# The CO2 Question:

# Technical Progress and the Climate Crisis<sup>1</sup>

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#### Abstract

Are companies gravitating towards green R&D and is corporate behavior, in particular carbon emissions, affected by green technical progress? Based on global patent filings and corporate financial reporting, we analyze corporate green and brown R&D activity and its effects in reducing carbon emissions. We find consistent evidence of limited green R&D by brown companies. 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, we find little evidence that green innovation reduces the future carbon emissions of 1) innovating firms, 2) non-innovating firms in the same sector, 3) firms in other sectors and, 4) across countries. Direct and indirect emissions are not significantly affected by green innovation across all sectors and around the world, whether in the short term (one year after filing a green patent) or in the medium term (three or five years after filing).

JEL codes G12, G23, G30, D62, D83

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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.

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 are able to 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.<sup>1</sup> 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 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

<sup>&</sup>lt;sup>1</sup> 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 A.II that most of Halliburton's innovation activity in recent years has been in brown innovation, which has steadily increased over time.

fuel energy are consistent with earlier studies that find evidence that innovation is path dependent (Acemoglu, 2002, Popp, 2002, and Aghion, Dechezlepretre, Hemous, Martin, and Van Reenen, 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).

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 do not find any significant spillover effects of green innovation on the carbon emissions of non-innovating firms in the same sector. And we do not find any spillover effects across sectors or across countries either. 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.

We also find evidence of other channels through which rebound effects can occur. For example, greater green innovation can result in higher future scope 2 emissions, presumably because of the greater reliance on electricity, which still results in substantial scope 2 emissions. Another striking channel 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. 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.<sup>2</sup> 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, Dimitropoulos, and Summerville (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 are able to identify substantially larger and more diverse forms of rebound effects.

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. All the green technological breakthroughs we have seen so far have not made a significant dent in carbon emissions, presumably because they have not yet been adopted on a very wide scale.

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, Gurun, and Nguyen (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.

 $<sup>^{2}</sup>$  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.

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, Sautner, and Vilkov (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, Van Lent, Vilkov, and Zhang (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.

The remainder of the paper is organized as follows. Section 2 describes the data and provides summary statistics. Section 3 discusses the results on the drivers of green innovation. Section 4 provides the results on the impact of innovation on future emissions and other corporate decisions. Section 5 concludes.

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

#### 2.1 Aggregate data by country

Table 1 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 A.I 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.

# 2.2 Green and brown innovation

We make a key distinction between *green innovation*, targeting renewable energy and environmentally friendly technologies, 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)<sup>3</sup>, the International Patent Classification (IPC) Green Inventory<sup>4</sup>, the efficiency-improving fossil fuel-technology categories of Lanzi, Verdolini, and Hascic (2011), as well as a self-identified classification based on patents from the Corporate Knights Clean 200. We classify patents into three broad categories<sup>5</sup>: 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 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 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 efficiency 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 A.II, 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

<sup>&</sup>lt;sup>3</sup> https://www.oecd.org/env/indicators-modelling-outlooks/green-patents.htm

<sup>&</sup>lt;sup>4</sup> <u>https://www.wipo.int/classifications/ipc/green-inventory/home</u>

<sup>&</sup>lt;sup>5</sup> We provide a detailed description of our approach and the underlying IPC/ CPC classes in the following online document: <u>https://wiedemannm.github.io/documents/DescriptionPatentClassification.pdf</u>

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 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.

## 2.3 Innovation Capacity: scale & scope

The summary statistics in Section 2.1 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 for dependent variables). We report our findings in Table 2, 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. 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 2 we turn to our second hypothesis, specialization through learningby-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 efficiency 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 efficiency patents (PATSTOCKBROWNEFFEP). Consistent with our hypothesis, we find strong evidence of specialization, with a higher stock of green patents (resp. brown efficiency patents) positively predicting future green innovation activity (resp. brown efficiency innovation activity). Moreover, a higher stock of green patents (resp. brown efficiency patents) negatively predicts future brown efficiency 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 pathdependency 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 pathdependency 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.

# 2.4 Green and brown innovation ratios

As we have shown in the preceding section, 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 efficiency patents filed at EUPO over the total number of patent filings in that year.

Table 3, 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.

# 2.5 Summary Statistics

In this section we provide summary statistics for the main variables in our models, conditional on whether firms file patents. We also report extreme deciles for each sample. 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 Envtech classification, calculated as the number of granted or purchased DECD patents over the total number of granted or purchased patents; GREENCITMAXEP (BROWNEFFCITMAXEP) is the maximum number of forward citations any green (brown efficiency) patent of a firm received; GREENBBCOUNTEP (BROWNEFFBBCOUNTEP) is the number of green (brown efficiency) 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.<sup>6</sup>

In our second category we include variables measuring corporate carbon emissions (direct and indirect) when available, and standard variables capturing key corporate characteristics.<sup>7</sup> 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 which stands for the natural logarithm of a listed company's market

<sup>&</sup>lt;sup>6</sup> 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.

<sup>&</sup>lt;sup>7</sup> 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.

capitalization (price times shares outstanding); ii) LOGPPE, which is given by the natural logarithm, of the firm's property, plant, and equipment (in \$ million); iii) LEVERAGE, which is the ratio of debt to book value of assets; iv) ROE, which is given by the ratio of firm *i*'s net yearly income divided by the value of its equity; v) M/B, which is the end of year market cap divided by the firm's book value; vi) BETA, which is the market beta of individual companies calculated over the preceding 12-month period; vii) VOLAT, which is the standard deviation of returns based on the past 12 monthly returns; viii) momentum, MOM, which 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, which is the past year's December return on stock *i*; x) capital expenditure INVEST/A, which we measure as the firm's capital expenditures divided by the book value of its assets; xi) MSCI, which 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, which is the natural logarithm of firm-level capital expenditures; and xiii) LOGCASH, which 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 A.III 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. 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 nonpatenting 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 two fundamental insights, the *Arrow replacement effect* (Arrow, 1962) and *Jevons' paradox* (Jevons 1865). Arrow (1962) has pointed out that "The pre-invention monopoly power acts as a strong disincentive to further innovation."<sup>8</sup> 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.

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 explore the effects of green innovation on the decarbonization of the economy.

#### 3. 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

<sup>&</sup>lt;sup>8</sup> 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.

produce green patents, whereas brown firms (which have expertise in fossil fuel-dependent technologies) are more likely to produce brown efficiency 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).

# 3.1 Green vs Brown Efficiency 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 be a value company. Similarly, a *green* firm is one that has low carbon emissions, is younger, may have smaller asset size and be a growth firm. 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 efficiency) patent ratios linked to firm type, specifically the firm's corporate carbon emissions, its age, and green and brown efficiency patent stocks? To answer this question, we estimate the following Pseudo Poisson Maximum Likelihood model with firm (i) and year (f) as units of observation<sup>9</sup>:

Patent Ratio<sub>i,t</sub> = 
$$a + b*Firm$$
 Type<sub>i,t-1</sub> +  $c*Controls_{i,t-1} + Fixed$  Effects +  $\varepsilon_{i,t}$  (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*.

We report our findings for the extensive margin (which includes all firms, whether they own any green, respectively brown efficiency, patents or not) in Table 4. In columns 1-3, we present the results for green innovation activity (GREENRATIOEP), and in columns 4-6 the results for brown efficiency 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 keep 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.<sup>10</sup> The results flip when we look at brown efficiency innovation activity (BROWNEFFRATIOEP) in columns 4-6. For this type of

<sup>&</sup>lt;sup>9</sup> Since many companies do not report any green patents a standard OLS regression is not suitable to estimate this relationship.

<sup>&</sup>lt;sup>10</sup> 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.

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 efficiency 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 (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 5, 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 to 3, and/or one brown efficiency 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 4, 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.

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 6, 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 efficiency 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 efficiency 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 pathdependency 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 efficiency 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 7, 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 7 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 efficiency 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 efficiency 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 efficiency 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 8. 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 efficiency 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 9. 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 interaction variables 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 efficiency) 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.

# 3.2 Robustness

We perform several robustness tests and report the findings in the Appendix. In Tables A.IV and A.V 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.

Third, we explore how sensitive our path-dependency results are to different patent classifications. In Table A.VII 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.

Fourth, we explore the sensitivity of our results to different patent filings than European patent office filings. In Table A.VIII 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 efficiency 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.

Fifth, we revisit the results of Table 4, using two alternative definitions of industry, based on 6-digit and 8-digit GICS scores. We report the results in Table A.IX. 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 A.X (for the extensive margin) and Panel B of Table A.X (for the intensive margin), our qualitative results are unchanged. We also explore how much mergers and acquisitions affect our findings. In Table A.XI 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 A.XII 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 efficiency innovation are concentrated in the tercile of firms with the largest emissions. Again, however, the stock of brown efficiency patents has similar predictive effects on brown efficiency innovation across all three terciles.

## 4. The effects of innovation on future carbon emissions: The Jevons Paradox

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 efficiency) 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. 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.

# 4.1 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:

Corporate 
$$Policy_{i,t+h} = a + b*Patent Ratio_{i,t} + c*Controls_{i,t-1} + FE + \varepsilon_{i,t}$$
 (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 country, year, and firm-fixed effects. We double cluster standard errors at the firm and year dimensions. Our coefficient of primary interest is *h*, which measures the impact of *Patent Ratio* on future corporate policy outcomes.

The results are reported in Table 10. 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 year, three years, 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<sup>11</sup>), 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

<sup>&</sup>lt;sup>11</sup> 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.

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 A.XIII 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 efficiency, patent (intensive margin). Second, in Table A.XIV we show the results from the regressions where we take patent counts rather than patent ratios as the main independent variable. The main difference is that the average count of green patents positively affects 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* affects future firm sales. In contrast, we find a strong negative effect of brown patent counts on 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 A.XV 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 A.XVI 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 A.XVII 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 A.XVIII 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 efficiency 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. 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 11 and of brown efficiency innovation in Table 12.

Consider first the effects of green innovation. In Panel A.1 we consider the effects on all firms within the same, highly granular Trucost industry classification, whether they are innovators themselves or not. We find no evidence of a significant reduction in direct or indirect carbon emissions. The only statistically significant effect of green innovation is on upstream scope 3 carbon intensity one year later: More green innovation is associated with significant upstream carbon intensity improvements.<sup>12</sup> We also take as our measure of green innovation the average of green patenting activity over three years (3YEARAVGGREENRATIO) to take account of the

<sup>&</sup>lt;sup>12</sup> Table A.XIX considers green citations. This table reports the findings that scope 1, 2, and 3 upstream emissions increase in year 5 for all patenting firms. However, emissions decrease for never-patenting firms. Interestingly, the results that green innovation improves scope 3 upstream intensity are confirmed when we look at green patent citations rather than green patent ratios. Table A.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 and 2 emissions for a 3-year lag, but this effect disappears for a 5-year lag for all firms.

fact that innovation is a gradual multi-year process. We find again that this measure is not associated with any future carbon emission reductions. Consistent with our other findings, it is, however, associated with industry-wide significant changes in carbon intensity. But these findings go in different directions. While more green innovation is associated with significant upstream scope 3 carbon intensity improvements, it is also associated with a worsening in carbon intensity for scope 2 emissions. 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. Note finally that we also find a small significant effect on industry-wide investment, with greater green innovation associated with a subsequent slight decline in investment.<sup>13</sup>

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 noninnovating firms are driven by adoption of the new green technologies. In Panel A.2 of Table 11 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. If anything, we find that greater green innovation is associated with higher downstream scope 3 emissions (in column 4). In Panel A.3 of Table 11 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.<sup>14</sup> 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 intensity for the non-innovating firms with a 3-year lag. 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. As a robustness, we therefore repeat the same analysis in Panel B of Table 11, but with a different industry classification: Instead of the finer Trucost classification we use the slightly coarser GICS-6 industry classification. Most of the qualitative results are similar, with some notable exceptions. We now find that industry-wide scope 2 emissions significantly increase in response to greater past green innovation, both for patenting and non-patenting firms. The same is true for scope 2 carbon intensity. Thus, one notable industry-wide effect of green innovation is to switch energy use towards electricity, but this results in higher scope 2 emissions (without any offsetting reduction

<sup>&</sup>lt;sup>13</sup> These finding are confirmed in Table A.XIX for patent citations as a measure of green innovation.

<sup>&</sup>lt;sup>14</sup> In Table A.XIX we find that carbon emissions as well as sales of non-innovators are lower, but carbon intensities remain unchanged except for a decline in downstream scope 3 intensity with a 3-year lag.

in scope 1 and scope 3 emissions). 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.

Consider next the industry-wide effects of brown efficiency innovation. The results are reported in Table 12. In Panel A.1 we again look at the effects on all firms in the industry, whether they are innovators themselves or not. Interestingly, we find that there is a significant reduction in direct or indirect carbon emissions following greater brown efficiency patenting activity.<sup>15</sup> The effect is most significant for scope 2 emissions, which suggests that improvements in brown efficiency reduces the industry's reliance on electricity. It is also quite significant for upstream scope 3 emissions. This is not entirely surprising. Another remarkable finding is that these effects on carbon emission reductions are confined to the innovating firms in the sector. As can be seen by comparing the findings in Table A.2 with those of Table A.3, except for scope 3 emissions, there are no spillover effects of brown efficiency innovation on non-innovating firms in the industry. Finally, another interesting finding is that greater brown efficiency innovation cuts into future sales of non-innovating firms in the industry (column 11 in Panel A.3), which could explain why downstream scope 3 emissions for these firms are lower when there is more brown efficiency patenting activity. We again repeat the same analysis in Panel B of Table 12 with the GICS-6 industry classification. Most of the qualitative results are similar, but with lower or no statistical significance, except for the reduction in scope 2 emissions for non-patenting firms.

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 A.XXII-A.XXVII of the Appendix). In Table 13 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

<sup>&</sup>lt;sup>15</sup> In Table A.XX we explore the robustness of these findings to using patent citations to measure brown efficiency innovation. Under this measure we find the opposite effect: a significant increase in scope 1, 2, and 3 emissions and an increase in sales across non-patenting and patenting firms. The effect on carbon intensities is insignificant, which means again that a Jevons effect is at work.

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 13, 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.

Another channel through which the Jevons paradox can manifest itself is product market competition. As we show in Table 14, green innovation and the adoption of green technologies can be a handicap in product market competition if green firms have higher costs than brown firms. Specifically, we link a company's market share (in terms of sales) within its GICS-6 industry to its past green or brown efficiency innovation activity. In Panel A we consider the model with firm fixed effects and in Panel B the model with industry\*year 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 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.

# 4.2 The relative importance of green innovation for decarbonization

Having highlighted the tenuous association between green (or brown efficiency) 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 15, 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 each measure of emissions (Panel A- Panel D) as well as the total level of direct and indirect emissions (Panel E). 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.

In Panel B, 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 Panel C 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 Panel D. Finally, the similarities in innovation ratios are also observed when we consider the sum of scope 1, scope 2, and scope 3 emissions in Panel E. 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 long-term changes in innovation and long-term changes in emissions, using the equal horizon split for each individual firm in our sample. This test uses one observation per firm and allows us to account for the fact that innovation can be a process with a long gestation period. We show the results of this test in Panel A of Table 16. We find that the long-term change in green innovation is not related to long-

term changes in emissions. If anything, the correlations between the two variables are positive, which suggests that companies that increase their patenting activity on average increased their emissions. In contrast, we find that over a more prolonged period, companies with higher brown efficiency patents reduced their scope 1, but NOT their scope 2 and scope 3 emissions.

Another question of interest is whether the effect of green innovation is economically large. This is the question we try to answer through Panel B of 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 measures explain 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.

