brown) patent ratios linked to firm type, specifically the firm's corporate carbon emissions, its age, and green and brown patent stocks? To answer this question, we estimate the following Pseudo Poisson Maximum Likelihood model with firm (*i*) and year (*t*) as units of observation[10]:

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

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) LOGS1TOT (and other carbon emission variables); ii) PATSTOCKGREENEP and PATSTOCKBROWNEFFEP, and iii) AGE/100. *Controls* is a vector of the following variables: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, 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 Trucost sector classification of 431 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*.

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

We report our findings for the extensive margin (which includes all firms, whether they own any green, respectively brown, patents or not) in Table 2. In columns 1-3, we present the results for green innovation activity (GREENRATIOEP), and in columns 4-6 the results for brown innovation activity (BROWNEFFRATIOEP). When industry fixed effects are not included (column 1) the coefficients of LOGS1TOT and PATSTOCKGREENEP are positive and statistically significant. The coefficient of AGE is 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 LOGS1TOT is highly significant and negative. The other two coefficients retain the same sign and significance as before. When we further include firm-fixed effects, in column 3, the coefficients of LOGS1TOT and PATSTOCKGREENEP become insignificant.[11] The results flip when we look at brown innovation activity (BROWNEFFRATIOEP) in columns 4-6. For this type of innovation activity, the association with direct carbon emissions is strongly positive across firms within the same industry (when we include firm fixed effects, in column 6, the association for LOGS1TOT 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 brown R&D. What is more, 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. 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 incumbents have responded by improving the carbon efficiency of their vehicles.

In Table 3, we further explore the link between green innovation and direct carbon emissions on the *intensive margin*. That is, we restrict the sample to the universe of firms that have engaged in innovation (all the firm-year observations with at least one green patent, in columns 1

[11] In the specification with firm-fixed effects we cannot uniquely identify the coefficient of AGE because its variation is collinear with that of firm and year fixed effects.

to 3, and/or one brown patent, in columns 4 to 6) and explore how the intensity of green (respectively brown) innovative activity is related to the stock of respectively green and brown efficiency patents the firm already owns, firm age, and the firm's direct carbon emissions. The empirical model follows that in Table 2, and it is estimated using OLS with standard errors double clustered at firm and year dimensions. Our findings for the intensive margin are broadly consistent with those for the extensive margin. If anything, they are stronger, except for firm age and scope 1 emissions, which are no longer significant for brown efficiency innovation, suggesting that entry and exit play a more important role in the relationship between the variables in the data.

Patent counts (or patent ratios) are somewhat coarse innovation performance metrics to the extent that many patents have limited applications. Accordingly, we also take patent citations (which reflect the importance of a patent) as an additional measure of innovation activity. In Table 4, Panel A, we associate the citation number of the patent with the maximum citations (respectively our GREENCITMAX and BROWNEFFCITMAX variables) with the same firm characteristics as in our previous regression for the green and brown patent ratios. We find very similar qualitative effects. Companies with higher emissions have lower citations for their green patents but higher citations for their brown patents. Also, companies with a greater stock of green (brown) patents are more likely to receive more citations of their green (brown) patents. Notably, firm age is positively associated with citations of both types of patents. This is to be expected since citations generally take time to accumulate. Similarly, our findings on the path-dependency of green R&D are confirmed when we focus on the most important new patents by citation count, *GREENBBCOUNTEP* and *BROWNEFFBBCOUNTEP*, in Panel B. Companies with a higher stock of green patents are more likely to make further important green innovations, and companies with a higher stock of brown patents are more likely to make additional brown efficiency innovations. The results for firm emissions and age are slightly weaker.