# 5. 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 fuelbased 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 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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# 7 Tables

#### TABLE 1: PATENT DATA BY COUNTRY

The sample period is 2005/2020. In Panel A, we report the number of firm observations by country for the full (public and private), public, private and Trucost sample. Columns 1 to 4 report unconditional numbers and columns 5 to 8 condition on having at least one granted or purchased patent at the European Patent Office. In Panel B, we report patent counts and arrange patent counts by dimensity. We report patent the total number of granted or purchased patent at the European Patent Office. In Panel B, we report patent counts and arrange patent counts in divergent patent be total numbers of patents at the European Patent Office. In Panel B, we report patent a we recoge patents at the European Patent Office in given country in columns 1 to 4 and the average number of patents at the European Patent Office in given country in columns 1 to 4 and the average number of patents at the European Patent Office in given with less than 30 tim-year observations in the full sample agregated by region under "Others". Others North America' include ARGULLA, ANTICUA & BARBUDA, BAHAMAS, BARBADOS, BELZE, COSTA RICA, CURACAO, DOMINICA, NDOMINICAN REPUBLIC, EL SALVADOR, GREENLAND, QUATEMALA, HONDURAS, MARSHALL ISALNOS, NICARAGUA, SANT BRATTELENY, SAINT KITTS & PUSY, SAINT LUICLA, SAINT MARTE, SAINT MARTE AND BARAGUA, SAINT BRATTE, HUYS, SAINT LUICLA, SAINT MARTE, SAINT MARTE AND BARAGUA, SAINT BRATTE, HUYS, SAINT LUICLA, SAINT MARTE, NEMECON, CARE VERDE, COT ENGACO, "Others Asia" include ARMENIA, AZERBAJIAN, BAHRAIN, BHUTAN, CAMBIOLE, NEWS, SAINT LUICLA, SAINT MARTE, NEWS, SAINT LUICLA, SAINT MARTE NEWS, SAINT TURE NEWS, SAINT LUICLA, SAINT MARTE, SAINT MARTE, AND, NACAO SAR, MYANMAR/BURMA, GABON, GAMBIA, CHANA, KENYA, LIBERIA, MALAWI, MALUTE, MCAZMBIQUE, NAMBIA, SENREGAL, SEVCHELLE, SUDAN, TOCO, TUNISLA, UCANDA, UNEDER PUBLIC, CHEANAND, CANDA, AZENSA, MARNA, AZENSA, MARNA, ALAR BERVELLE, CONTE, MCAZMBIQUE, NAMBIA, SENREGAL, SEVCHELLE, SUDAN, TOCO, TUNISLA, UCANDA, UNEDER PUBLIC, CHEANAND, ALACAO SAN MARINO, SVALBARD MARCON, SAMER EU (5) (4) (7) (2) (6) (8)(1) Panel A: Firm count Full sample Patenting sample Full Public Private Trucost Full Public Private Trucost ARGENTINA 
 17%

 1645

 5227

 1645

 5227

 1844

 26380

 8011

 333

 15649

 15649

 15649

 15649

 15649

 15649

 15649

 15649

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 15649

 15649

 156733

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 628 49 7 80 67 0 AUSTRALIA AUSTRIA BANGLADESH BELGIUM 116 93 150 708 0 24 470 195 4831 206 69 0 84 58 0 0 59 6 495 137 33 624 61 0 540 3 0 52 BERMUDA BOLIVIA BOSNIA & HERZEGOVINA BRAZIL 89 27 532 30 21 37 39 209 5 560 BRAZIL BULGARIA CANADA CANARY ISLANDS CAYMAN ISLANDS CHILE CHINA COLOMBIA CROATIA 140 962 216 5760 44 49 2751 52 22 1358 36 19 910 16 3 448 6 19 73 727 0 5 3 16 69 657 102 67 20 208 CROATIA CROATIA CYPRUS CZECH REP DENMARK ECUADOR EGYPT ESTONIA FINLAND 10 8 66 0 41 3 74 70 0 3 0 182 21 191 660 869 255 362 1611 1523 32 0 105 367 429 23 0 257  $^{0}_{47}$ FRANCE GERMANY GREECE GUADELOUPE 315 49 0 1094 198 GUADELOUPE GUERNSEY HONG KONG HUNGARY ICELAND INDIA INDONESIA IRAQ IREAND ISLAMIC REPUBLIC OF IRAN ISPA EL 1251 42 34 3249 668 0 94 0 734 124 26 19 349 15 85 191 0 45 0 0 36 0 0 50 0 0 95 0 69 0 ISLAMIC F ISRAEL ITALY JAMAICA JAPAN 74 96 0 1063 468 37 6148 38 157 11 196 27 41 84 1234 1234 15 0 71 170 181 1732 210 1522 2328 14 3 2 3 2103 2535 17 6 5 36 0 2 48 255 7 225 JAPAN JERSEY JORDAN KAZAKHSTAN KUWAIT LATVIA LITHUANIA LUXEMBOURG MALAYSIA MALTA MARTINIQUE MAURTIUS MEXICO 244 74 17 0 3 29 56 1 26 1 16 0 MAUKITUS MEXICO MONGOLIA MONGOCIA MOROCCO NETHERLANDS NEW ZEALAND NIGERIA NORTH MACEDONIA NORWAY 255 484 114 9120 221 55 1124 0 0 0 0 2 0 0 2 17 29 122 72 23 0 39 0 3 11 0 3 114 93 24 399 68 317 28 0 0 12 0 0 NORWAY OMAN PAKISTAN PANAMA PARAGUAY 0 0 0 0 0 59 274 45 67 160 199 11865 14224 10 64 1 0 PERU PHILIPPINES POLAND PORTUGAL 5020 126066 5773 9511 2100 83224 40930 3000 57133 41455 56311 30866 9398 6055 44266 2655 44266 2655 447531 603 3282 2811 2171 28300 114 30589 915467 119 303 741 64 48 0 83 79 23 34 0 13 130 82 4 10 2 0 0 72 2 6 0 0 QATAR REPUBLIC OF MOLDOVA 951 2100 8222 40548 41 5702 3339 5614 3062 157 2917 44027 32 46696 287 826 1991 1697 28276 21 29406 2455 119 REUNION ROMANIA 102 382 259 11 806 17 24 241 3148 233 1035 316 2456 820 474 24 93 1183 13002 RUMANIA RUSSIA SAUDI ARABIA SERBIA SINGAPORE SLOVAKIA 10 155 11 84 3 35 0 192 42 20 34 23 40 53 1089 588 1 1171 241 596 29 56 1 SLOVANIA SLOVENIA SOUTH AFRICA SOUTH KOREA SPAIN 185 1240 115 5 284 243 904 232 120 47 843 92 1 450 41 488 53 246 496 0 721 73 48 6 15 1 0 SPAIN SRI LANKA SWEDEN SWITZERLAND TAIWAN THAILAND TURKEY LUCRAINE 143 283 14 25 0 4 548 23 41 0 UKRAINE UNITED ARAB EMIRATES UNITED KINGDOM UNITED STATES 49 769 3864 4053 3783 270 1735 URUGUAY UZBEKISTAN VIETNAM VIRIGIN ISL ZIMBABWE 2873 194 66 225 162 39 190 233 79 2110 49 61 158 112 35 161 165 76 24 4 145 5 67 50 4 29 68 3 ZIMBABWE Others Africa Others Asia Others Australia Others Europe Others North America Others South America 13 Total 

Panel B: Patent count and firm av	erage patent c	ount	at count		· A	rage no of pat	te cond on nat	ting
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
ARGENTINA	76	75	1	21	4.5	4.7	1.0	2.6
AUSTRALIA	3235	2523	711	1957	3.0	3.1	2.8	4.1
AUSTRIA BANCI ADESH	121	7464	5137	5441	13.2	20.0	8.8	24.6
BELGIUM	14715	8346	6358	5961	7.5	19.0	4.2	22.4
BERMUDA	792	777	15	117	4.4	4.6	1.4	.6
BOLIVIA BOSNIA & HERZEGOVINA	3		3		1.5	•	1.5	•
BRAZIL	1285	12	183	694	4.3	5.0	2.3	4.4
BULGARIA Canada	49	8 737	41	12958	1.1	1.1	1.1	1
CANARY ISLANDS	1	131	1155	12930	1.0	13.0	1.0	20. <del>4</del>
CAYMAN ISLANDS	4	599	5	33	7.2	7.9	5.7	5.5
CHINA	37614	1364 28888	8643	768 249	14.6 .6	15.9 11.7	1.4 8.5	14.8 17.6
COLOMBIA	8	8		8	1.1	1.1		1.1
CROATIA	13	7	5 31	5	1.4 1 7	1.2	2.5	25
CZECH REP	269	11	258	5	1.8	1.4	1.9	1.4
DENMARK	12374	5813	6561	5489	7.1	13.8	5.0	18.5
EGYPT	446	436		2	21.2	29.1	1.7	2.0
ESTONIA	41		41	-	1.2		1.2	
FINLAND FRANCE	26119 122293	23534	2585 31923	22769 866	19.2	.7 46 4	3.3 8 1	62.4 64.0
GERMANY	157776	1232	37456	9786	22.9	51.0	8.3	83.6
GREECE	114	95	19	35	1.5	1.6	1.1	1.6
GUADELOUPE GUERNSEY	44	38	6	9	29	3.2	2 0	. 23
HONG KONG	43	5971	72	53	14.9	15.4	4.2	21.6
HUNGARY	5	199	4	134	4.6	6.0	3.2	7.4
ICELAND INDIA	776	449 6116	327 74	31 5113	9.7 6.0	15.0 6.6	6.5 4.0	15.5 8.7
INDONESIA	4	4		3	1.0	1.0		1.0
IRAQ IRFLAND	5211	4247	Q	3826	19.0	24.5	Q Q	25.2
ISLAMIC REPUBLIC OF IRAN	5211		7					
ISRAEL	3374	82	292	03	4.6	5.0	2.6	8.1
JAMAICA	24051	12232	126	033	4.6	14.0	2.8	21.5
JAPAN	3351	324325	775	59	27.7	29.7	9.3	48.0
JERSEY IORDAN	68 11	59 11	9	44	2.6	3.1	1.3	3.1
KAZAKHSTAN	4	11	4		1.2	1.2	1.0	
KUWAIT	5	4	1	1	1.0	1.0	1.0	1.0
lai via LITHUANIA	35 11	29 2	6		1.9 1.1	2.2	1.2	•
LUXEMBOURG	5334	944	4371	879	6.8	8.6	6.5	
MALAYSIA	461	359	2	259	2.3	2.3	2.2	2.8
MARTINIQUE	65	1	62	1	1.9	1.0	1.9	1.0
MAURITIUS	3	1	.2		1.0	1.0	1.0	<u>.</u>
MEXICO MONGOLIA	5	876	29	816	6.9	7.7	1.6	8.8
MONTENEGRO					•			•
MOROCCO	24	2	22	245	2.4	1.0	2.8	
NEW ZEALAND	361	261	81 77	345 177	31.8	3.3	9.4 2.6	6.1
NIGERIA	_		_					•
NORTH MACEDONIA NORWAY	3 3645	24	3 1621	1669	1.0	4.8	1.0	66
OMAN	1	27	1021	1007	1.0		1.0	
PAKISTAN	2		2		1.0		1.0	
PARAGUAY	2		2		1.0	•	1.0	•
PERU	5	1	4	1	1.3	1.0	1.3	1.0
PHILIPPINES POLAND	136	77	59 184	53	2.2	2.0	2.6	2.0
PORTUGAL	362	39	323	22	1.8	1.5	1.7	4.9
QATAR	5	1	4		1.0	1.0	1.0	
REPUBLIC OF MOLDOVA REUNION	1	•	1		1.0		1.0	•
ROMANIA	11	2	9	•	1.1	2.0	1.0	
RUSSIA SALIDI ARABIA	573	216	357	181	2.6	3.2	2.4	3.8
SERBIA	4815	3226	1589	2488	145.9	2.0	264.8	191.4
SINGAPORE	1316	924	392	545	3.4	3.6	3.2	3.7
SLOVAKIA SLOVENIA	52 244	12	01		1.3	1.7	1.2	
SOUTH AFRICA	1376	1354	22	1322	2.6 8.0	5.7 8.4	2.2	0.9 9.1
SOUTH KOREA	1929	65	2836	5775	.8	38.4	3.6	55.0
SRI LANKA	6422 1	35/1	2839	3118	4.0 1.0	9.0 1.0	2.4	11.5
SWEDEN	65276	54618	657	51619	17.9	39.1	4.7	1.0
	444	410	24	3	33.2	39.5	1.0	46.8
SWITZERLAND	13//4	662	263	633	6.4	7.9	1.8	7.9
SWITZERLAND TAIWAN THAILAND	678		269	2868	15.7	18.0	6.4	23.3
SWITZERLAND TAIWAN THAILAND TURKEY	678 3353	84			1.0		1.0	
SWITZERLAND TAIWAN THAILAND TURKEY UKRAINE UNITED AR AR EMIPATES	678 3353 1	84	1	25	· · · A	2 5	1.0	25
SWITZERLAND TAIWAN THAILAND TURKEY UKRAINE UNITED ARAB EMIRATES UNITED KINGDOM	678 3353 1 26 41791	84 25 204	1 1 12779	25 27599	2.4 9.1	2.5 12.2	1.0 5.7	2.5 15.1
SWITZERLAND TAIWAN THAILAND TURKEY UKRAINE UNITED ARAB EMIRATES UNITED STATES	678 3353 1 26 41791 33	84 25 204 3520	1 1 12779 7948	25 27599 1597	2.4 9.1 19.5	2.5 12.2 .7	1.0 5.7 5.6	2.5 15.1 33.2
SWITZERLAND TAIWAN THALAND TURKEY UKRAINE UNITED ARAB EMIRATES UNITED STATES URUGUAY UTREVISTAN	678 3353 1 26 41791 33	84 25 204 3520	1 1 12779 7948	25 27599 1597	2.4 9.1 19.5	2.5 12.2 .7	1.0 5.7 5.6	2.5 15.1 33.2
SWITZERLAND TAIWAN THALAND TURKEY UKRAINE UNITED ARAB EMIRATES UNITED STATES URUGUAY UZBEKISTAN VIETNAM	678 3353 1 26 41791 33	84 25 204 3520	1 1 12779 7948	25 27599 1597	2.4 9.1 19.5	2.5 12.2 .7	1.0 5.7 5.6	2.5 15.1 33.2
SWITZERLAND TAIWAN TAIWAN THAILAND TURKEY UKRAINE UNITED ARAB EMIRATES UNITED KINGDOM UNITED STATES URUGUAY UZBEKISTAN VIETINAM VIETINAM VIETINAM	678 3353 1 26 41791 33	84 25 204 3520	1 12779 7948 1	25 27599 1597	2.4 9.1 19.5	2.5 12.2 .7 1.6	1.0 5.7 5.6	2.5 15.1 33.2
SWITZERLAND TAIWAN THAILAND TURKEY UKRAINE UNITED KINGDOM UNITED KINGDOM UNITED STATES URUGUAY UZBEKISTAN VIETNAM VIETNAM VIRIGIN ISL ZIMBABWE Obers Africa	678 3353 1 26 41791 33 32 7 2	84 25 204 3520	1 12779 7948 1 7 2	25 27599 1597	2.4 9.1 19.5	2.5 12.2 .7 1.6	1.0 5.7 5.6 1.0 7.0 25.6	2.5 15.1 33.2
SWITZERLAND TAIWAN THAILAND TURKEY UKKAINE UNITED ARAB EMIRATES UNITED KINGOOM UNITED STATES URUGUAY UZBEKISTAN VIETNAM VIETNAM VIETNAM ZIMBABWE Others Africa Others Asia	678 3353 1 26 41791 33 32 7 2	84 25 204 3520	1 12779 7948 1 7 2	25 27599 1597	2.4 9.1 19.5	2.5 12.2 .7	1.0 5.7 5.6	2.5 15.1 33.2
SWITZERLAND TAIWAN THAILAND TURKEY UKRAINE UNITED ARAB EMIRATES UNITED STATES URUGUAY UZEEKISTAN VIETNAM VIETNAM VIRIGI ISL ZIMBABWE Others Asia Others Australia	678 3353 1 26 41791 33 32 7 2	84 25 204 3520	1 1 12779 7948 1 7 2	25 27599 1597	2.4 9.1 19.5	2.5 12.2 .7	1.0 5.7 5.6	2.5 15.1 33.2
SWITZERLAND TAIWAN TAIWAN THAILAND TURKEY UKRAINE UNITED ARAB EMIRATES UNITED KINGDOM UNITED STATES URUGUAY UZBEKISTAN VIETNAM VIETNAM VIETNAM VIETNAM Others Asia Others Asia Others Asia	678 3353 1 26 41791 33 32 7 2 1118 139	84 25 204 3520	1 12779 7948 1 7 2 1117	25 27599 1597	2.4 9.1 19.5	2.5 12.2 .7	1.0 5.7 5.6	2.5 15.1 33.2

#### TABLE 2: CAPACITY CONSTRAINTS

The unit of observation is firm-year. The sample period is 2005-2020. In Panel A, the dependent variable is ANYCOUNTEP in columns 1 to 3 and ANYCOUNTEP w/o zeros in columns 4 to 6. ANYCOUNTEP is the number of granted or purchased patents by the European Patent Office (EP) per firm and year. In Panel B the dependent variable is GREENCOUNTEP in columns 1 to 3 and BROWNEFFCOUNTEP in columns 4 to 6. GREENCOUNTEP is the number of granted or purchased "green" patents by the EP per firm and year, while BROWNEFFCOUNTEP in columns 4 to 6. GREENCOUNTEP is the number of granted or purchased "green" patents by the EP per firm and year, while BROWNEFFCOUNTEP cores "brown efficiency" patents. The independent variables are defined as follows: "Age is the firm age based on its year of incorporation; PATSTOCKANVEP (PATSTOCKARENEP and PATSTOCKBROWNEFFEP) is the firm's patent stock of all (green and brown efficiency) granted or purchased patents by the EPO from 1990 up to year t; LOGASETS is the natural logarithm of that assets (in § million); LOGS1ZE is the natural logarithm of market capitalization (in § million); LOGNOEMPL is the natural logarithm of the number of employees; LOGPDE is the natural logarithm of plant, property & equipment (in § million); LEVERAGE is the book value of devalue of equity; INVEFTA/ is CAPEX divided by the book value of assets; BETA is the firm-level market beta estimated over the one-year period; VOLAT is the monthly stock return volatility calculated over the one year period; MOM is the cumulative stock return over the one-year period; RET is the monthly stock return volatility calculated over the one year period; MOM is the MSCI ACWI in a given year and zero otherwise. All independent variables are lagged by one year. The model is estimated ousing Poisson pseudo-maximum likelihood. All regression include country and year fixed effects. Columns 2 and 5 also include Trucost industry-year fixed effects and columns 3 and 6 firm fixed effects. We double cluster standard errors at the firm and year dime