We find more direct evidence of Arrow's replacement effect at work in Table 5, where we explore how the firm's market share affects the path-dependence of innovation. If the replacement effect is at work, we would expect to see firms with larger market share do less green innovation other things equal. In Table 5 we explore how a firm's market share based on its sales relative to total public and private firms' sales in the same Trucost sector (MKTSHRSALES TRUIND) affects its green innovation activity. Strikingly, we find that firms with a larger market share do significantly less green innovation, but they do more brown innovation. Note that when we replace industry*year FE with firm FE market share is no longer a significant variable, so that this effect is entirely driven by selection in the industry. An additional prediction of the model is that firms with greater market share should be in a better position to switch their innovation profile because of their stronger competitive position. To test this hypothesis, we interact the firms' market share with their type (measured by scope 1 emissions, firm age, and the stock of green and brown efficiency patents). In the model in column 2 that accounts for industry-year fixed effects, we find that green innovation is less path dependent when firms have a larger market share. This result holds for all three measures of firm type. The results based on brown innovation are similar for firm type measured by scope 1 emissions but are weaker when we measure firm type with the stock of brown patents, or firm age. Note that the interaction effect is again driven by selection in the industry. Indeed, when we replace industry*year FE with firm FE we find that a higher stock of green patents induces more green innovation (and a higher stock of brown patents induces more brown efficiency innovation). These findings are all consistent with Arrow's replacement effect: more entrenched firms (as measured by their market share) have lower incentives to do R&D and they are also more likely to switch their type because of their greater flexibility to do so.

Our findings so far are that brown companies (with higher direct emissions) do not tend to engage in green R&D. This may be due to replacement and/or learning-by-doing effects. Another possibility is that brown companies may be locked into fossil-fuel dependent technologies through their production networks. If input suppliers or downstream firms/customers also rely on fossil fuel-dependent technologies, then an individual firm in the supply chain may not be able to easily switch to green technologies. We investigate the presence of such technological complementarities across firms by exploring whether indirect (scope 2, upstream and downstream scope 3) emissions are linked to corporate green R&D. We report the findings of this analysis in Table 6. It is indeed the case that the technological ecosystem in which a firm operates affects its incentives to engage in green R&D. As can be seen in columns 1, 2, and 3 of Panel A, the higher are the firms' indirect levels of emissions along the vertical production chain the less likely the firm is to engage in green R&D. Also (as is shown in Panel B), when it comes to brown efficiency innovation, the higher are firms' upstream scope 3 emissions the stronger are their brown innovation activities. Similar, but slightly weaker results hold for scope 2 and downstream scope 3 emissions. All in all, these latter findings reveal the presence of a much broader replacement effect than the firm-specific replacement effect identified by Arrow (1962): Replacing an old technology with a new one is more costly and less profitable if other firms along the supply chain do not follow in making the switch. This key finding suggests that in order to induce firms to transition from brown to green technologies, industrial policy that helps coordinate this transition across all firms linked through the supply chain may be needed.

We also explore the change in path dependency of R&D over time in response to the rise in climate change awareness and tighter mitigation policy responses following the Paris 2015 landmark agreement. We split our sample into two sub-periods, before and after 2015. We report our results in Table 7. The results in Panel A are for the full sample, and those in Panel B are only for the legacy sample (the firms for which we have carbon emissions data before 2015). The interactions LOGS1TOT*Post2015, AGE*Post2015, and PATSTOCKGREENEP*Post2015 (resp. PATSTOCKBROWNEP*Post2015) capture the change in path-dependency around the Paris agreement (where Post2015 is an indicator variable taking the value 0 for all observations before 2015 and 1 after 2015). Interestingly, there is no significant change in the link between carbon emissions and green (or brown) patent activity. However, the stock of green patents matters more for future green R&D post 2015, suggesting that green R&D has become more valuable post 2015 and is pursued by the (new entrant) green firms.

4.2 Robustness

We perform several robustness tests and report the findings in the Appendix. In Tables IA.VI and IA.VII we report the findings of our main regression analysis industry by industry for each GICS6 industry to better understand in which industries our results are strongest. Overall, path-dependency results are found in most industries, especially for the regressions with green patents as dependent variable.

Second, we explore how sensitive our path-dependency results are to different patent classifications. In Table IA.VIII we replace our green patent classification with the broader OECD classification of green patents, which includes more general technologies related to environmental applications, biodiversity, and wastewater management, as well as a green classification capturing both green and general efficiency patents. We find that the qualitative predictions uncovered for our green patent classification also hold for this broader green classification. Firms with higher emissions, that are older, larger, and have a smaller stock of green patents do less green R&D.