Panal A: Donondont variable contur	(1)	(2)	(3)	(4)	(5)	(6)	
Panel A: Dependent variable capture	AN	YCOUNTEP w. zero	95	ANY	COUNTEP w/o zer	ros	
PATSTOCKANYEP (/100)	0.017***	0.012***	$-0.002^{***}$	0.016***	0.013***	$-0.002^{***}$	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
LOGASSETS	-0.121***	0.465***	0.192***	0.058**	0.411***	0.178***	
	(0.019)	(0.054)	(0.057)	(0.023)	(0.048)	(0.057)	
LOGNOEMPL	0.333***	0.127***	0.049**	0.284***	0.132***	0.050**	
	(0.015)	(0.020)	(0.024)	(0.017)	(0.018)	(0.024)	
AGE (/100)	0.153***	0.115***		0.073**	0.096***		
	(0.032)	(0.026)		(0.030)	(0.025)		
LOGSIZE	0.620***	0.266***	0.028	0.408***	0.238***	0.032	
	(0.024)	(0.029)	(0.023)	(0.024)	(0.024)	(0.023)	
LOGPPE	-0.026**	0.004	0.114**	-0.116***	-0.038	0.112**	
	(0.013)	(0.035)	(0.045)	(0.019)	(0.037)	(0.045)	
LEVERAGE	-0.010***	-0.004***	-0.003***	-0.008***	-0.003***	-0.003**	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
ROE	-0.210**	-0.036	-0.086**	-0.123*	-0.011	-0.089**	
	(0.087)	(0.069)	(0.041)	(0.070)	(0.057)	(0.041)	
M/B	-0.028***	0.007	0.001	$-0.015^{**}$	-0.001	0.001	
	(0.008)	(0.006)	(0.005)	(0.007)	(0.006)	(0.005)	
INVEST/A	-0.017***	-0.000	-0.001	0.003	0.007	-0.001	
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	
BETA	0.330***	0.122***	0.029	0.262***	0.153***	0.033	
	(0.037)	(0.034)	(0.022)	(0.035)	(0.032)	(0.022)	
VOLAT	2.890***	1.458***	-0.313	2.223***	1.123***	-0.265	
	(0.251)	(0.273)	(0.242)	(0.327)	(0.328)	(0.244)	
MOM	$-2.715^{***}$	$-0.949^{*}$	0.199	$-2.334^{***}$	$-0.988^{*}$	0.182	
	(0.623)	(0.555)	(0.300)	(0.580)	(0.513)	(0.301)	
RET	0.000	0.070	-0.009	-0.006	0.035	-0.002	
	(0.181)	(0.138)	(0.074)	(0.163)	(0.130)	(0.075)	
MSCI	0.025	0.028	0.055*	-0.014	0.013	0.044	
	(0.044)	(0.032)	(0.029)	(0.040)	(0.029)	(0.029)	
Constant	$-4.678^{***}$	$-4.577^{***}$	1.497***	-2.763***	-3.365***	1.621***	
	(0.137)	(0.143)	(0.318)	(0.136)	(0.142)	(0.321)	
Observations	68496	63945	37250	24960	23699	23828	
Pseduo R2	0.654	0.835	0.921	0.642	0.809	0.910	
Panel B: Dependent variable capture	s only green or brown		BROWNEFFCOUNTEP				

	Ċ.	REENCOUNTEP		BRU	JWNEFFCOUNTEI	, , , , , , , , , , , , , , , , , , ,
PATSTOCKGREENEP (/100)	0.120***	0.138***	0.013***	$-0.175^{***}$	-0.045***	-0.073***
	(0.007)	(0.009)	(0.004)	(0.018)	(0.012)	(0.011)
PATSTOCKBROWNEFFEP (/100)	-0.037***	-0.086***	-0.022***	0.305***	0.134***	0.060***
	(0.012)	(0.010)	(0.008)	(0.017)	(0.012)	(0.015)
AGE (/100)	0.240***	0.040	(0.000)	0.638***	0.342***	(0.010)
1102 () 100)	(0.044)	(0.039)		(0.053)	(0.065)	
LOGSIZE	0.350***	0.367***	0.154***	0.322***	0.390***	0.200***
	(0.028)	(0.038)	(0.029)	(0.048)	(0.064)	(0.050)
LOGPPE	0.189***	0.329***	0.091**	0.270***	0.346***	-0.071
LOGITE	(0.023)	(0.040)	(0.035)	(0.040)	(0.078)	(0.048)
LEVERAGE	-0.009***	-0.004***	-0.006***	-0.002	0.004	0.016***
EE VERTICE	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.005)
ROE (/100)	-0.321***	-0.231***	-0.183***	0.052	0.129	-0.257**
	(0.111)	(0.077)	(0.065)	(0.341)	(0.185)	(0.121)
M/B	-0.016	-0.016	-0.017**	-0.057**	-0.061***	-0.024*
	(0.011)	(0.011)	(0.007)	(0.022)	(0.020)	(0.012)
INVEST/A	0.000	-0.019***	-0.004	-0.003	-0.022***	0.012
	(0.007)	(0.005)	(0.005)	(0.009)	(0.008)	(0.010)
BETA	0.605***	0.224***	0.003	0.564***	0.182***	-0.053
	(0.051)	(0.045)	(0.031)	(0.084)	(0.071)	(0.060)
VOLAT	2.912***	2.740***	-0.276	1.606**	0.726	-0.580
	(0.459)	(0.341)	(0.347)	(0.739)	(0.698)	(0.611)
MOM	$-1.460^{*}$	$-1.707^{**}$	-0.902**	-0.049	-1.940	0.467
	(0.811)	(0.715)	(0.387)	(1.365)	(1.238)	(0.673)
RET	0.202	0.210	0.275**	-0.810**	0.086	-0.304
	(0.236)	(0.226)	(0.117)	(0.381)	(0.327)	(0.234)
MSCI	0.234***	0.127***	0.003	0.045	0.186**	0.093
	(0.053)	(0.047)	(0.049)	(0.101)	(0.076)	(0.062)
Constant	-3.773***	-4.191***	1.352***	-5.265***	-5.107***	1.513***
	(0.170)	(0.144)	(0.370)	(0.262)	(0.281)	(0.488)
Observations	27822	24785	20173	27729	20117	12186
Pseudo R2	0.561	0.730	0.832	0.529	0.756	0.825
Country F.E.	ves	ves	ves	ves	ves	ves
Year F.E.	ves	ves	ves	ves	ves	ves
Industry X Year F.E.	no	ves	no	no	ves	no
Firm EE.	no	no	ves	no	no	ves
			,			, 20

### TABLE 3: DISTRIBUTIONS OF PATENT RATIOS

The sample period is 2005-2020. We report average patent ratios for the full (public and private), public, private and Trucost sample by country in Panel A, by GICS 6-Industry in Panel B, and by year in Panel C. Countries with less than 300 firm-year observations in the full sample are aggregated by region under "Others" as in Table 1. We report the average *GREENRATIOEP* in columns 1 to 4 and the average *BROWNEFFRATIOEP* in columns 5 to 8. *GREENRATIOEP* is the number of greene patents over the total number of patents at the European Patent Office atents. *BROWNEFFRATIOEP* simularly is the number of patents at the European Patent Office

D 14 D 4 4 1 1 4	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Patent ratio by country		GREENR/	ATIOEP			BROWNEFF	RATIOEP	
_	Full	Public	Private	Trucost	Full	Public	Private	Trucost
ARGENTINA	3 431	3 646	0	2 083	17 157	18 229	0	21.875
AUSTRALIA	11.335	10.935	12.656	9.587	5.674	6.389	3.416	6.384
AUSTRIA	10.090	11.574	9.143	9.645	4.036	3.823	4.172	4.031
BERMUDA	7 001	6 865	9.288	14.196	2.787	5.099	2.122	5.433
BOSNIA & HERZEGOVINA	0	0.000	0	10.001	0	0.017	ő	10.712
BRAZIL	14.423	11.860	21.616	15.956	1.982	2.156	1.496	2.298
CANADA	27.778	50 15 155	23.684	50 16 274	3.333	7.143	2.632	0 3 476
CANARY ISLANDS	0	10.100	0	10.271	0	0.019	0	0.110
CAYMAN ISLANDS	17.005	24.333	1.535	2.381	2.279	2.042	2.778	0
CHINA	8.534 12.888	9.328	13 503	11.928	2./// 2.617	2 725	2 394	2 651
COLOMBIA	42.857	42.857	10.000	42.857	14.286	14.286	2.071	14.286
CROATIA	0	0	0	12 500	2.778	0	12.500	0
CZECH REP	6.597 9.070	6.250	4.386	12.500	8.333	0	2.158	0
DENMARK	14.545	13.927	14.742	15.292	3.416	1.981	3.874	2.296
EGYPT	11.003	8.737	16.667	0	0	0	0	0
FINLAND	24.242	11.649	24.242	14.699	5.073	4.676	5.030	6.480
FRANCE	9.405	11.070	8.580	11.561	2.420	2.930	2.167	2.957
GERMANY	9.828	12.607	8.377	14.677	3.666	4.160	3.410	5.142
GUERNSEY	3.896	5.000	0	4.545	5.519	5.417	5.882	10.227
HONG KONG	11.840	11.637	16.492	12.372	0.897	0.937	ő	1.158
HUNGARY	4.131	3.788	4.600	5.556	4.478	3.030	6.061	0
INDIA	9.711	9.790	2.400	11 933	0 5 518	4 553	8 877	0 5.691
INDONESIA	0	0	5.511	0	0	0	0.077	0
IRELAND	7.254	7.880	6.437	7.572	2.016	1.227	3.505	1.020
ISRAEL	8.234	7.782	10.707	7.689	1.838	1.850	1.770	1.800
JAPAN	11.976	11.955	12.095	13.117	4.024	4.201	2.355	4.486
JERSEY	14.853	12.431	21.429	16.871	0	0	0	0
JORDAN KAZAKHSTAN	22.222	22.222	50		0	0	0	
KUWAIT	0	0	0	0	ŏ	0	ő	0
LATVIA	10.648	7.051	20		0	0	0	
LITHUANIA	0 8.940	0 7 933	0 9 172	4 758	0 5 241	0 3 172	0 5 620	2 828
MALAYSIA	10.953	11.377	9.574	12.131	7.248	7.060	7.859	9.465
MALTA	8.571	0	6.250	0	0	0	0	0
MAURITIUS	0	0	0	14.065	0	0	0 5 5 5 6	3 967
MOROCCO	44.833	50	43.542	14.000	0	0	0	5.767
NETHERLANDS	12.611	12.433	12.720	12.195	3.582	3.047	3.911	3.352
NEW ZEALAND NORTH MACEDONIA	6.357	3.455	11.296	5.271	1.001	0	3.704	0
NORWAY	16.424	13.161	17.859	12.324	5.551	5.212	5.701	5.507
OMAN	0		0		0		0	
PARISIAN	0		0		0		0	
PERU	õ	0	0	0	õ	0	õ	0
PHILIPPINES	9.677	10.256	8.696	14.815	0.645	0	1.739	0
POLAND PORTUGAL	8.217	8.870 13.462	10.358	21.875	3.593	4.160	2.599	12.500
QATAR	0	0	0		20	0	25.000	
REPUBLIC OF MOLDOVA	0		0		0		0	
ROMANIA	0	0	0		15.000	50	11.111	
RUSSIA	18.456	15.124	19.956	17.780	1.666	1.779	1.615	1.479
SAUDI ARABIA	14.928	16.602	7.391	19.058	4.057	4.475	2.178	4.298
SINGAPORE	16.440	17.319	14.588	19.931	5.226	5.325	5.018	7.019
SLOVAKIA	7.317	0	8.824		2.439	0	2.941	
SLOVENIA SOUTH AFPICA	8.759	2.596	11.279	1.852	1.767	0	2.489	0
SOUTH KOREA	15.372	16.302	12.043	17.506	2.794	2.911	2.381	3.130
SPAIN	13.853	18.659	12.159	23.800	1.846	1.846	1.854	2.707
SRI LANKA	100	100	10.759	100	0	0	2 212	0
SWEDEN SWITZERLAND	10.000	9.246	13.929	9.153	1.728	1.853	1.273	1.988
TAIWAN	11.622	11.502	13.067	11.997	0.914	0.931	0.699	1.040
THAILAND	12.456	13.514	4.167	15.567	1.823	2.055	0	2.415
UKRAINE	4.555	4.445	0	3.690	0	2.495	2.389	5.054
UNITED ARAB EMIRATES	23.485	25.833	Ó	25.833	0	0	0	0
UNITED KINGDOM	10.440	11.591	9.227	10.907	4.198	3.960	4.461	4.397
VIRIGIN ISL	18.333	19.945	0	10.044	2.012	0	0	3.204
ZIMBABWE	14.286		14.286		0	-	0	
Others Africa Others Europe	0.915	0	0.915	0	5.711	0	5.711	0
Others North America	0.333	0.333	2.300	0	0.556	0.556	3.201	0
Others South America	83.333		83.333		11.111		11.111	
Total	10.996	11.419	10.261	12.107	3.328	3.374	3.258	3.737

	(1)	(2)	(2)	(4)	(E)	(6)	(7)	(9)
Panel B: Patent ratio by GICS-6 industry	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		GREENF	RATIOEP			BROWNER	FRATIOEP	
	Full	Public	Private	Trucost	Full	Public	Private	Trucost
Aerospace & Defense	9.546	9.776	8.489	9.142	5.571	5.821	4.417	6.052
Air Freight & Logistics	8.466 3.901	7.540	14.286	6.616 3.520	0.140	0.162	0.000	0.176
Auto Components	9.354	9.061	11.002	10.058	8.601	8.935	6.873	7.116
Automobiles	26.585	25.135	50.806	24.230	14.375	14.882	5.914	15.878
Banks	8.887	7.953	8.925	7.554	3.178	3.142	3.186	2.862
Beverages	11.106	11.573	9.074	12.240	0.449	0.552	0.000	0.642
Building Products	16.320	16.143	16.849	17.474	6 223	0.068	6 318	0.028
Capital Markets	9.787	9.255	9.956	8.949	3.558	3.120	3.756	2.446
Chemicals	13.959	14.723	11.033	14.545	3.402	3.451	3.220	3.631
Commercial Services & Supplies	9.595	10.431	9.063	9.935	4.935	4.980	4.917	4.980
Communications Equipment	4.964	5.030	4.604	4.859	0.478	0.520	0.249	0.238
Construction Materials	23.092	21.477	30.020	23.978	9.303	9.857	6.928	8.658
Consumer Finance	20.295 6.814	6 233	6 979	25.216	9.203	8 333	7.299	9 722
Containers & Packaging	4.010	3.615	5.037	3.757	0.384	0.355	0.461	0.471
Distributors	4.788	3.876	6.127	4.832	3.454	1.314	6.596	1.479
Diversified Consumer Services	6.048	0.111	7.175	0.390	2.204	0.297	2.736	1.039
Diversified Financial Services	8.471	8.471	0.000	8.671	5.316	5.316	0.000	4.935
Diversified Telecommunication Services	3.223	3.396	2.686	2.053	0.204	0.243	0.082	0.099
Electrical Equipment	28.820	40.750 31.144	21,228	44.105 32.485	3.671	3,602	0.057 3.903	3,780
Electronic Equipment, Instruments & Components	11.566	11.373	13.533	11.268	1.541	1.466	2.279	1.362
Energy Equipment & Services	14.896	13.723	40.333	13.969	19.947	20.498	8.000	20.610
Entertainment	5.655	2.757	30.000	1.755	0	0	0	0
Equity Real Estate Investment Trusts (REITs)	9.220	10.465	9.045	25.532	2.580	0.088	2.931	0
Food Products	12.424	11.571	15.232	11.788	0.586	0.691	0.240	0.959
Cas Utilities	8.376 36.688	6.544 37.006	10.408	7.078	7.004	0.833	5.008 11.111	7 446
Health Care Equipment & Supplies	4.071	3.689	5.710	3.969	0.418	0.429	0.376	0.349
Health Care Providers & Services	7.657	8.786	5.719	7.269	0.239	0.424	0	0.108
Health Care Technology	8.689	8.689		8.253	0.040	0.040		0.048
Hotels, Restaurants & Leisure	2.827	1.641	5.395	2.506	3.149	1.746	6.186	0
Household Durables	5.827	5.722	6.822	7.087	2.355	2.457	1.607	3.161
IT Services	5.400 7.248	5.400 4 573	17 885	5.114 4 531	2 090	1.255	4 231	1 444
Independent Power and Renewable Electricity Producers	53.779	48.510	63.180	49.417	12.500	14.531	8.571	21.250
Industrial Conglomerates	12.975	12.975		13.045	5.100	5.100		5.065
Insurance	8.517	8.334	8.722	7.572	1.775	3.399	0.319	2.989
Interactive Media & Services	3.000	3.000		3.111	0.143	0.143		0.148
Internet Software & Services (discont. 2018)	2.430	0.544	55.556	0.681	0.007	0.007	0	0.009
Leisure Products	4.202	2.903	1.471	12 864	1 303	1.495	1.724	1 909
Life Sciences Tools & Services	11.390	11.390	1.010	11.224	0.431	0.431	0	0.530
Machinery	8.209	8.126	8.220	8.839	6.813	7.424	5.138	8.299
Marine	15.618	11.964	20.204	12.761	7.920	6.185	10.098	6.597
Media	5.193	4.091	8.527	4.039	0.824	1.096	0	0.031
Media (discont. 2018) Metals & Mining	5.066	5.249	3.906	5.908	1.126	1.304	U 7 401	0.566
Multi-Utilities	36.686	36,686	10.910	37,253	11.821	11.821	7.421	12.005
Multiline Retail	8.252	9.407	0	10.225	0	0	0	0
Oil, Gas & Consumable Fuels	32.715	33.910	27.335	38.453	11.586	11.588	11.579	9.716
Paper & Forest Products	10.728	10.720	10.781	11.814	1.104	1.252	0.062	1.171
Personal Products	4.075	4.404	2.272	2.891	0.174	0.206	0	0.117
rnarmaceuticals Professional Services	7.554	7.326	8.409 9.524	5.992	0.074	0.076	0.067	0.074
Real Estate Management & Development	12.250	20.326	10,191	17,834	3,453	2,062	3,807	1.760
Road & Rail	18.430	16.606	21.548	14.477	0.689	0	1.867	0
Semiconductors & Semiconductor Equipment	17.575	17.899	15.816	20.064	0.888	0.653	2.159	0.653
Software	4.065	3.203	6.545	1.935	1.213	0.759	2.513	0.228
Specialty Retail	7.821	5.661	11.536	5.651	1.035	1.354	0.520	0.495
Iechnology Hardware, Storage & Peripherals	4.645	4.773	3.395	4.816	0.495	0.430	0.595	0.528
Tobacco	0.144 11.293	4.045	0.870	5.595 10.258	2.034	2.279	1.697	0.245
Trading Companies & Distributors	10.613	11.126	10.367	10.904	3.780	5.679	2.823	3.283
Transportation Infrastructure	7.075	3.427	10.505	2.326	2.290	0	4.412	0
Water Utilities	21.083	20.426	22.768	29.206	4.118	2.981	7.031	1.111
Wireless Telecommunication Services	2.232	2.232		2.016	0.158	0.158		0.166
Total	10.996	11.419	10.261	12.107	3.328	3.374	3.258	3.737