Third, we explore the sensitivity of our results to different patent filings than European patent office filings. In Table IA.IX we count all patent filings anywhere in the world. The dependent variables now are the ratio of green to total worldwide patent filings in year t (GREENRATIOWW in columns 1 to 3) and the ratio of brown to total worldwide patent filings (BROWNEFFRATIOWW in columns 4 to 6). Similarly, the stock of patents (PATSTOCKGREENWW and PATSTOCKBROWNEFFWW) now includes all patents filed anywhere in the world. The results clearly show that the qualitative results on path dependency also obtain when we look at the noisier measure of patent activity based on worldwide filings.

Fourth, we revisit the results of Table 2, using two alternative definitions of industry, based on 6-digit and 8-digit GICS scores. We report the results in Table IA.X. We find that qualitatively changes in industry classification do not affect our results on path dependence. Another robustness test we conduct is to restrict our sample to those firms for which we have carbon emissions data before 2015 (our legacy sample). Again, as reported in Panel A of Table IA.XI (for the extensive margin) and Panel B of Table IA.XI (for the intensive margin), our qualitative results are unchanged. We also explore how much mergers and acquisitions affect our findings. In Table IA.XII we report the findings of our regressions based on a sample that excludes all companies engaged in mergers and acquisitions (M&A) over our sample period. The results are qualitatively similar to our baseline findings. M&A activity is largely orthogonal to the determinants of corporate innovation activity even if some acquisitions are motivated by access to innovation.

We also explore how green innovation is distributed across firms by the size of their carbon emissions. In Table IA.XIII, we report the findings when we split our sample into terciles based on firms' initial scope 1 emissions (the first year when we observe a firm's scope 1 emissions). In Panel A the dependent variable is the green patent ratio and in Panel B the dependent variable is the brown efficiency ratio. Interestingly, the most significant negative effects of carbon emissions on green innovation are concentrated in the tercile of firms with the lowest emissions. But the stock of green patents has similar predictive effects on green innovation across all three terciles. In contrast, the most significant effects of carbon emissions on brown innovation are concentrated in the tercile of firms with the largest emissions. Again, however, the stock of brown patents has similar predictive effects on brown efficiency innovation across all three terciles.

5. The effects of innovation on future carbon emissions

We have shown that green and brown efficiency innovation is strongly path dependent. Green companies (which tend to be younger) are more likely to produce green patents, while brown companies are more likely to produce brown efficiency patents. That is, brown companies do not redirect their innovation towards green innovations. Rather, they focus on squeezing out efficiency gains in their brown operations. These results suggest that companies are unlikely to decarbonize through the switch of their innovation profiles.

In this section we systematically evaluate the effects of (green and brown) innovation on future carbon emission reductions. Much is predicated on the assumption that technological change is the solution to the climate crisis. But do green and brown efficiency innovation significantly reduce 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 the displacement effects. Similarly, with brown 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 greater phone usage. It is therefore unclear how much green and brown efficiency innovation has affected direct and indirect carbon emissions. These are the questions we explore in this section by exploring 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; iii) the effects on carbon emissions across other, broadly related industries; and iv) the effects on carbon emissions across countries within the same industry.

5.1 Green Innovation and the CO2 Problem

We begin our analysis of the impact of green R&D on carbon emissions by estimating the following regression model linking future firm-level corporate policy outcomes, such as future carbon emissions, to measures of contemporaneous green and brown efficiency patent ratios. Our first model exploits both extensive and intensive margins of patenting. Formally, we estimate the following linear regression model:

$$\text{Corporate Policy}_{i,t+h} = a + b\text{*Patent Ratio}_{i,t} + c\text{*Controls}_{i,t-1} + \text{FE} + \varepsilon_{i,t} \quad (2)$$

where *Corporate Policy* is a generic response variable that includes: i) the total level of emissions; ii) emission intensity; iii) INVEST/A; iv) LOGCAPEX; and v) LOGSALES, measured *t+h* years ahead. We let *h* take the value of respectively 1, 3, and 5 years to reflect the possibility that there may be a "time to build" lag in corporate adjustments. We also use the average value of patenting activity over the previous 3 years to predict corporate outcomes to take account of the fact that innovation breakthroughs are lumpy. The variable *Patent Ratio* is defined as before, and all regressions include year and firm-fixed effects. 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 corporate policy outcomes.