	(1)	(2)	(2)	(1)	(=)	(1)		(2)			
<b>D</b> 10	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)			
Panel C	: Patent ratio	by year									
		GREENR	ATIOEP		BROWNEFFRATIOEP						
	Full	Public	Private	Trucost	Full	Public	Private	Trucost			
2005	8.000	8.441	7.121	9.147	2.888	3.101	2.464	3.408			
2006	8.034	8.782	6.540	9.120	3.188	3.407	2.753	4.487			
2007	8.952	9.742	7.372	9.734	3.230	3.555	2.581	3.703			
2008	8.641	9.739	6.524	10.598	3.272	3.353	3.118	4.080			
2009	9.449	10.223	7.992	10.784	3.072	3.344	2.560	3.819			
2010	9.944	10.515	8.776	11.105	3.188	3.255	3.061	4.024			
2011	10.052	10.615	9.053	11.356	3.313	3.432	3.103	4.261			
2012	10.876	11.300	10.198	12.992	3.446	3.817	2.884	4.811			
2013	11.799	11.859	11.680	12.626	3.324	3.620	2.873	4.192			
2014	11.935	12.216	11.467	13.725	3.467	3.256	3.835	3.688			
2015	11.568	12.115	10.663	13.242	3.519	3.461	3.628	4.219			
2016	12.007	12.782	10.792	13.012	3.253	3.231	3.301	3.505			
2017	12.124	12.083	12.160	11.979	3.618	3.411	3.952	3.352			
2018	12.103	12.194	11.954	12.050	3.599	3.533	3.672	3.801			
2019	12.802	13.505	11.744	13.404	3.239	3.182	3.348	3.318			
2020	12.974	13.087	12.740	13.173	3.198	2.984	3.679	2.970			
Total	10.996	11.419	10.261	12.107	3.328	3.374	3.258	3.737			

## TABLE 4: PATENT RATIOS AND FIRM TYPE

The unit of observation is firm-year. The sample period is 2005-2020. The dependent variable is *GREENRATIOEP* in columns 1 to 3 and *BROWNEFFRATIOEP* in columns 4 to 6. *LOGS1TOT* is the natural logarithm of firm-level scope 1 emissions. All other variables are defined in Table 2 and Table 3. All independent variables are lagged by one year. The model is estimated using Poisson pseudo-maximum likelihood. All regression include country and year fixed effects. Columns 2 and 5 also include Trucost industry-year fixed effects and columns 3 and 6 firm fixed effects. We double cluster standard errors at the firm and year dimension. \*\*\* 1% significance, \*\* 5% significance \* 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	GF	REENRATIOEP		BROV	VNEFFRATIO	EP
-						
LOGS1TOT	0.091***	$-0.053^{***}$	0.013	0.057***	0.048**	$-0.064^{**}$
	(0.008)	(0.011)	(0.015)	(0.014)	(0.020)	(0.032)
AGE (/100)	$-0.299^{***}$	$-0.185^{***}$		0.236***	0.218***	
	(0.033)	(0.030)		(0.045)	(0.050)	
PATSTOCKGREENEP (/100)	0.051***	0.035***	-0.002			
	(0.004)	(0.004)	(0.003)			
PATSTOCKBROWNEFFEP (/100)				0.099***	0.046***	-0.001
				(0.009)	(0.008)	(0.008)
LOGSIZE	$-0.190^{***}$	$-0.110^{***}$	0.049**	$-0.306^{***}$	$-0.083^{***}$	-0.072
	(0.017)	(0.018)	(0.022)	(0.032)	(0.031)	(0.046)
LOGPPE	$0.124^{***}$	0.137***	$-0.043^{*}$	0.281***	0.042	-0.016
	(0.016)	(0.018)	(0.023)	(0.033)	(0.031)	(0.052)
LEVERAGE	$-0.006^{***}$	$-0.004^{***}$	0.001	$-0.005^{***}$	-0.001	$-0.005^{*}$
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
ROE (/100)	$-0.370^{***}$	$-0.155^{***}$	-0.022	0.559***	0.226**	-0.028
	(0.057)	(0.055)	(0.039)	(0.105)	(0.097)	(0.097)
M/B	0.021***	0.021***	-0.004	$-0.029^{**}$	$-0.019^{*}$	0.003
	(0.006)	(0.006)	(0.005)	(0.011)	(0.011)	(0.015)
INVEST/A	0.010***	0.008**	0.005*	-0.001	0.003	0.006
	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.008)
BETA	0.203***	0.094**	-0.017	0.312***	-0.013	0.034
	(0.035)	(0.037)	(0.027)	(0.062)	(0.058)	(0.047)
VOLAT	1.930***	1.327***	-0.006	0.248	0.118	0.402
	(0.222)	(0.234)	(0.178)	(0.473)	(0.527)	(0.492)
MOM	0.458	0.048	0.057	1.406	0.713	0.535
	(0.458)	(0.454)	(0.289)	(0.904)	(0.857)	(0.657)
RET	-0.126	$-0.244^{**}$	0.042	-0.328	0.052	-0.166
	(0.122)	(0.116)	(0.073)	(0.232)	(0.235)	(0.179)
MSCI	0.068**	0.042	0.050	0.030	0.121**	-0.079
	(0.032)	(0.032)	(0.035)	(0.057)	(0.053)	(0.064)
Constant	$2.476^{***}$	3.200***	3.078***	1.291***	2.315***	$4.214^{***}$
	(0.094)	(0.096)	(0.199)	(0.171)	(0.185)	(0.458)
Country FF	Ves	Ves	Ves	Ves	Ves	Ves
Year FE	ves	ves	ves	ves	ves	ves
Industry X Year F.E.	no	ves	no	no	ves	no
Firm E.E.	no	no	ves	no	no	ves
Observations	27822	24785	20173	27729	20117	12186
Pseudo R2	0.0772	0.317	0.516	0.100	0.439	0.527
			0.0 20			

### TABLE 5: PATENT RATIOS AND FIRM TYPE - INTENSIVE MARGIN

The unit of observation is firm-year. The sample period is 2005-2020 and the sample restricts inclusion to firm-years with *at least* one green patent at the European Patent Office in columns 1 to 3 and one brown efficiency patent at the European Patent Office in columns 4 to 6. The dependent variable is *GREENRATIOEP* in columns 1 to 3 and *BROWNEFFRATIOEP* in columns 4 to 6. All variables are defined in Table 2, Table 3 and Table 4. All independent variables are lagged by one year. The model is estimated using a pooled regression model. All regression include country and year fixed effects. Columns 2 and 5 also include Trucost industry-year fixed effects and columns 3 and 6 firm fixed effects. We double cluster standard errors at the firm and year dimension. \*\*\* 1% significance, \*\* 5% significance \* 10% significance.

	(1) GR	(2) REENRATIOEP	(3)	(4) BRO	(5) WNEFFRATIO	(6) EP
LOGS1TOT	1.571***	$-1.587^{***}$	-0.291	0.376*	-0.400	-0.253
	(0.170)	(0.252)	(0.273)	(0.197)	(0.340)	(0.506)
AGE (/100)	-6.809***	-3.153***		-0.989	-0.406	
	(0.601)	(0.603)		(0.649)	(0.803)	
PATSTOCKGREENEP (/100)	0.756***	1.024***	0.477***			
	(0.091)	(0.103)	(0.072)	1.0(0****	4 404***	0.044
PAISIOCKBROWNEFFEP (/100)				1.360***	1.101***	0.266*
LOCCIZE	( 740***	E 207***	0 (01	(0.140)	(0.176)	(0.140)
LUGSIZE	-6./49	-5.38/***	(0.200)	-5.912	$-4.414^{+}$	-0.884
LOCDRE	(0.348)	(0.425)	(0.399)	(0.415)	(0.5/4)	(0.724)
LUGITE	(0.242)	(0.206)	-1.067	(0.282)	-2.183	-0.977
LEVEDACE	(0.342)	(0.390)	(0.450)	(0.362)	(0.409)	(0.769)
LEVENAGE	-0.0/1	-0.117 (0.021)	(0.027)	-0.006	-0.124	-0.016
POF	(0.020)	(0.021)	0.626	(0.027)	(0.055)	0.041)
NUL	(1 269)	(1.276)	(0.736)	(1.804)	(2.027)	(1.307)
M/B	0.530***	0.517***	-0.017	0.169	0.063	0.127
WI/ D	(0.128)	(0.131)	(0.091)	(0.186)	(0.211)	(0.127
INVEST / A	0.375***	0 314***	0.088	0.493***	0.250*	0.046
1111201/11	(0.088)	(0.095)	(0.085)	(0.126)	(0.151)	(0.123)
BETA	1 175	1 230	-0.667	0.266	0.051	-0.185
<b>DEIII</b>	(0.724)	(0.827)	(0.480)	(0.898)	(1 121)	(0.681)
VOLAT	37.812***	32.622***	6.636	-3.494	-13.215	-2.030
	(7.437)	(8,186)	(4.126)	(10.481)	(12.975)	(6.867)
MOM	15.039	0.793	-5.105	5.322	15.162	16.336*
	(11.472)	(12.330)	(6.025)	(15.864)	(19.737)	(9.515)
RET	-2.251	-3.345	-0.178	-4.578	1.966	$-4.710^{*}$
	(3.029)	(3.253)	(1.620)	(3.993)	(4.982)	(2.474)
MSCI	-0.925	-0.650	-1.292 <sup>**</sup>	-0.937	1.520	$-1.771^{*}$
	(0.665)	(0.693)	(0.594)	(0.839)	(0.975)	(0.925)
Constant	69.208 <sup>***</sup>	83.076 <sup>***</sup>	30.172 <sup>***</sup>	67.068 <sup>***</sup>	80.924***	37.162***
	(2.276)	(2.655)	(3.701)	(2.984)	(4.158)	(6.783)
Country E.E.	ves	ves	ves	ves	ves	Ves
Year F.E.	ves	ves	ves	ves	ves	ves
Industry X Year F.E.	no	ves	no	no	ves	no
Firm F.E.	no	no	ves	no	no	ves
Observations	12187	10957	11352	5550	4550	5114
R2	0.220	0.534	0.815	0.187	0.526	0.762

#### TABLE 6: PATENT CITATIONS AND FIRM TYPE

The unit of observation is firm-year. The sample period is 2005-2020. The dependent variable is *GREENCITMAXEP* in columns 1 to 3 and *BROWNEFFCITMAXEP* in columns 4 to 6 in Panel A and *GREENBBCOUNTEP* in columns 1 to 3 and *BROWNEFFEITMAXEP* in columns 4 to 6 in Panel B. *GREENCITMAXEP* (*BROWNEFFEITMAXEP*) is the maximum number of forward citations any green (brown efficiency) patent of a firm received in a given year. *GREENBBCOUNTEP* (*BROWNEFFBBCOUNTEP*) is the number of green (brown efficiency) 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. The regressions also include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. All independent variables are lagged by one year and are defined in Table 2 and Table 4. The model is estimated using Poisson pseudo-maximum likelihood. All regression include country and year fixed effects. Columns 3 and 6 include firm fixed effects. We double cluster standard errors at the firm and year dimension. \*\*\* 1% significance, \*\* 5% significance \* 10% significance.

Den 1 A. Marianan actant sitetian	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Maximum patent citation	GRE	ENCITMAXEI	)	BROW	NEFFCITMAX	EP
LOGS1TOT	-0.042*	-0.217***	-0.063	0.018	0.096***	0.118
AGE (/100)	(0.022) 0.414**	(0.058) 0.670***	(0.064)	(0.029) 0.371***	(0.033) 0.085	(0.080)
PATSTOCKGREENEP (/100)	(0.167) 0.064*** (0.008)	(0.161) $0.062^{***}$ (0.010)	$-0.030^{**}$	(0.112)	(0.085)	
PATSTOCKBROWNEFFEP (/100)	(0.008)	(0.010)	(0.013)	$\begin{array}{c} 0.110^{***} \\ (0.010) \end{array}$	$\begin{array}{c} 0.084^{***} \\ (0.011) \end{array}$	$\begin{array}{c} 0.015 \\ (0.015) \end{array}$
Observations Pseudo R2	27814 0.343	24464 0.626	19494 0.707	27729 0.336	19574 0.649	11433 0.665
Panel B: Blockbuster counts	CDDT		D	DD OHU	EEEDBOOLDY	
	GREE	ENBBCOUNTE	P	BROWN	IEFFBBCOUN	TEP
LOGS1TOT	$-0.034^{**}$	-0.015	-0.016	0.081***	$0.096^{**}$	-0.027
AGE (/100)	0.055	0.044	(0.000)	0.557***	0.208***	(0.001)
PATSTOCKGREENEP (/100)	0.098***	0.075***	-0.010	(0.035)	(0.070)	
PATSTOCKBROWNEFFEP (/100)	(0.000)	(0.000)	(0.007)	$0.145^{***}$ (0.011)	$\begin{array}{c} 0.119^{***} \\ (0.012) \end{array}$	$\begin{array}{c} 0.030 \\ (0.020) \end{array}$
Observations Results P2	27669	17886	10607	27141	9925 0.564	5439 0 517
rseudo R2	0.314	0.444	0.459	0.348	0.364	0.517
Controls.	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes
iear F.E.	yes	yes	yes	yes	yes	yes
Firm FF	no	yes	IIU VOS	no	yes	no
1 11 11 1.1.	110	110	yes	110	110	yes

#### **TABLE 7: PATENT RATIOS AND FIRM TYPE: MARKET SHARE INTERACTIONS**

The unit of observation is firm-year. The sample period is 2005 to 2020. The dependent variable is GREENRATIOEP in columns 1 to 3 and BROWNEFFRATIOEP in columns 4 to 6. MKTSHR TRUIND is a firm's market share based on its sales relative to total public and private firms' sales in a given Trucost sector. We report the coefficient on MKTSHR TRUIND as well as LOGS1TOT, AGE, PATSTOCKGREENPEP (PATSTOCKBREWNEFFEP) and their interactions with MKTSHR TRUIND. The regressions also include the following controls: LOGS1ZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCL All independent variables are lagged by one year. The variables are defined in Table 2, Table 3 and Table 4. The model is estimated using Poisson pseudo-maximum likelihood. All regression include country and year fixed effects. Columns 2 and 5 also include Trucost industry-year fixed effects and columns 3 and 6 firm fixed effects. We double cluster standard errors at the firm and year dimension. \*\*\* 1% significance. \*\* 5% significance \* 10% significance.