The results are reported in Table 8. Panel A reports the effects of green innovation (GREENRATIOEP) on corporate policy outcomes one year (L1), three years (L3), and five years (L5) ahead. We also report the effects of green innovation averaged over the previous three years (3YEARAVGGREENRATIOEP) on these corporate policy outcomes. As shown in column 1, green innovation has no significant effects on firms' direct emissions, one, three, or five 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[12]), although we observe a small reduction in indirect emissions with a 10% statistically significant negative coefficient of -0.042 for scope 2 emissions three years after the green patent filings. Future emissions are also not significantly related to innovation activity averaged over the past three years. We conclude that green innovation has not resulted in significant carbon emission reductions for the innovating firms even after five years since the patent filing. Columns 4 to 8 further report the lack of any significant effects of green innovation on direct or indirect emission intensity, so that the green technical progress does not appear to have materialized in any significant carbon efficiency gains. The only significant effect of green innovation on future corporate policies has been on future investment (with a three-year lag), with a substantial reduction in investment following the green patent filings. This latter finding is somewhat surprising, given that one expects research breakthroughs to be followed by development (i.e., more investment).

Panel B reports the effects of brown efficiency innovation (BROWNEFFRATIOEP) on corporate policy outcomes again respectively one year (L1), three years (L3), and five years (L5) ahead. As before we also report the effects of brown efficiency innovation averaged over the previous three years (3YEARAVGBROWNEFFRATIOEP) on these corporate policy outcomes. We find few significant effects of innovation on future corporate policies, except for a small increase in direct emissions with a 10% statistically significant positive coefficient of 0.065 for scope 1 emissions five years after the brown efficiency patent filings (in column 1), and a stronger, positive effect of average brown innovation on scope 1 emissions. This finding suggests that far from reducing future emissions, brown efficiency innovations result in increased future emissions. However, we also find a small improvement in scope 2 emission intensity, with a 10% statistically significant negative coefficient of -0.019 for scope 2 emission intensity five years after the brown efficiency patent filings (in column 7). Yet, this latter effect must be set against the significant effects on other corporate policies such as an increase in sales (column 12). Overall, what emerges from these findings is a picture that is consistent with the Jevons paradox: although brown efficiency innovation produces carbon intensity efficiency gains (for scope 2 emissions), these gains are offset by operating expansions (sales), which on net result in higher scope 1 emissions.

For robustness, we consider several alternative specifications. First, in Table IA.XIV we confirm the insignificance of firm-level green and brown innovation in affecting future carbon emissions and other corporate outcomes, for the specification where we include only observations of firms that hold at least one green, respectively brown, patent (intensive margin). Second, in Table IA.XV we show the results from the regressions where we take patent counts rather than

[12] Note that since downstream scope 3 emissions data has become available only in recent years, we do not have sufficient data to explore the effects on downstream scope 3 emissions over a 5-year horizon.