-	(1) (2) (3) GREENRATIOEP			(4) BRC	, (6)	
LOGS1TOT	0.090***	$-0.058^{***}$	0.011	0.085***	0.058***	$-0.069^{**}$
AGE (/100)	$-0.363^{***}$	$-0.260^{***}$ (0.037)	(0.015)	0.216***	0.192***	(0.055)
PATSTOCKGREENEP (/100)	0.061***	0.059***	-0.006	(0.000)	(0.000)	
PATSTOCKBROWNEFFEP (/100)	(0.000)	(0.000)	(0.001)	0.101***	0.058***	$-0.016^{*}$
MKTSHRSALES TRUIND	$-1.372^{***}$ (0.344)	$-2.142^{***}$ (0.427)	-0.466 (0.357)	2.325*** (0.415)	0.689	-0.181 (0.423)
LOGS1TOT X MKTSHRSALES TRUIND	0.048	0.155****	0.043	-0.323*** (0.055)	$-0.115^{*}$ (0.064)	0.038
AGE (/100) X MKTSHRSALES TRUIND	0.761*** (0.152)	1.085*** (0.182)	(0.022)	0.184 (0.196)	0.224 (0.284)	(0.000)
PATSTOCKGREENEP X MKTSHRSALES TRUIND	$-0.079^{**}$ (0.032)	$-0.186^{***}$ (0.028)	0.039*** (0.014)	(	()	
PATSTOCKBROWNEFFEP X MKTSHRSALES TRUIND	()	()		$\begin{array}{c} -0.004 \\ (0.042) \end{array}$	-0.068 (0.069)	$\begin{array}{c} 0.094^{***} \\ (0.030) \end{array}$
Controls Country F.E. Year F.E.	yes yes	yes yes ves	yes yes ves	yes yes ves	yes yes ves	yes yes
Industry X Year F.E. Firm F.E.	no	yes	no ves	no	yes	no ves
Observations Pseudo R2	27856 0.080	24814 0.319	20170 0.516	27763 0.102	20140 0.439	12183 0.527

#### **TABLE 8: PATENT RATIOS AND ALTERNATIVE EMISSIONS**

The unit of observation is firm-year. The sample period is 2005-2020. The dependent variable is *GREENRATIOEP* in Panel A and *BROWNEFFRATIOEP* in Panel B. *LOGS2TOT* (*LOGS3UPTOT* and *LOGS3DOWNTOT*) is the natural logarithm of firm-level scope 2 (upstream 3 and downstream 3) emissions; *S1INT* (*S2INT*, *S3UPINT* and *S3DOWNINT*) is the the firm-level scope 1 (2, upstream 3 and downstream 3) emission intensity defined as the level of emission divided by the firm sales. The regressions also include the following controls: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. All independent variables are lagged by one year. The other variables are defined in Table 2 and Table 3. The model is estimated using Poisson pseudo-maximum likelihood. All regression include country and Trucost industry-year fixed effects. We double cluster standard errors at the firm and year dimension. \*\*\* 1% significance, \*\* 5% significance \*10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LOGS2TOT	$-0.056^{***}$						
LOGS3UPTOT	(0.012)	$-0.128^{***}$					
LOGS3DOWNTOT		(0.010)	$-0.025^{**}$				
S1INT (/100)			(0.010)	0.018			
S2INT				(0.335)	0.021		
S3UPINT					(0.025)	$-0.036^{*}$	
S3DOWNINT						(0.018)	0.005***
AGE (/100)	-0.189***	-0.176***	-0.186***	-0.195***	-0.194***	-0.194***	(0.002) -0.193***
PATSTOCKGREENEP (/100)	(0.031) 0.036*** (0.004)	(0.031) 0.035*** (0.004)	(0.059) 0.031*** (0.006)	(0.031) 0.035*** (0.004)	(0.031) 0.035*** (0.004)	(0.031) $0.034^{***}$ (0.004)	(0.059) 0.031*** (0.006)
Controls	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	yes	yes	yes	yes	yes	yes	yes
Pseudo R2	0.317	0.319	0.269	0.316	0.316	0.316	0.270
Panel B: Dependent variable BROW	WNEFFRATIOEP						
LOGS2TOT	-0.031						
LOGS3UPTOT	(0.025)	0.149***					
LOGS3DOWNTOT		(0.031)	0.005				
S1INT			(0.023)	0.017***			
S2INT				(0.006)	-0.130**		
S3UPINT					(0.053)	0.139***	

S3UPINT						0.139*** (0.028)	
S3DOWNINT							0.001 (0.003)
AGE (/100)	0.217*** (0.050)	0.204*** (0.050)	0.301*** (0.098)	0.215*** (0.050)	0.213*** (0.050)	0.215*** (0.050)	0.304*** (0.098)
PATSTOCKBROWNEFFEP (/100)	0.048 <sup>***</sup> (0.008)	0.047*** (0.008)	0.058*** (0.015)	0.047 <sup>***</sup> (0.008)	0.047 <sup>***</sup> (0.008)	0.049 <sup>***</sup> (0.008)	0.058 <sup>***</sup> (0.015)
Controls	yes	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes	yes
Industry-Year F.E.	yes	yes	yes	yes	yes	yes	yes
Observations	20143	20143	6426	20143	20143	20143	6426
Pseudo R2	0.439	0.440	0.420	0.439	0.439	0.440	0.420

#### TABLE 9: PATENT RATIOS AND FIRM TYPE POST 2015

The unit of observation is firm-year. The sample period is 2005 to 2020. The dependent variable is GREENRATIOEP in columns 1 to 3 and BROWNEFFRATIOEP in columns 4 to 6. Panel A covers the full sample and Panel B the legacy sample, which restricts inclusion of firms into those that Trucost covers in its database before 2016. POST2015 is a dummy that is equal to 1 for all years after 2015 and zero otherwise. We interact this variable with all control variables. We report the coefficients of the following interactions: LOGSITOT X POST2015, AGE X POST2015, PATSTOCKGREENEP (PATSTOCKBROWNEFFEP) X POST2015 and the triple interaction LOGSITOT X AGE X POST2015. The regression also include the following controls and their POST2015 interaction: LOGSIZE, LOGPPE, LEVERAGE, ROE, M/B, INVEST/A, BETA, VOLAT, MOM, RET, and MSCI. All independent variables other than POST2015 are lagged by one year. The variables are defined in Table 2, Table 3 and Table 4. The model is estimated using Poisson pseudo-maximum likelihood. All regression include the country and year fixed effects. Columns 2 and 5 also include the rest include country and year fixed effects. Columns 2 and 6 firm fixed effects. We double cluster standard errors at the firm and year dimension. \*\*\* 1% significance, \*\* 5% significance \* 10% significance.

Dan al A. Fall comple	(1)	(2)	(3)	(4)	(5)	(6)
Panei A: Full sample	C	GREENRATIOEP		BRC	WNEFFRATIOE	Р
LOGS1TOT	0.069***	$-0.072^{***}$	0.020	0.116***	0.071**	-0.085
AGE (/100)	(0.013) $-1.036^{***}$ (0.146)	$-0.914^{***}$ (0.135)	(0.022)	0.775***	0.478**	(0.000)
PATSTOCKGREENEP (/100)	0.087***	0.059***	0.008	(0.107)	(0.171)	
PATSTOCKBROWNEFFEP (/100)	(0.007)	(0.005)	(0.007)	0.136***	$0.021^{*}$	0.008
LOGS1TOT X POST2015	$-0.062^{***}$	-0.028	-0.013	-0.030 (0.036)	-0.036	-0.003
LOGS1TOT X Age (/100)	0.081***	0.082***	-0.005 (0.036)	$-0.068^{***}$	$-0.038^{*}$ (0.021)	0.033
AGE (/100) X POST2015	0.012	0.218	(0.000)	0.014	-0.306 (0.297)	(0.007)
LOGS1TOT X POST2015 X Age	0.023	-0.012 (0.021)	0.007	-0.006 (0.034)	0.053	0.014
PATSTOCKGREENEP X POST2015	$-0.049^{***}$ (0.009)	-0.037***	-0.010** (0.005)	(01001)	(0.000)	(0.005)
PATSTOCKBROWNEFFEP X POST2015	(0.005)	(0.010)	(0.000)	$egin{array}{c} -0.046^{**} \ (0.019) \end{array}$	$0.036^{**}$ (0.015)	$\begin{array}{c} -0.004 \\ (0.010) \end{array}$
Observations Pseudo R2	27860 0.0836	24818 0.321	20072 0.516	27767 0.108	20143 0.443	12147 0.529

Panel B: Legacy sample		DEENDATIOED		PD		P
		SKEENKAHOEP	<u>_</u>	BRU	JWNEFFRATIOEI	P
LOGS1TOT	0.069*** (0.015)	$-0.074^{***}$ (0.018)	0.019 (0.024)	0.116*** (0.025)	$0.064^{**}$ (0.031)	-0.078 (0.055)
AGE (/100)	$-1.061^{***}$ (0.147)	$-0.945^{***}$ (0.136)	(1 1 1 1 )	0.796*** (0.188)	0.508*** (0.194)	()
PATSTOCKGREENEP (/100)	0.087*** (0.009)	0.058 <sup>***</sup> (0.009)	0.008 (0.007)			
PATSTOCKBROWNEFFEP (/100)				0.136*** (0.017)	$0.022^{*}$ (0.012)	0.009 (0.013)
LOGS1TOT X POST2015	-0.024 (0.023)	0.001 (0.026)	-0.011 (0.013)	$ \begin{array}{c} -0.015 \\ (0.039) \end{array} $	$ \begin{array}{c} 0.005 \\ (0.046) \end{array} $	$ \begin{array}{c} -0.002 \\ (0.023) \end{array} $
LOGS1TOT X Age (/100)	$0.082^{***}$ (0.016)	$0.084^{***}$ (0.014)	$ \begin{array}{c} -0.002 \\ (0.038) \end{array} $	$-0.069^{***}$ (0.021)	$-0.040^{*}$ (0.022)	0.023 (0.069)
AGE (/100) X POST2015	0.343 (0.227)	$0.422^{**}$ (0.204)		$ \begin{array}{c} 0.098 \\ (0.311) \end{array} $	-0.157 (0.323)	
LOGS1TOT X POST2015 X Age (/100)	-0.019 (0.025)	-0.034 (0.022)	0.007 (0.005)	-0.006 (0.037)	$ \begin{array}{c} 0.048 \\ (0.038) \end{array} $	$0.015^{*}$ (0.009)
PATSTOCKGREENEP X POST2015	$-0.047^{***}$ (0.009)	$-0.030^{***}$ (0.010)	$-0.011^{**}$ (0.005)			
PATSTOCKBROWNEFFEP X POST2015				$-0.034^{*}$ (0.020)	0.037** (0.015)	-0.003 (0.010)
Observations Pseudo R2	22990 0.100	20155 0.364	18275 0.509	22922 0.108	16164 0.454	11551 0.524
Controls	yes	yes	yes	yes	yes	yes
Country F.E.	yes	yes	yes	yes	yes	yes
Year F.E. Inductory V Vear E.E.	yes	yes	yes	yes	yes	yes
Firm FE	no	yes	Ves	no	yes	110 Ves
			, 03			, 00

### TABLE 10: PATENT RATIOS AND FIRM-LEVEL OUTCOMES

The unit of observation is firm-year. The sample period is 2005 to 2020. The dependent variables are logs of cumulative sums of SITOT, S2TOT, S3UPTOT, S3DOWNTOT, S123UPTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively long-term averages of SINT, S2INT, S2INT, S3UPTOT, S3DOWNINT, and INVEST/A for 1, 3 or 5 years. In Panel A, the key independent variable is *GREENRATIOEP* lagged by 1, 3, or 5 years as well as a 3-year rolling ratio lagged by 1 year. In Panel B, the key independent variables is *GREENRATIOEP* lagged by 1, 3, or 5 years as well as a 3-year rolling ratio lagged by 1 able 2 and rationalized lagged by 1, 3, or 5 years. The model is estimated using pooled regression model. All regressions include country, year, and firm fixed effects. We double cluster standard errors at the firm and year dimension. \*\* 1% significance, \* 5% significance \* 10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) LOGS123UPTOT	(6) S1INT	(7) S2INT	(8) S3UPINT	(9) S3DOWNINT	(10) INVEST/A	(11) LOGCAPEX	(12) LOGSALES
Panel A: Green innovation												
L1 GREENRATIOEP	0.021 (0.026)	-0.019 (0.025)	0.007 (0.015)	-0.046 (0.077)	0.004 (0.015)	$\begin{array}{c} 0.019 \\ (0.070) \end{array}$	$^{-0.006}_{(0.010)}$	$\begin{array}{c} -0.009 \\ (0.018) \end{array}$	-0.018 (0.389)	-0.048 (0.100)	-0.011 (0.014)	0.003 (0.012)
Observations R2	29585 0.953	29585 0.948	29584 0.980	10349 0.931	29585 0.981	29585 0.922	29585 0.843	29585 0.961	10349 0.898	29578 0.720	29578 0.917	29580 0.980
L3 GREENRATIOEP	0.002 (0.026)	$-0.042^{*}$ (0.025)	$\begin{array}{c} 0.000\\ (0.014) \end{array}$	0.032 (0.118)	$\begin{array}{c} -0.002 \\ (0.014) \end{array}$	0.048 (0.070)	$\begin{array}{c} -0.000 \\ (0.010) \end{array}$	0.002 (0.016)	-0.000 (0.396)	$-0.166^{**}$ (0.078)	-0.009 (0.013)	-0.004 (0.011)
Observations R2	22261 0.967	22261 0.962	22261 0.986	4160 0.982	22261 0.986	22261 0.955	22261 0.902	22261 0.974	4166 0.986	25158 0.827	25153 0.945	25155 0.986
L5 GREENRATIOEP	0.015 (0.028)	-0.036 (0.026)	0.009 (0.017)		0.013 (0.017)	0.125* (0.069)	0.004 (0.010)	0.018 (0.018)		-0.109 (0.079)	-0.015 (0.013)	-0.006 (0.013)
Observations R2	15482 0.973	15482 0.965	15482 0.985		15482 0.986	15482 0.972	15482 0.933	15482 0.981		18347 0.888	18347 0.956	18343 0.989
L1 3YEARAVGGREENRATIOEP	0.007 (0.029)	-0.039 (0.031)	0.005 (0.016)	-0.157 (0.127)	-0.004 (0.017)	0.001 (0.092)	$\begin{array}{c} -0.003 \\ (0.014) \end{array}$	0.002 (0.021)	0.079 (0.607)	-0.156 (0.116)	-0.004 (0.016)	-0.014 (0.013)
Observations R2	38221 0.958	38221 0.951	38220 0.982	14552 0.935	38221 0.982	38221 0.928	38221 0.847	38221 0.965	14552 0.907	38210 0.718	38210 0.923	38214 0.980
Panel B: Brown efficiency innovation												
L1 BROWNEFFRATIOEP	0.031 (0.043)	$-0.045 \\ (0.041)$	-0.015 (0.020)	-0.241 (0.167)	-0.012 (0.022)	$\begin{array}{c} 0.044 \\ (0.144) \end{array}$	0.008 (0.015)	0.017 (0.025)	0.392 (0.968)	-0.072 (0.147)	0.007 (0.021)	-0.012 (0.018)
Observations R2	29585 0.953	29585 0.948	29584 0.980	10349 0.931	29585 0.981	29585 0.922	29585 0.843	29585 0.961	10349 0.898	29578 0.720	29578 0.917	29580 0.980
L3 BROWNEFFRATIOEP	0.051 (0.037)	-0.001 (0.038)	0.004 (0.020)	-0.105 (0.110)	0.003 (0.021)	-0.095 (0.135)	0.003 (0.013)	0.011 (0.022)	-0.945 (0.761)	-0.093 (0.125)	-0.004 (0.018)	0.006 (0.016)
Observations R2	22261 0.967	22261 0.962	22261 0.986	4160 0.982	22261 0.986	22261 0.955	22261 0.902	22261 0.974	4166 0.986	25158 0.827	25153 0.945	25155 0.986
L5 BROWNEFFRATIOEP	0.065* (0.036)	0.010 (0.034)	0.022 (0.020)		0.020 (0.021)	-0.067 (0.131)	$\begin{array}{c} -0.019^{*} \\ (0.011) \end{array}$	0.004 (0.022)		0.170 (0.130)	0.025 (0.017)	0.029* (0.017)
Observations R2	15482 0.973	15482 0.965	15482 0.985		15482 0.986	15482 0.971	15482 0.933	15482 0.981		18347 0.888	18347 0.956	18343 0.989
L1 3YEARAVGBROWNEFFRATIOEP	0.151*** (0.049)	-0.027 (0.049)	0.012 (0.024)	-0.136 (0.223)	0.028 (0.027)	0.095 (0.190)	$\begin{array}{c} 0.004 \\ (0.018) \end{array}$	0.024 (0.031)	-1.373 (1.354)	-0.014 (0.224)	-0.005 (0.024)	0.025 (0.023)
Observations R2	38221 0.958	38221 0.951	38220 0.982	14552 0.935	38221 0.982	38221 0.928	38221 0.847	38221 0.965	14552 0.907	38210 0.718	38210 0.923	38214 0.980
Controls Country F.E. Year F.E. Firm F.E.	yes yes yes	yes yes yes	yes yes yes yes	yes yes yes yes	yes yes yes yes	yes yes yes yes	yes yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes

## TABLE 11: GREEN PATENT RATIOS AND INDUSTRY-LEVEL OUTCOMES

The unit of observation is Trucost industry-year in Panel A and GICS6 industry-year in Panel B. The sample period is 2005 to 2020. The dependent variables are logs of industry level cumulative sums of SITOT, S2IDT, S3DPNNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums for SIINT, S2INT, S3DUNNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for SIINT, S2INT, S3DUNNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for SIINT, S2INT, S3DPNNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for SIINT, S2INT, S3DUNNTA and INVEST/A for 1, 3 or 5 years. In Panel A.1 and B.3, dependent variables are calculated across all firms within the given industry. The key explanatory variables of interest is *GREENRATIOEP*. Controls include *LOCSIZE*, *LOCGPE*, *LEVERAGE*, *ROE*, *M*/B, *INVEST/A*, *BETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. Independent variables are either industry level logs of sums (LOCSIZE and LOCPFE), sum over sums (GREENRATIOEP, LEVERAGE, *ROE*, *M*/B, *INVEST/A*, *DETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. Independent variables are either industry level logs of sums (LOCSIZE and LOCPFE), sum over sums (GREENRATIOEP, LEVERAGE, *ROE*, *M*/B, *INVEST/A*, *DETA*, *VOLAT*, *MOM*, *RET*, *MSCI*. Independent variables are either industry and year dimension. \*\*\* 1% significance \*\*5% significance \*\*10% significance.

Panel A: Within Trucost Industry Panel A 1: GREENRATIOEP on all fi	(1) LOGS1TOT	LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
L1 GREENRATIOEP	-0.067 (0.071)	0.017 (0.073)	-0.032 (0.055)	0.092 (0.133)	0.157 (0.437)	0.046 (0.136)	-0.241*** (0.083)	0.266 (1.606)	-0.001 (0.001)	-0.039 (0.054)	0.009 (0.052)
Observations R2	4486 0.939	4486 0.923	4486 0.943	1343 0.951	4486 0.873	4486 0.565	4486 0.880	1343 0.860	4486 0.764	4486 0.942	4486 0.950
L3 GREENRATIOEP	-0.051 (0.076)	0.033 (0.077)	-0.043 (0.062)	-0.020 (.)	0.164 (0.431)	$\begin{array}{c} 0.172^{*} \\ (0.096) \end{array}$	$-0.068 \\ (0.059)$	-1.347 (.)	-0.001 (0.001)	-0.046 (0.053)	-0.032 (0.058)
Observations R2	3745 0.959	3745 0.943	3745 0.954	644 0.992	3745 0.947	3745 0.731	3745 0.978	644 0.988	3745 0.848	3745 0.956	3745 0.960
L5 GREENRATIOEP	0.046 (0.081)	0.057 (0.074)	0.005 (0.068)		0.290 (0.362)	0.082 (0.052)	0.002 (0.049)		-0.001 (0.001)	-0.004 (0.054)	-0.006 (0.063)
Observations R2	3030 0.971	3030 0.959	3030 0.965		3030 0.965	3030 0.847	3030 0.985		3030 0.890	3030 0.967	3030 0.970
L1 3YEARAVGGREENRATIOEP	-0.036 (0.089)	0.103 (0.098)	-0.012 (0.071)	0.358 (0.224)	0.661 (0.513)	0.207** (0.100)	-0.213** (0.098)	-6.362 (5.112)	$-0.003^{**}$ (0.001)	-0.013 (0.055)	0.035 (0.066)
Observations R2	4861 0.936	4861 0.921	4861 0.939	1458 0.950	4861 0.874	4861 0.569	4861 0.886	1458 0.931	4861 0.763	4861 0.935	4861 0.945
Panel A.2: GREENRATIOEP on ever	patenting firms										
L1 GREENRATIOEP	0.032 (0.107)	0.092 (0.106)	$\begin{array}{c} -0.018 \\ (0.079) \end{array}$	$\begin{array}{c} 0.508^{**} \\ (0.224) \end{array}$	$\begin{array}{c} 0.418 \\ (0.593) \end{array}$	$\begin{pmatrix} 0.025\\ (0.285) \end{pmatrix}$	$\substack{-0.279 \\ (0.171)}$	0.925 (2.559)	$^{-0.002^{st}}_{(0.001)}$	-0.044 (0.067)	0.030 (0.072)
Observations R2	4459 0.923	4459 0.905	4459 0.930	1337 0.919	4459 0.384	4459 0.304	4459 0.822	1337 0.798	4459 0.769	4459 0.904	4459 0.937
L3 GREENRATIOEP	$\begin{array}{c} -0.154 \\ (0.101) \end{array}$	-0.029 (0.099)	-0.119 (0.081)	0.275 (.)	0.258 (0.405)	0.264 (0.173)	$\begin{array}{c} -0.134 \\ (0.085) \end{array}$	-2.049 (.)	0.000 (0.001)	$\begin{array}{c} -0.049 \\ (0.065) \end{array}$	-0.076 (0.073)
Observations R2	3702 0.949	3702 0.932	3702 0.946	640 0.990	3702 0.923	3702 0.560	3702 0.969	640 0.983	3702 0.851	3702 0.936	3702 0.951
L5 GREENRATIOEP	0.005 (0.096)	0.025 (0.087)	$^{-0.033}_{(0.076)}$		$\begin{array}{c} 0.214 \\ (0.268) \end{array}$	$\begin{array}{c} 0.126 \\ (0.078) \end{array}$	$\begin{array}{c} -0.089 \\ (0.087) \end{array}$		$\begin{array}{c} -0.000 \\ (0.001) \end{array}$	$\begin{array}{c} -0.017 \\ (0.058) \end{array}$	$\begin{array}{c} -0.025 \\ (0.070) \end{array}$
Observations R2	2982 0.965	2982 0.952	2982 0.961		2982 0.955	2982 0.749	2982 0.980		2982 0.883	2982 0.955	2982 0.964
L1 3YEARAVGGREENRATIOEP	$\begin{array}{c} -0.012 \\ (0.151) \end{array}$	0.192 (0.151)	-0.084 (0.112)	$1.164^{**}$ (0.469)	$1.143 \\ (0.716)$	0.343* (0.177)	$-0.358^{*}$ (0.213)	-1.764 (3.907)	-0.002 (0.002)	-0.070 (0.082)	0.003 (0.101)
Observations R2	4778 0.917	4778 0.901	4778 0.924	1426 0.920	4778 0.412	4778 0.306	4778 0.830	1426 0.879	4778 0.754	4778 0.901	4778 0.929
Panel A.3: GREENRATIOEP on neve	r patenting firms	s									
L1 GREENRATIOEP	-0.105 (0.098)	0.001 (0.093)	-0.083 (0.066)	-0.144 (0.175)	0.240 (0.627)	$\begin{array}{c} 0.029 \\ (0.080) \end{array}$	$\begin{array}{c} -0.151 \\ (0.134) \end{array}$	-1.772 (2.021)	$-0.000 \\ (0.002)$	-0.017 (0.065)	-0.046 (0.063)
Observations R2	3112 0.927	3112 0.910	3112 0.931	1226 0.949	3112 0.642	3112 0.656	3112 0.331	1226 0.895	3112 0.622	3112 0.910	3112 0.940
L3 GREENRATIOEP	$\begin{array}{c} -0.080 \\ (0.094) \end{array}$	0.025 (0.092)	$\begin{array}{c} -0.048 \\ (0.074) \end{array}$	$^{-0.083}_{(0.081)}$	$\begin{array}{c} -0.075 \\ (0.509) \end{array}$	0.139** (0.062)	$\begin{array}{c} -0.074 \\ (0.111) \end{array}$	-0.484 (1.423)	-0.002 (0.001)	-0.095 (0.060)	-0.034 (0.073)
Observations R2	2396 0.949	2396 0.931	2396 0.942	576 0.994	2396 0.972	2396 0.840	2396 0.994	576 0.991	2396 0.713	2396 0.931	2396 0.946
L5 GREENRATIOEP	-0.061 (0.109)	-0.051 (0.102)	-0.030 (0.080)		-0.231 (0.506)	-0.007 (0.063)	0.101 (0.094)		$-0.000 \\ (0.001)$	$-0.026 \\ (0.060)$	-0.022 (0.080)
Observations R2	1736 0.959	1736 0.941	1736 0.950		1736 0.980	1736 0.897	1736 0.986		1736 0.775	1736 0.947	1736 0.953
L1 3YEARAVGGREENRATIOEP	$-0.137 \\ (0.116)$	0.123 (0.111)	0.008 (0.083)	-0.349 (0.299)	-0.336 (0.517)	0.131* (0.071)	$\begin{array}{c} -0.083 \\ (0.163) \end{array}$	-7.870** (3.776)	-0.006*** (0.002)	-0.102 (0.072)	0.019 (0.079)
Observations R2	3402 0.925	3402 0.906	3402 0.927	1331 0.945	3402 0.647	3402 0.658	3402 0.336	1331 0.945	3402 0.623	3402 0.908	3402 0.936
Controls Year F.E. Industry F.E.	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes

	(1) LOGSITOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel B: Within GICS6 Industry Panel B.1: GREENRATIOEP on all fi	rms	20052101	2003301101	LOGSSDOWNIOI	Shivi	521141	55011141	3500000000	1111251/11	LOGENIEX	LOGSINELS
L1 GREENRATIOEP	$\begin{array}{c} 0.117 \\ (0.174) \end{array}$	$\begin{array}{c} 0.327^{*} \\ (0.180) \end{array}$	-0.084 (0.092)	0.073 (0.497)	$\begin{array}{c} -0.192 \\ (1.106) \end{array}$	$0.195^{**}$ (0.097)	$\begin{array}{c} -0.289^{**} \\ (0.131) \end{array}$	1.249 (3.118)	$\begin{array}{c} 0.001^{*} \\ (0.001) \end{array}$	0.022 (0.061)	$\begin{array}{c} -0.006 \\ (0.087) \end{array}$
Observations R2	976 0.962	976 0.932	976 0.959	261 0.961	976 0.988	976 0.734	976 0.976	261 0.842	976 0.911	976 0.924	976 0.936
L3 GREENRATIOEP	0.208 (0.156)	0.321** (0.129)	-0.003 (0.081)	-1.005 (0.915)	-2.647** (1.207)	0.264** (0.111)	-0.339*** (0.114)	-2.551 (2.939)	0.001 (0.001)	0.016 (0.057)	0.085
Observations R2	837 0.981	837 0.978	837 0.990	122 0.990	837 0.994	837 0.784	837 0.988	122 0.974	837 0.957	837 0.984	837 0.986
L5 GREENRATIOEP	0.191 (0.139)	0.274***	-0.009 (0.075)		$-1.562^{*}$ (0.796)	0.191* (0.110)	$-0.153^{*}$ (0.089)		0.001	-0.030 (0.047)	0.046
Observations R2	708 0.986	708 0.986	708 0.991		708 0.997	708 0.852	708 0.993		708 0.966	708 0.984	708 0.987
L1 3YEARAVGGREENRATIOEP	0.435*	1.273*** (0.326)	0.138	-1.699 (1.398)	$-5.143^{**}$	0.660**	* -0.679*** (0.209)	-7.100 (10.840)	0.003*	0.336*	0.308*
Observations R2	988 0.962	988 0.933	988 0.960	267 0.967	988 0,989	988 0.735	988 0.977	267 0.843	988 0.904	988 0.914	988 0.937
Panel B.2: GREENRATIOEP on ever	patenting firm	s									
L1 GREENRATIOEP	-0.257 (0.224)	0.212 (0.199)	-0.146 (0.121)	0.567 (0.822)	-1.984 (1.491)	0.230* (0.122)	-0.260** (0.108)	1.521 (3.659)	0.001* (0.001)	0.045 (0.072)	-0.037 (0.125)
Observations R2	974 0.962	974 0.960	974 0.984	261 0.954	974 0.926	974 0.679	974 0.973	261 0.695	974 0.955	974 0.979	974 0.981
L3 GREENRATIOEP	-0.206 (0.223)	0.294 (0.197)	-0.087 (0.100)	-0.388 (0.931)	-4.062** (1.993)	0.347** (0.172)	-0.359*** (0.097)	-4.782 (7.610)	0.001** (0.001)	0.007 (0.071)	0.067 (0.109)
Observations R2	834 0.976	834 0.973	834 0.988	122 0.986	834 0.954	834 0.741	834 0.984	122 0.936	834 0.967	834 0.982	834 0.986
L5 GREENRATIOEP	-0.122 (0.243)	0.223 (0.171)	-0.098 (0.100)		-0.574 (1.489)	0.225 (0.152)	$-0.193^{**}$ (0.088)		0.001* (0.000)	-0.032 (0.059)	0.005 (0.108)
Observations R2	705 0.982	705 0.982	705 0.991		705 0.970	705 0.824	705 0.989		705 0.975	705 0.986	705 0.988
L1 3YEARAVGGREENRATIOEP	-0.416	0.938***	-0.076	-0.218 (1.847)	-6.652** (3.294)	0.697**	-0.657***	-8.575	0.002	0.126	0.181
Observations R2	985 0.963	985 0.962	985 0.984	265 0.956	985 0.928	985 0.683	985 0.974	265 0.695	985 0.950	985 0.979	985 0.982
Panel B.3: GREENRATIOEP on neve	er patenting fir	ns									
L1 GREENRATIOEP	-0.068 (0.171)	0.384* (0.200)	-0.144 (0.105)	0.168 (0.451)	1.701 (1.419)	0.229** (0.106)	$-0.403^{**}$ (0.192)	2.908 (2.700)	0.001 (0.002)	0.006 (0.068)	-0.048 (0.096)
Observations R2	964 0.941	964 0.921	964 0.940	261 0.972	964 0.980	964 0.735	964 0.630	261 0.959	964 0.794	964 0.938	964 0.939
L3 GREENRATIOEP	0.127 (0.149)	0.088 (0.121)	-0.050 (0.101)	0.040 (0.424)	-0.835 (1.057)	0.122* (0.071)	-0.333** (0.151)	-1.203 (3.143)	0.002 (0.001)	0.004 (0.073)	0.017 (0.088)
Observations R2	819 0.960	819 0.948	819 0.961	122 0.998	819 0.993	819 0.846	819 0.860	122 0.996	819 0.824	819 0.958	819 0.960
L5 GREENRATIOEP	0.100 (0.148)	-0.025 (0.133)	-0.066 (0.103)		-1.051 (0.680)	0.088 (0.080)	-0.139 (0.128)		0.001 (0.001)	-0.096 (0.084)	-0.037 (0.093)
Observations R2	685 0.973	685 0.959	685 0.967		685 0.996	685 0.898	685 0.929		685 0.866	685 0.963	685 0.966
L1 3YEARAVGGREENRATIOEP	0.110 (0.276)	0.977*** (0.349)	-0.033 (0.215)	-0.303 (1.072)	-1.057 (1.746)	0.437** (0.154)	* -0.823** (0.362)	6.390 (5.121)	0.005* (0.003)	0.113 (0.138)	0.064 (0.191)
Observations R2	976 0.941	976 0.920	976 0.939	267 0.974	976 0.979	976 0.736	976 0.631	267 0.959	976 0.793	976 0.932	976 0.937
Controls Year F.E.	yes yes	yes yes	yes yes	yes yes	yes yes	yes yes	yes yes	yes yes	yes yes	yes yes	yes yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

#### **TABLE 12: BROWN EFFICIENCY PATENT RATIOS AND INDUSTRY-LEVEL OUTCOMES**

The unit of observation is Trucost industry-year in Panel A and GICS6 industry-year in Panel B. The sample period is 2005 to 2020. The dependent variables are logs of industry level cumulative sums of S1TOT, S2TOT, S3UPTOT, S3DOWNIOT, CAPEX, and SALES over 1, 3 or 5 years, respectively cumulative sums over sums for S1INT, S2INT, S3UPINT, S3DOWNIOT, CAPEX, and SALES over 1, 3 or 5 years. In Panel A.1 and B.1, dependent variables are calculated across all new perturbing firms within the given industry. In Panel A.2 and B.2, dependent variables are calculated across all never perturbing firms within the given industry. The panel A.2 and B.2, dependent variables are calculated across all never perturbing firms within the given industry. They explanatory variables of interest is BROWNEFFRATIOEP. Controls include LOCSIZE, LOGPPE, LEVERAGE, ROCF, M/B, INVEST/A, BEAT, VOLAT, MOM, RET, MSCI. Independent variables are calculated across all over perturbing firms within the given industry and hable 11 and are lagged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include country, year, and industry fixed effects. We double cluster standard errors at the given industry and year dimension. \*\*1% significance, \*5% significance \*10% significance.