patent ratios as the main independent variable. The main difference is that the average count of green patents *positively* predicts future scope 1, scope 2, and upstream scope 3 emissions (in Panel A). Another related effect is that the average count of green patents *positively* predicts future firm sales. In contrast, we find a strong negative relationship between brown patent counts and scope 2 emissions (in Panel B). We also find a decrease in upstream scope 3 intensities in some specifications. Third, we explore how the importance of the patent matters for future corporate outcomes. In Table IA.XVI we consider the maximum number of cites a firm's patent receives. We find a strong positive effect of green patent cites on future scope 2 emissions, and a slightly weaker effect on upstream scope 3 emissions. In turn, green patent citations negatively predict downstream scope 3 emissions one year and three years into the future. Brown patent citations do not seem to affect future emissions, except for scope 1 emissions which fall in the next 1-3 years for companies with high citations of brown patents. In Table IA.XVII we look at the number of blockbuster patents a firm generates. As before, we find that, if anything, a higher incidence of blockbuster green patents is associated with higher levels of total emissions and particularly upstream scope 3 emissions. All other emissions components are unrelated to this measure. We also find little evidence that blockbuster brown patents lead to any reduction in future emissions. In Table IA.XVIII we restrict our analysis to companies whose cumulative patent ratio falls in the top quintile of the empirical distribution based on the previous 5-year data. Among all these innovation metrics, we find that the only model that predicts a reduction in future emissions is the 3-year moving average measure of green patents, which is negatively associated with scope 2 emissions. For brown patents, we find instead that the moving average of brown innovation strongly predicts a future increase in scope 1 emissions. Finally, in Table IA.XIX we show the results from using alternative, OECD-based, patent classifications. For green patents, we find some evidence of a reduction in future scope 2 emissions based on the ratio of green patents. Still, total future emissions are not negatively associated with this predictor. We also find a reduction in scope 2 emissions for some specifications based on brown patents, but the overall evidence of a link between green innovation and future decarbonization is weak. The conclusion we draw is that companies' green R&D activities are largely divorced from their other operations. Based on this evidence we conclude that the *green industrial revolution* has not yet materialized and that green innovation *per se* as the solution to the energy transition and the path to net-zero is still more of a promise than a reality.

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? We explore this question by linking industry-level direct and indirect carbon emissions, carbon intensity, and investment, to respectively green and brown efficiency innovation activity in the industry. Our baseline specification uses the GICS-6 industries classification. All regressions include the same controls as before, except that they are now measured at the industry level. 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 green innovation in Table 9, Panel A, and of brown innovation in Table 9, Panel B.

Consider first the effects of green innovation. In Panel A.1 we consider the effects on all firms within the same industry, whether they are innovators themselves or not. We find that green innovation is positively associated with future scope 1 emissions in the same industry, especially in the longer 5-year horizon. This result is largely driven by an increase in industry sales, in line with Jevons' paradox. In fact, we find that scope 1 emission-intensity at the industry level goes down. We further find that a greater rate of green innovation in the industry is associated with higher future scope 2 emissions, consistent with the displacement effect. Finally, we find that more green innovation is associated with significant upstream carbon emission-intensity improvements.[13] One consistent interpretation of these latter findings could be that reduced upstream scope 3 intensity is achieved by switching energy sources towards electricity, and the increase in electricity usage may have been met by electricity produced by fossil-fuel based power plants, which would increase scope 2 intensity. We note that the above results do not change much if we take as our measure of green innovation the average of green patenting activity over three years (3YEARAVGGREENRATIO) to take account of the fact that innovation is a gradual multi-year process. Finally, we also find a small significant effect on industry-wide investment, with greater green innovation associated with a subsequent slight increase in investment, especially in the longer run.

We also break down within industry spillover 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 green technologies. In Panel A.2 of Table 9 we report the results of the effects of green innovation on corporate policies of all the innovating firms in the industry. Again, we find no effect of green innovation on subsequent carbon emission reductions even though the direction of the effect for scope 1 emissions becomes negative, suggesting a more beneficial effect of green innovation. Still, we find that greater green innovation

[13] Table IA.XX considers green citations. While the results on absolute scope 1 emissions, intensities, and sales have the same sign, they are statistically weaker. Table IA.XXI looks at OECD green patent ratios. The results reported in this table broadly confirm our findings. Scope 3 upstream intensities again improve with more green innovation. Note that we also find small reductions in scope 1 emissions for a 3-year lag for ever-patenting firms, but this effect disappears for a 5-year lag.

is associated with higher scope 2 emissions, especially over the longer 3-year period. In Panel A.3 we report the results of the effects of green innovation on corporate policies of all the non-innovating firms in the industry. We find no evidence of any within-industry *spillover* between green innovators and non-innovators.[14] There is no significant subsequent carbon emission reduction by the non-innovators in the industry. There is, however, a significant increase in scope 2 carbon emission levels and intensity for the non-innovating firms. We also find a positive effect for scope 1 emissions.