	(1) LOGS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: Within Trucost Industry Panel A.1: BROWNEFFRATIOEP on all f	irms										
L1 BROWNEFFRATIOEP	$\begin{array}{c} -0.377^{**} \\ (0.185) \end{array}$	$\begin{array}{c} -0.438^{***} \\ (0.139) \end{array}$	-0.221* (0.119)	$\begin{pmatrix} -0.020\\ (0.341) \end{pmatrix}$	$^{-1.322}_{(1.011)}$	$\begin{array}{c} -0.111 \\ (0.075) \end{array}$	0.005 (0.190)	-7.431 (7.885)	0.003 (0.002)	$-0.046 \\ (0.102)$	$\begin{array}{c} -0.193^{*} \\ (0.109) \end{array}$
Observations R2	4486 0.939	4486 0.923	4486 0.943	1343 0.951	4486 0.873	4486 0.565	4486 0.880	1343 0.860	4486 0.764	4486 0.942	4486 0.950
L3 BROWNEFFRATIOEP	$\begin{array}{c} -0.145 \\ (0.158) \end{array}$	$\begin{array}{c} -0.245^{*} \\ (0.137) \end{array}$	-0.120 (0.127)	-0.242 (.)	$^{-1.512}_{(0.946)}$	$\begin{array}{c} -0.018 \\ (0.065) \end{array}$	$\begin{array}{c} -0.092 \\ (0.128) \end{array}$	6.606 (.)	0.002 (0.002)	$\begin{pmatrix} 0.005 \\ (0.091) \end{pmatrix}$	-0.089 (0.121)
Observations R2	3745 0.959	3745 0.943	3745 0.954	644 0.992	3745 0.947	3745 0.731	3745 0.978	644 0.988	3745 0.848	3745 0.956	3745 0.960
L5 BROWNEFFRATIOEP	-0.090 (0.146)	$-0.160 \\ (0.135)$	-0.039 (0.123)		$\begin{array}{c} -0.547 \\ (0.733) \end{array}$	0.008 (0.050)	$\begin{array}{c} -0.020 \\ (0.083) \end{array}$		0.003* (0.002)	0.049 (0.100)	-0.035 (0.123)
Observations R2	3030 0.971	3030 0.959	3030 0.965		3030 0.965	3030 0.847	3030 0.985		3030 0.890	3030 0.967	3030 0.970
L1 3YEARAVGBROWNEFFRATIOEP	-0.367 (0.230)	$\begin{array}{c} -0.474^{***} \\ (0.183) \end{array}$	$\begin{array}{c} -0.305^{**} \\ (0.145) \end{array}$	0.002 (0.524)	-2.244* (1.307)	-0.057 (0.088)	$-0.168 \\ (0.145)$	26.777 (16.300)	0.001 (0.003)	-0.063 (0.110)	-0.231* (0.128)
Observations R2	4861 0.936	4861 0.922	4861 0.939	1458 0.950	4861 0.874	4861 0.569	4861 0.886	1458 0.931	4861 0.763	4861 0.935	4861 0.945
Panel A.2: BROWNEFFRATIOEP on even	patenting firms										
L1 BROWNEFFRATIOEP	-0.254 (0.182)	$\begin{array}{c} -0.424^{***} \\ (0.160) \end{array}$	-0.050 (0.135)	$ \begin{array}{c} 0.164 \\ (0.464) \end{array} $	$\begin{array}{c} -0.420 \\ (1.004) \end{array}$	$\begin{array}{c} -0.321^{***} \\ (0.117) \end{array}$	$\begin{array}{c} 0.113 \\ (0.141) \end{array}$	$^{-1.371}_{(8.440)}$	0.004 (0.003)	0.039 (0.113)	$\begin{array}{c} -0.049 \\ (0.125) \end{array}$
Observations R2	4459 0.923	4459 0.906	4459 0.930	1337 0.919	4459 0.384	4459 0.304	4459 0.822	1337 0.798	4459 0.769	4459 0.904	4459 0.937
L3 BROWNEFFRATIOEP	$-0.096 \\ (0.149)$	$-0.278^{*}$ (0.145)	-0.024 (0.124)	-0.377 (.)	$-0.539 \\ (0.553)$	$\begin{array}{c} -0.162 \\ (0.108) \end{array}$	$\begin{array}{c} -0.076 \\ (0.067) \end{array}$	-2.798 (.)	0.004** (0.002)	0.028 (0.103)	$\begin{array}{c} -0.004 \\ (0.119) \end{array}$
Observations R2	3702 0.949	3702 0.932	3702 0.946	640 0.990	3702 0.923	3702 0.559	3702 0.969	640 0.983	3702 0.851	3702 0.936	3702 0.951
L5 BROWNEFFRATIOEP	$\begin{array}{c} -0.105 \\ (0.143) \end{array}$	-0.190 (0.137)	0.010 (0.125)		$\begin{array}{c} -0.130 \\ (0.470) \end{array}$	$\begin{array}{c} -0.019 \\ (0.075) \end{array}$	$\begin{array}{c} 0.046 \\ (0.067) \end{array}$		0.004** (0.002)	0.097 (0.107)	$-0.005 \\ (0.121)$
Observations R2	2982 0.965	2982 0.952	2982 0.961		2982 0.955	2982 0.749	2982 0.980		2982 0.883	2982 0.955	2982 0.964
L1 3YEARAVGBROWNEFFRATIOEP	-0.177 (0.231)	$-0.486^{**}$ (0.247)	-0.155 (0.162)	-0.180 (0.870)	-0.995 (1.340)	$\begin{array}{c} -0.365^{**} \\ (0.149) \end{array}$	$-0.165 \\ (0.142)$	-0.177 (23.636)	0.005* (0.003)	0.043 (0.131)	-0.064 (0.139)
Observations R2	4778 0.917	4778 0.901	4778 0.924	1426 0.920	4778 0.412	4778 0.305	4778 0.830	1426 0.879	4778 0.754	4778 0.901	4778 0.929
Panel A.3: BROWNEFFRATIOEP on new	er patenting firms	5									
L1 BROWNEFFRATIOEP	0.152 (0.258)	$\begin{array}{c} -0.049 \\ (0.179) \end{array}$	$\begin{array}{c} -0.195^{*} \\ (0.113) \end{array}$	-0.568* (0.330)	$\begin{array}{c} 2.221 \\ (1.442) \end{array}$	$\begin{array}{c} 0.287 \\ (0.194) \end{array}$	$\begin{array}{c} -0.088 \\ (0.397) \end{array}$	-15.837* (9.223)	0.002 (0.005)	-0.071 (0.123)	-0.177 (0.119)
Observations R2	3112 0.927	3112 0.910	3112 0.931	1226 0.949	3112 0.642	3112 0.656	3112 0.331	1226 0.896	3112 0.623	3112 0.910	3112 0.940
L3 BROWNEFFRATIOEP	-0.044 (0.257)	-0.094 (0.210)	$-0.045 \\ (0.182)$	0.016 (0.123)	0.179 (1.248)	$\begin{array}{c} -0.061 \\ (0.157) \end{array}$	0.025 (0.414)	12.087* (6.709)	-0.001 (0.003)	-0.003 (0.126)	-0.017 (0.183)
Observations R2	2396 0.949	2396 0.931	2396 0.942	576 0.994	2396 0.972	2396 0.840	2396 0.994	576 0.991	2396 0.713	2396 0.931	2396 0.946
L5 BROWNEFFRATIOEP	0.283 (0.173)	0.085 (0.182)	0.087 (0.155)		0.909 (1.029)	-0.097 (0.130)	$\begin{array}{c} -0.164 \\ (0.189) \end{array}$		0.000 (0.002)	$\begin{array}{c} 0.084 \\ (0.091) \end{array}$	0.084 (0.154)
Observations R2	1736 0.959	1736 0.941	1736 0.950		1736 0.980	1736 0.897	1736 0.986		1736 0.775	1736 0.947	1736 0.953
L1 3YEARAVGBROWNEFFRATIOEP	-0.102 (0.255)	-0.188 (0.213)	-0.396*** (0.143)	0.252 (0.455)	2.241 (1.682)	0.218 (0.215)	0.147 (0.586)	20.808 (13.606)	0.002 (0.004)	-0.248 (0.162)	$-0.414^{***}$ (0.146)
Observations R2	3402 0.925	3402 0.906	3402 0.927	1331 0.945	3402 0.647	3402 0.658	3402 0.336	1331 0.945	3402 0.622	3402 0.908	3402 0.936
Controls Year F.E. Industry F.E.	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes

Panel B.1: BROWNEFFRATIOEP on all fir	ms										
L1 BROWNEFFRATIOEP	-0.082 (0.185)	-0.365 (0.383)	-0.097 (0.146)	1.501 (2.008)	8.373** (3.554)	-0.184 (0.210)	0.649* (0.387)	43.304 (41.529)	0.000 (0.001)	-0.134 (0.092)	-0.144 (0.112)
Observations	976	976	976	261	976	976	976	261	976	976	976
R2	0.902	0.932	0.939	0.901	0.909	0.7.54	0.970	0.855	0.911	0.924	0.930
L3 BROWNEFFRATIOEP	-0.138 (0.175)	-0.323 (0.247)	$-0.228^{*}$ (0.127)	2.308 (2.795)	7.251*** (2.645)	<sup>e</sup> -0.069 (0.227)	0.284 (0.315)	23.340 (29.000)	0.000 (0.001)	$-0.155^{*}$ (0.091)	$-0.167^{*}$ (0.095)
Observations R2	837 0.981	837 0.978	837 0.990	122 0.990	837 0.995	837 0.782	837 0.988	122 0.974	837 0.957	837 0.984	837 0.986
L5 BROWNEFFRATIOEP	0.146 (0.179)	-0.148 (0.192)	-0.142 (0.126)		1.564 (2.466)	0.015 (0.249)	-0.278 (0.227)		0.000 (0.001)	0.001 (0.114)	0.018 (0.120)
Observations R2	708 0.986	708 0.985	708 0.991		708 0.997	708 0.852	708 0.993		708 0.966	708 0.984	708 0.987
L1 3YEARAVGBROWNEFFRATIOEP	-0.104 (0.245)	-0.540 (0.380)	-0.130 (0.171)	6.213** (2.568)	13.254*** (4.362)	<sup>e</sup> -0.183 (0.191)	0.724** (0.359)	96.369 (69.150)	-0.001 (0.001)	-0.211 (0.139)	-0.166 (0.159)
Observations R2	988 0.962	988 0.931	988 0.960	267 0.968	988 0.990	988 0.733	988 0.976	267 0.864	988 0.903	988 0.914	988 0.937
Panel B.2: BROWNEFFRATIOEP on ever p	atenting firms										
L1 BROWNEFFRATIOEP	0.288 (0.268)	-0.260 (0.532)	-0.078 (0.187)	0.435 (2.965)	13.008** (6.495)	$\begin{array}{c} -0.199 \\ (0.260) \end{array}$	0.573** (0.270)	82.622 (69.540)	0.002* (0.001)	0.075 (0.106)	-0.241 (0.228)
Observations R2	974 0.962	974 0.960	974 0.984	261 0.954	974 0.932	974 0.679	974 0.973	261 0.727	974 0.954	974 0.979	974 0.981
L3 BROWNEFFRATIOEP	0.094 (0.251)	-0.230 (0.397)	$\begin{array}{c} -0.220^{*} \\ (0.115) \end{array}$	1.391 (2.703)	8.228 (5.915)	$\begin{array}{c} -0.182 \\ (0.301) \end{array}$	0.211 (0.200)	24.203 (36.508)	0.001 (0.001)	0.128 (0.097)	$\begin{array}{c} -0.235 \\ (0.149) \end{array}$
Observations R2	834 0.976	834 0.973	834 0.988	122 0.986	834 0.955	834 0.740	834 0.984	122 0.937	834 0.967	834 0.982	834 0.986
L5 BROWNEFFRATIOEP	0.192 (0.303)	$\begin{array}{c} -0.175 \\ (0.303) \end{array}$	-0.151 (0.118)		-4.654 (3.254)	$\begin{array}{c} -0.029 \\ (0.269) \end{array}$	$\begin{array}{c} -0.308^{*} \\ (0.169) \end{array}$		0.000 (0.001)	0.183** (0.088)	0.018 (0.150)
Observations R2	705 0.982	705 0.982	705 0.991		705 0.970	705 0.824	705 0.989		705 0.975	705 0.986	705 0.988
L1 3YEARAVGBROWNEFFRATIOEP	-0.106 (0.466)	-0.493 (0.592)	-0.199 (0.241)	9.066** (4.014)	17.600** (8.717)	-0.227 (0.243)	0.675** (0.330)	191.709 (131.078)	0.001 (0.002)	0.184 (0.135)	-0.396 (0.283)
Observations R2	985 0.963	985 0.961	985 0.984	265 0.959	985 0.934	985 0.681	985 0.973	265 0.754	985 0.950	985 0.979	985 0.982
Panel B.3: BROWNEFFRATIOEP on never	patenting firms										
L1 BROWNEFFRATIOEP	-0.295 (0.285)	$\begin{array}{c} -0.728^{*} \\ (0.391) \end{array}$	-0.113 (0.234)	-0.495 (1.423)	3.302 (2.278)	$\begin{array}{c} -0.383^{**} \\ (0.177) \end{array}$	0.251 (0.583)	-10.842 (8.039)	$-0.003 \\ (0.003)$	-0.133 (0.140)	-0.087 (0.170)
Observations R2	964 0.941	964 0.921	964 0.940	261 0.972	964 0.980	964 0.735	964 0.629	261 0.959	964 0.794	964 0.938	964 0.939
L3 BROWNEFFRATIOEP	$-0.585^{**}$ (0.268)	$\begin{array}{c} -0.712^{***} \\ (0.263) \end{array}$	$-0.467^{**}$ (0.231)	-0.109 (0.761)	4.589** (2.047)	$egin{array}{c} -0.030 \ (0.142) \end{array}$	$\begin{array}{c} 0.082 \\ (0.417) \end{array}$	3.322 (5.100)	0.000 (0.003)	$-0.275^{*}$ (0.143)	$\begin{array}{c} -0.278 \\ (0.174) \end{array}$
Observations R2	819 0.960	819 0.948	819 0.961	122 0.998	819 0.993	819 0.846	819 0.860	122 0.996	819 0.824	819 0.958	819 0.960
L5 BROWNEFFRATIOEP	$-0.615^{**}$ (0.260)	$\begin{array}{c} -0.655^{**} \\ (0.275) \end{array}$	-0.675*** (0.210)		$2.368 \\ (1.838)$	$egin{array}{c} -0.100 \ (0.148) \end{array}$	$\begin{array}{c} -0.404 \\ (0.289) \end{array}$		0.002 (0.003)	-0.319* (0.166)	$\begin{array}{c} -0.374^{*} \\ (0.198) \end{array}$
Observations R2	685 0.973	685 0.959	685 0.967		685 0.996	685 0.898	685 0.929		685 0.866	685 0.963	685 0.966
L1 3YEARAVGBROWNEFFRATIOEP	-0.790** (0.402)	$-1.274^{***}$ (0.405)	-0.489* (0.276)	1.409 (1.611)	8.154* (4.320)	$\begin{array}{c} -0.332^{*} \\ (0.170) \end{array}$	0.006 (0.616)	-2.571 (10.075)	$-0.004 \\ (0.004)$	$-0.321^{*}$ (0.193)	-0.247 (0.204)
Observations R2	976 0.941	976 0.920	976 0.940	267 0.974	976 0.980	976 0.735	976 0.630	267 0.959	976 0.793	976 0.932	976 0.937
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Panel B: Within GICS6 Industry

(1) (2) (3) (4) (5) (6) (7) (8) (9) (10) (11) LOGSITOT LOGSZTOT LOGSZUPTOT LOGSZDOWNTOT SIINT SZINT SZUPNT SZDOWNINT INVEST/A LOGCAPEX LOGSALES

### TABLE 13: PATENT RATIOS AND CROSS-INDUSTRY OUTCOMES

The unit of observation is GICS8 industry-year. The sample period is 2005 to 2020. We aggregate the dependent variables at a given GICS8 industry's higher GICS2 level including all GICS8 industries but the given GICS8 industry used for the independent variables. The dependent variables are thus GICS2-industry level logs of cumulative sums of SITOT, S2IOT, S3UPTOT, S3DOWNTOT, CAPEX, and SALES over 1, 3 or 5 years, respectively GICS2-industry level cumulative sums over sums for S1INT, S3DIPINT, S3DOWNINT and INVEST/A for 1, 3 or 5 years. In Panel A.1 and B.1, dependent variables are calculated across all firms in the broader GICS1 industry except the given GICS8 industry. In Panel A and B.2, dependent variables are similarly calculated only for ever-patenting firms. In Panel A, the key independent variable of interest is the GICS8 industry level GRES industry level GRESS are as a genged by 1, 3 or 5 years respectively. The model is estimated using pooled regression model. All regression include country, year, and industry fixed effects. We double cluster standard errors at the GICS8-industry and year dimension. \*\*1 % significance, \*5 % significance \* 10% significance.