In our tests, we assume a particular granularity in which innovation propagates within industries. The choice of a proper sectoral clustering is ex ante difficult even though GICS-6 is the preferred classification of investors. As a robustness, we therefore repeat the same analysis in Panel A of Table IA.XXII, but with a different industry classification: Instead of the coarser GICS-6 classification we use the slightly finer Trucost industry classification. Most of the qualitative results are similar, with some notable exceptions. We now find that most of the industry-level emission metrics are unrelated to industry-level green ratios. The exceptions are for scope 2 intensity and scope 3 downstream emissions, both being positively related to green innovation. In sum, what emerges from these findings is that there is no evidence of significant industry-wide direct and indirect emission reductions following greater green patenting activity and if anything, some of the emissions, especially scope 2 emissions go up, consistent with the displacement effect.

We consider next the industry-wide effects of brown efficiency innovation. The results are reported in Panel B of Table 9. In Panel B.1 we again look at the effects on all firms in the industry, whether they are innovators themselves or not. Interestingly, we find some reduction in direct or indirect carbon emissions following greater brown patenting activity even though the results are statistically insignificant.[15] We further find that scope 1 and scope 3 upstream carbon emission-intensity goes up. Another remarkable finding is the apparent heterogeneity between innovating and non-innovating firms. While emissions of innovating companies in the same GICS-6 industry increase slightly, carbon emissions of the non-innovating firms in the sector (both direct and indirect) go down. Interestingly, this effect is to a large extent driven by a reduction in sales, and investments, of that group of companies. Hence, the carbon emissions reduction of this subset of companies is largely coming from their loss of market share and not from a greater carbon efficiency of production. We again repeat the same analysis in Panel B of Table IA.XXII with the Trucost industry classification. Most of the qualitative results are similar, even though we find that

[14] We confirm these results in Table IA.XX with patent citations as a measure of green innovation. The only notable difference is an increase in scope 3 downstream emissions with a three-year lag.

[15] In Table IA.XX, we explore the robustness of these findings to using patent citations to measure brown innovation. Under this measure, the results are broadly confirmed, although absolute scope 1 emission and intensities increase in the long-run.

scope 2 emissions of innovating companies go down due to increased efficiency of energy production. At the same time, we again find that the market share of non-innovating companies goes down by a significant margin thus explaining some of the reduction in total emissions.

If there are no significant effects of green innovation on industry-wide carbon emissions, could there be cross-industry effects? Could it be that technological improvements in green energy in one industry mainly result in carbon emission reductions in other, closely related industries? We explore this question next (we also look at cross-country spillovers within individual sectors in Tables IA.XXIII-IA.XXVIII of the Appendix). In Table 10 we associate industry-wide direct and indirect carbon emissions, scope 1, 2, and 3 carbon intensity, capital expenditures, and sales in a given industry with green innovation activity by firms outside the narrow sector, but within the broader sector, and ask to what extent green innovation works by reducing emissions across sectors. Specifically, we link innovation activity in a given GICS-8 industry to corporate outcomes in a corresponding GICS-2 industry, excluding the specific GICS-8. In Panel A.1 we include all firms, in Panel A.2 we only look at cross-sector spillovers on innovating firms and in Panel A.3 we only look at cross-sector spillovers on non-innovating firms. Interestingly, we find a significant cross-industry spillover effect on carbon emissions with a 1-year lag for upstream scope 3 emissions, and for downstream scope 3 emissions for green innovation activity averaged over three years (3YEARAVGGREENRATIOEP). This effect works entirely through innovating firms, as is shown in Panels A.2 and A.3.

As for the cross-industry effects of brown efficiency innovation reported in Panel B of Table 10, we find that the only significant cross-industry effect on the level of emissions is an increase in downstream scope 3 emissions. The other cross-industry effect is a significant worsening of scope 1 and scope 2 carbon intensity for patenting firms. These findings point to other channels through which rebound effects can take place. An efficiency gain in brown technology in one sector can result in increased carbon emissions in another sector (through the supply chain) by inducing greater use of a complementary brown technology.

These findings are consistent with the general idea that cross-sector innovation is highly complementary, and that it takes innovation breakthroughs in multiple sectors to be able to implement new technologies that reduce carbon emissions at scale. Moreover, technological innovation in one sector can result in rebound effects in another sector, largely eliminating any reductions in direct emissions from the innovation. This points to the complexity of green innovation as a solution to the CO2 problem. Decentralized, market-based, innovation may not be all that effective in decarbonizing the economy, if adoption and scaling of green technologies is held back by the lack of coordination of innovation across firms and sectors.

5.2 Spillovers from the universe of privately held companies

Our results so far relate firm-level and industry-level emissions to innovation of publicly listed companies. Our focus on publicly listed firms is dictated by the availability of carbon emissions data for these companies. However, one could argue that such firms may benefit from innovation not only of similar publicly listed companies but also from innovation of privately held firms. In this section, we examine this spillover channel by looking at industry-level responses to green and brown innovation by publicly listed and privately held companies, separately.

In Table 11, we report the results from the analysis that considers innovation and output in the same GICS-6 industry, similar to our setting in Table 9. In Panel A, we look at the role of green innovation. We define two new variables: GREENRATIOEP PUBLIC takes innovation activity of all publicly listed companies, GREENRATIOEP PRIVATE uses the innovation of private companies. Both measures incorporate scaling by total innovation activity. In Panel A.1, we focus on all firms with emissions data. We find that neither public nor private innovation is associated with any statistically significant reduction in industry-level emissions. Notably, we find that green innovation in the public sector is more positively correlated with future scope 2 emissions, as well as scope 1 and upstream scope 3 emissions, though the effects for the latter two are statistically insignificant. The stronger positive association of public innovation mostly comes from the subset of innovating companies (as reported in Panel A.2), which are also the ones whose sales go up by more.

In Table 11, Panel B, we repeat the same analysis for brown innovation. The corresponding new variables of interest are BROWNEFFRATIOEP PUBLIC and BROWNEFFRATIOEP PRIVATE. In contrast to the results in Panel A, we find that public and private innovation do not seem to have markedly different impacts on future industry-level emissions. This result is consistent with the common perception that private firms are more involved in green innovation.

In Table 12, we provide additional evidence on the role of public and private innovation through the lens of cross-industry spillovers. Here, our research design follows that in Table 10. In Panel A, we consider green innovation. Several interesting findings emerge. First, in aggregate, private innovation seems to have a large impact on industry-level emission reductions in the public sector. This result largely comes through the reduction of scope 3 emissions, both upstream and downstream. Second, this effect is mostly driven by the fact that an increase in private green innovation predicts a reduction in sales of public firms. It seems that innovating private firms are encroaching on the market position of public firms. Third, the effect on upstream scope 3 emission reductions is mostly due to the impact on innovating firms, while downstream scope 3 emission reductions are more associated with green innovation in public firms. In Panel B, we report corresponding results for brown innovation. We find some evidence that brown innovation, both in the public and private firms, reduces scope 1 emissions, although the results are generally statistically weak. The only notable exception is the positive effect of innovation of public firms on the reduction in scope 1 emissions of innovating firms. In turn, innovation among public firms positively predicts scope 2 emissions, especially those of innovating firms.

Another channel through which the Jevons paradox can manifest itself is through product market competition. Our measure of competition is the company's market share (in terms of sales) relative to the total sales of both public and private firms within the same GICS-6 industry. As we show in Table 13, 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. In Panel A, we estimate a model with industry*year fixed effects and in Panel B a model with firm fixed effects. As is shown in columns 1 to 3, a firm's market share is significantly negatively impacted by past green innovation activity, whether on a 1-year, 3-year, or 5-year lag. This effect is largely due to cross-firm variation, given that the effects become weaker when we account for firm-fixed effects. In contrast, there is no significant effect of brown efficiency innovation activity on firms' market share. If anything, the effect of brown efficiency innovation is to increase market share. Thus, even if green innovation could reduce future carbon emissions of green firms, this positive effect is partially undone by the increased market share of brown firms.

5.3 The relative importance of green innovation for decarbonization

Having highlighted the tenuous association between green (or brown) innovation and future carbon emission reductions, we explore next the extent to which corporate carbon emissions are explained by green innovation. In the first test, reported in Table 14, we conduct a balance test by comparing two samples of firms: those with decreasing emissions and those with increasing emissions. We perform this comparison for scope 1 emissions in Panel A and the total level of direct and indirect emissions in Panel E. In Table IA.XXIX, we also consider scope 2, scope 3 upstream, and scope 3 downstream emissions. In the group of firms that decrease (increase) their emissions over time we further divide firms into the 50% of companies with the largest emission reductions (surges). For each group, we report the means and standard deviations of different characteristics and the test of differences in means between each pair.

In Panel A, we show the results based on scope 1 emissions. We find that companies with extreme increases and decreases in emissions are not very different from each other in terms of their green patent ratios as well as their brown efficiency patent ratios. The two types of companies have also very similar levels of patent citations. On the other hand, firms that decrease their scope 1 emissions are on average larger and older than companies that increase their emissions; they also have lower M/B ratios, and negative sales growth. However, they are not very different in their

ROE or leverage metrics. The similarities in innovation ratios are also observed when we consider the sum of scope 1, scope 2, and scope 3 emissions in Panel B.

In Table IA.XXIX Panel A, we report the results for scope 2 emissions. Results are qualitatively similar to those for scope 1 emissions, except that now emission reducing companies on average have higher brown efficiency patent ratios. They are also less profitable and have lower leverage ratios. In Table IA.XXIX Panel B we look at the differences for upstream scope 3 emissions. For these indirect emissions, we find that emission reducing companies have higher green and brown efficiency patent ratios. These differences, however, disappear when we look at sorts based on downstream scope 3 emissions, as shown in Table IA.XXIX Panel C. Overall, we conclude that companies that reduce their emissions the most are not necessarily more innovative than those that increase their emissions the least. We find that the two sets of companies significantly differ in their sales performance (changes in sales are negative on average for companies reducing emissions and positive for companies increasing emissions across all scopes) pointing again to the limited decoupling of growth and emissions.

In another set of tests, we study the economic significance of green innovation using the two following specifications. First, we look at the relationship between the stock of innovation and subsequent long-term changes in emissions. This test allows us to account for the fact that innovation can be a process with a long gestation period. Specifically, we predict the firm-level absolute change in average emission levels and their intensities between the periods 2005-2014 and 2015-2020 using measures of the stock of innovations (measured either as patent ratios or as patent counts) over two time periods: (i) 1990-2004; and (ii) 1990-2014. We perform the tests separately for green and brown innovation. We show the results of this test in Table 15. Panel A presents the results based on patent ratios. We find that the long-term stock of green or brown innovation measured by patent ratio is not related to long-term changes in emissions. Whether we use the shorter or the longer period to cumulate innovation, the results are not statistically significant. If anything, the correlations between the stock of green innovation and future emission changes is positive, which suggests that companies with greater patenting activity on average increased their emissions. In contrast, we find some albeit weak evidence that over a more prolonged period, companies with higher brown efficiency patents reduced their emissions. The results become slightly stronger when we look at the cumulative number of patents, as presented in Panel B. Now the number of green patents accumulated over a longish period predicts subsequent reductions in future scope 1 and scope 3 upstream emissions. The result is statistically weaker when we look at brown innovation. Overall, even though we find some evidence that over the long-run innovation may lead, in some cases, to reductions in emissions this result may not necessarily offer a silver bullet from the perspective of supporting current innovations, simply because we do not have that much time to wait for the emissions reductions from innovation to materialize.

Another question of interest is whether the effect of green innovation is economically large. This is the question we try to answer in Table 16. Here we evaluate the partial R2 of the regression model that tries to explain future emissions levels using patent ratios. As before, we focus on green and brown efficiency patents, and consider various predictive horizons. The consistent message that emerges from this analysis is that green innovation activity explains a very small fraction of the variation in future emissions levels. The partial R2s typically do not exceed 1% and more frequently are significantly smaller. We conclude that green innovation is not a primary source of firm-level variation in future carbon emissions. Even if some companies do decarbonize their operations, this decarbonization is explained only to a very limited extent by these firms' green patenting 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 brown efficiency innovation, these technological advances have not materialized in lower carbon emissions. 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 brown 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.

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 innovation without regard to the likely adoption of new technologies may simply be too wasteful and costly.

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