	(1) LOGSITOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) S1INT	(6) S2INT	(7) S3UPINT	(8) S3DOWNINT	(9) INVEST/A	(10) LOGCAPEX	(11) LOGSALES
Panel A: Green innovation Panel A.1: GREENRATIOEP on all j	firms	20002101	2003001101	Loussborntion	01111	020111		3020111111	1111201/11	Loocin LX	2000/1220
L1 GREENRATIOEP/100	$\begin{array}{c} 0.274 \\ (4.448) \end{array}$	1.152 (4.302)	-7.787** (3.592)	-0.381 (13.828)	18.915 (20.521)	3.968* (2.174)	-1.746 (3.815)	-24.219 (87.962)	0.005 (0.016)	-2.646 (1.647)	$-6.478^{*}$ (3.573)
Observations R2	1958 0.986	1958 0.972	1958 0.985	561 0.982	1958 0.989	1958 0.976	1958 0.983	561 0.964	1958 0.957	1958 0.982	1958 0.966
L3 GREENRATIOEP/100	6.055* (3.639)	4.386 (3.466)	-1.757 (3.450)	0.409 (8.701)	4.019 (15.199)	3.694* (1.920)	0.193 (2.905)	-57.379 (87.317)	-0.007 (0.018)	-1.278 (1.441)	-0.288 (3.596)
Observations R2	1649 0.993	1649 0.984	1649 0.989	262 0.997	1649 0.993	1649 0.983	1649 0.991	262 0.995	1649 0.969	1649 0.987	1649 0.974
L5 GREENRATIOEP/100	6.013 (3.874)	7.693** (3.214)	1.466 (3.532)		9.338 (14.879)	3.574* (2.119)	-0.715 (2.763)		-0.009 (0.017)	-1.256 (1.379)	2.251 (3.551)
Observations R2	1363 0.995	1363 0.990	1363 0.992		1363 0.995	1363 0.989	1363 0.995		1363 0.979	1363 0.991	1363 0.981
L1 3YEARAVGGREENRATIOEP	0.049 (0.064)	0.167** (0.068)	-0.069 (0.055)	$-0.474^{**}$ (0.203)	-0.237 (0.309)	0.097*** (0.029)	$-0.116^{**}$ (0.058)	$-4.151^{***}$ (1.430)	-0.000 (0.000)	-0.028 (0.025)	-0.020 (0.056)
Observations R2	2065 0.986	2065 0.972	2065 0.985	589 0.982	2065 0.989	2065 0.976	2065 0.983	589 0.965	2065 0.956	2065 0.982	2065 0.966
Panel A.2: GREENRATIOEP on even	r-patenting firms										
L1 GREENRATIOEP/100	-3.978 (6.353)	1.691 (4.376)	-8.359*** (3.083)	-7.007 (18.423)	$^{-45.317^{\ast}}_{(27.009)}$	4.770* (2.491)	$-3.065 \ (4.517)$	-148.941 (139.989)	0.007 (0.012)	-3.186 (2.003)	-7.948** (3.180)
Observations R2	1949 0.979	1949 0.975	1949 0.989	558 0.972	1949 0.971	1949 0.968	1949 0.980	558 0.903	1949 0.967	1949 0.982	1949 0.974
L3 GREENRATIOEP/100	5.368 (5.636)	2.574 (3.783)	-5.273** (2.670)	-6.927 (12.794)	$-28.576^{*}$ (15.220)	3.857 (2.412)	$\begin{array}{c} -2.080 \\ (3.515) \end{array}$	-90.323 (117.378)	$\begin{array}{c} -0.001 \\ (0.012) \end{array}$	$-4.267^{**}$ (2.011)	-3.135 (2.997)
Observations R2	1640 0.988	1640 0.984	1640 0.993	262 0.993	1640 0.985	1640 0.976	1640 0.989	262 0.985	1640 0.976	1640 0.986	1640 0.981
L5 GREENRATIOEP/100	1.362 (6.032)	4.321 (3.079)	-4.812* (2.770)		-21.360 (17.893)	3.715 (2.502)	$-4.175 \\ (3.455)$		$-0.006 \\ (0.012)$	$-4.868^{**}$ (2.053)	-1.294 (2.948)
Observations R2	1353 0.992	1353 0.991	1353 0.995		1353 0.992	1353 0.984	1353 0.994		1353 0.985	1353 0.990	1353 0.985
L1 3YEARAVGGREENRATIOEP	-0.039 (0.095)	$\begin{array}{c} 0.088 \\ (0.064) \end{array}$	$\begin{array}{c} -0.134^{***} \\ (0.048) \end{array}$	$-0.682^{**}$ (0.337)	$-1.471^{***}$ (0.390)	0.075** (0.032)	$^{-0.171^{\ast\ast}}_{(0.071)}$	-7.135** (2.909)	$\begin{array}{c} -0.000 \\ (0.000) \end{array}$	$\begin{array}{c} -0.094^{***} \\ (0.030) \end{array}$	$-0.065 \\ (0.048)$
Observations R2	2053 0.979	2053 0.976	2053 0.990	584 0.971	2053 0.972	2053 0.968	2053 0.980	584 0.902	2053 0.967	2053 0.984	2053 0.977
Panel A.3: GREENRATIOEP on nev	er-patenting firm:	s									
L1 GREENRATIOEP/100	$2.807 \\ (6.418)$	$^{-1.513}_{(6.789)}$	$^{-4.849}_{(4.666)}$	-6.752 (8.003)	$\substack{48.319 \\ (38.510)}$	$\begin{pmatrix} 0.381 \\ (4.259) \end{pmatrix}$	$3.234 \\ (4.524)$	15.569 (71.305)	$^{-0.016}_{(0.043)}$	$^{-2.543}_{(2.830)}$	$^{-6.171}_{(3.832)}$
Observations R2	1901 0.971	1901 0.940	1901 0.970	561 0.993	1901 0.987	1901 0.965	1901 0.978	561 0.993	1901 0.923	1901 0.964	1901 0.961
L3 GREENRATIOEP/100	9.768* (5.355)	0.179 (5.988)	2.869 (4.508)	-2.011 (5.221)	22.789 (34.406)	$1.462 \\ (2.154)$	3.915 (3.990)	-75.320 (52.497)	$\begin{array}{c} -0.083^{**} \\ (0.041) \end{array}$	-1.346 (2.461)	1.827 (3.795)
Observations R2	1579 0.984	1579 0.954	1579 0.977	262 0.999	1579 0.992	1579 0.988	1579 0.985	262 0.999	1579 0.953	1579 0.970	1579 0.968
L5 GREENRATIOEP/100	9.663** (4.820)	0.665 (5.306)	3.754 (4.758)		33.909 (34.028)	$1.466 \\ (2.037)$	$^{-0.088}_{(4.106)}$		$\begin{array}{c} -0.053 \\ (0.038) \end{array}$	-2.322 (2.586)	$3.194 \\ (3.984)$
Observations R2	1285 0.992	1285 0.963	1285 0.982		1285 0.994	1285 0.994	1285 0.992		1285 0.973	1285 0.976	1285 0.975
L1 3YEARAVGGREENRATIOEP	0.172 (0.107)	0.159 (0.112)	0.019 (0.074)	$-0.557^{***}$ (0.161)	0.729 (0.536)	0.100 (0.070)	-0.005 (0.070)	-4.192*** (1.185)	-0.002*** (0.001)	-0.044 (0.041)	0.012 (0.060)
Observations R2	2006 0.971	2006 0.940	2006 0.970	589 0.993	2006 0.988	2006 0.965	2006 0.977	589 0.993	2006 0.924	2006 0.963	2006 0.961
Controls Year F.E.	yes ves	yes ves	yes ves	yes ves	yes ves	yes ves	yes ves	yes ves	yes ves	yes yes	yes ves
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	(1) LOCSITOT	(2) LOCS2TOT	(3) LOCS3UPTOT	(4) LOCS3DOWNTOT	(5) S1INT	(6) S2INIT	(7) S3UPINIT	(8) S3DOWNINT	(9) INIVEST / A	(10) LOCCAPEX	(11) LOCSALES
Panel B: Brown efficiency innovation	20001101	10002101	200301101	Logssbownioi	511111	521111	5501111	55000000	1111101/11	LOGGINEX	LOGS/ILLS
Panel B.1: BROWNEFFRATIOEP on all f	ïrms										
L1 BROWNEFFRATIOEP/100	-2.188 (6.250)	3.363 (8.202)	6.716 (5.807)	-9.622 (32.729)	39.080 (50.465)	2.628 (4.144)	8.503 (9.709)	-219.445 (234.536)	-0.034 (0.025)	-0.060 (3.624)	6.925 (5.957)
Observations	1958	1958	1958	.561	1958	1958	1958	561	1958	1958	1958
R2	0.986	0.972	0.985	0.982	0.989	0.976	0.983	0.964	0.957	0.982	0.966
L3 BROWNEFFRATIOEP/100	-2.626	5.427	1.591	30.222	44.805	4.714	3.224	62.765	-0.013	0.681	2.981
	(5.124)	(5.862)	(5.337)	(20.141)	(37.907)	(3.383)	(7.785)	(248.948)	(0.024)	(3.281)	(5.355)
Observations	1649	1649	1649	262	1649	1649	1649	262	1649	1649	1649
R2	0.993	0.984	0.989	0.997	0.993	0.983	0.991	0.995	0.969	0.987	0.974
L5 BROWNEFFRATIOEP/100	-3.082	3.236	1.976		30.790	-0.465	3.151		$-0.043^{**}$	0.853	3.844
Observations	(4.490)	1262	(3.199)		(20.101)	(2.302)	1362		1262	1262	1262
R2	0.995	0.990	0.992		0.995	0.989	0.995		0.979	0.991	0.981
L1 3YEARAVGBROWNEFFRATIOEP	-0.036	-0.015	0.051	0.382**	1.661**	* 0.024	0.077	1.320	-0.000	0.036	0.079
	(0.083)	(0.105)	(0.077)	(0.162)	(0.632)	(0.063)	(0.113)	(2.356)	(0.000)	(0.040)	(0.071)
Observations	2065	2065	2065	589	2065	2065	2065	589	2065	2065	2065
R2	0.986	0.972	0.985	0.981	0.989	0.976	0.983	0.964	0.956	0.982	0.966
Panel B.2: BROWNEFFRATIOEP on ever	r-patenting firm	s									
L1 BROWNEFFRATIOEP/100	-0.658	9.914	9.224*	-7.806	67.476	5.614	9.864	-165.991	-0.006	1.267	9.585*
	(7.179)	(8.810)	(5.575)	(41.345)	(52.164)	(4.597)	(10.708)	(310.706)	(0.018)	(4.037)	(5.638)
Observations R2	1949	1949	1949	558	1949	1949	1949	558	1949	1949	1949
	0.979	0.975	0.909	0.972	0.971	0.900	0.900	0.905	0.907	0.702	0.774
L3 BROWNEFFRATIOEP/100	-4.455 (5.905)	6.194 (7.620)	0.886 (5.421)	25.638 (22.319)	25.937 (38.253)	5.418 (4.025)	4.176 (8.566)	208.613 (296.275)	0.005	1.386 (4.182)	3.324 (5.227)
Observations	1640	1640	1640	262	1640	1640	1640	262	1640	1640	1640
R2	0.988	0.984	0.993	0.993	0.985	0.976	0.989	0.985	0.976	0.986	0.981
L5 BROWNEFFRATIOEP/100	-5.222	2.829	-0.121		4.514	-0.498	3.030		-0.011	1.877	3.485
	(5.042)	(5.053)	(5.000)		(29.609)	(2.838)	(5.168)		(0.012)	(3.904)	(5.005)
Observations P2	1353	1353	1353		1353	1353	1353		1353	1353	1353
N2	0.992	0.991	0.993		0.992	0.964	0.994		0.985	0.990	0.965
L1 3YEARAVGBROWNEFFRATIOEP	-0.015 (0.111)	0.141	0.067	0.260	1.652**	0.134**	* 0.098 (0.127)	2.303	-0.000	0.017	0.109
Observations	2053	2053	2053	584	2053	2053	2053	584	2053	2053	2053
R2	0.979	0.976	0.990	0.970	0.972	0.968	0.980	0.899	0.967	0.984	0.977
Panel A.3: BROWNEFFRATIOEP on nev	er-patenting fir	ms	12 100	15.050	16.000	2 200	10.070	200 252	0.110	1.026	10.025
LI BROWNEFFRATIOEP/100	6.986 (14.793)	-1.889 (15.539)	(8.499)	-17.850 (15.141)	(76.488)	-3.298 (10.258)	(8.781)	-309.372 (241.999)	-0.112 (0.078)	(5.863)	(6.996)
Observations	1901	1901	1901	561	1901	1901	1901	561	1901	1901	1901
R2	0.971	0.940	0.970	0.993	0.987	0.965	0.978	0.993	0.923	0.964	0.961
L3 BROWNEFFRATIOEP/100	0.705	6.288	6.648	-12.721	-27.280	1.284	3.952	-171.316	-0.043	1.270	5.746
	(10.829)	(11.021)	(8.563)	(12.774)	(64.711)	(5.104)	(8.204)	(219.561)	(0.072)	(5.887)	(6.651)
Observations R2	1579 0 984	1579 0.954	1579	262 0 999	1579 0.992	1579 0.988	1579 0.985	262 0.999	1579 0.953	1579 0.970	1579 0.968
		0.001	0.577	0		0.000		0	0.500	0.570	
L5 BROWNEFFRATIOEP/100	-7.126 (8.393)	-2.038 (9.430)	(9.103)		-2.111 (57.376)	-2.379 (3.130)	4.280 (5.925)		-0.090 (0.057)	-2.578 (4.938)	0.036 (6.932)
Observations	1285	1285	1285		1285	1285	1285		1285	1285	1285
R2	0.992	0.963	0.982		0.994	0.994	0.992		0.973	0.976	0.975
L1 3YEARAVGBROWNEFFRATIOEP	0.061	-0.253	0.108	0.150	1.150	-0.226	0.071	1.519	-0.001	0.070	0.107
	(0.164)	(0.205)	(0.109)	(0.117)	(0.958)	(0.153)	(0.106)	(2.395)	(0.001)	(0.065)	(0.085)
Observations R2	2006	2006	2006	589 0 993	2006	2006	2006	589 0.993	2006	2006	2006 0.961
Controls	0.771	0.710	0.770	0.555	3.700	3.705	0.777	0.775	0.724	0.705	
Year F.E.	yes yes	yes yes	yes	yes	yes	yes yes	yes yes	yes yes	yes yes	yes yes	yes yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

### TABLE 14: PATENT RATIOS AND FIRM-LEVEL MARKET SHARE

The unit of observation is firm-year and covers both public and private firms, as we do not rely on public firms' emission data. The sample period is 2005 to 2020. The dependent variable is MKTSHR GICS6, which is a firm's market share based on its sales relative to total public and private firms' sales in a given GICS6 industry. The key dependent variable is *GREENRATIOEP* lagged by 1, 3, or 5 years in columns 1 to 3 and *BROWNEFFRATIOEP* lagged by 1, 3 or 5 years in column 4 to 6. Controls include: *LOGASSETS*, *LOGPPE*, *LEVERAGE*, *ROE*, *INVEST/A*, and, *PUBLIC*. *LOGASSETS* is the log of total assets in million USD and *PUBLIC* is an indicator equal to 1 for public firms. All other variables are defined in Table 2 and Table 3. All independent variables are lagged by 1, 3, or 5 years. The model is estimated using pooled regression model. In Panel A, we include country, year, and firm fixed effects and in Panel B we include country and GICS6 industry-year fixed effects. We double cluster standard errors at the firm and year dimension. \*\*\* 1% significance, \*\* 5% significance \* 10% significance.

	(1)	(2)	(3) MKTSHR	(4) GICS6	(5)	(6)
L1 GREENRATIOEP	-0.025					
L3 GREENRATIOEP	(0.021)	-0.046*				
L5 GREENRATIOEP		(0.025)	-0.042			
L1 BROWNEFFRATIOEP			(0.029)	0.017		
L3 BROWNEFFRATIOEP				(0.042)	0.040	
L5 BROWNEFFRATIOEP					(0.037)	$-0.012 \\ (0.046)$
Observations R2 Controls Country F.E. Year F.E. Firm F.E.	43346 0.869 yes yes yes yes	33147 0.887 yes yes yes yes	24189 0.903 yes yes yes yes	43346 0.869 yes yes yes yes	33147 0.887 yes yes yes yes	24189 0.903 yes yes yes yes
			MKTSHR	GICS6		
L1 GREENRATIOEP	-0.076***					
L3 GREENRATIOEP	(0.028)	-0.070**				
L5 GREENRATIOEP		(0.032)	$-0.122^{***}$			
L1 BROWNEFFRATIOEP			(0.043)	0.034		
L3 BROWNEFFRATIOEP				(0.049)	0.028	
L5 BROWNEFFRATIOEP					(0.033)	-0.010 (0.067)
Observations R2	44202 0.462	34043 0.469	25036 0.477	44202 0.461	34043 0.469	25036 0.477
Controls Country F.E. GICS6-Year F.E.	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes	yes yes yes

#### TABLE 15: EX-POST CHARACTERISTICS OF EMISSION DECREASING VS INCREASING FIRMS

The unit of observation is firm-year and the sample period is 2005 to 2020. To split firms in emission reduction samples (column 1 to 4) and emission increase samples (column 5 to 8) we calculate changes in emissions over three years. Panel A covers total scope 1 emissions, Panel B total scope 2 emissions, Panel C upstream scope 3 emissions and Panel D downstream scope 3 emissions. Panel E defines emission reduction firms as those that decreased emissions across scope 1, 2 and upstream 3 and emission increase firms as all others. We calculate mean, standard deviation, median and the count for each sample as well as the difference and p-value between the two samples for a variety of variables at the three year lag. Panel A.1, B.1, C.1, D.1 and E.1 cover the full Trucost sample. Panel A.2, B.2, C.2, D.2, and E.2 zoom in on the Trucost sample with at least one patent at the European Patent Office emission increase sample, we focus on the 50% with the greatest emission decrease. Similarly within the emission increase sample, we focus on the 50% with the greatest emission decrease. Similarly within the emission increase sample, we focus on the 50% with the greatest emission decrease. Similarly within the emission increase sample, we focus on the 50% with the greatest emission and event and zero otherwise. SALES3YRCHG is the change in sales across the three year period in decimals. All other variables are defined in Table 2, Table 3 and Table 6.

	(1)	(2) Emission dec	(3) rease samp	(4) ole	(5)	(6) Emission in	(7) crease samp	(8) le	(9) Differe	(10) ence
	Mean	Std. Dev.	Median	Count	Mean	Std. Dev.	Median	Count	Difference	p-value
Panel A: 3-year changes in so	ope 1 em	issions								1
Panel A.1: Patenting and non-p	atenting fi	rms								
DUMMYANYEP	0.310	0.463	0	32068	0.28	0 0.449	0	39100	0.030	0.000
DUMMYGREENEP	0.149	0.356	0	32068	0.11	6 0.321	0	39100	0.032	0.000
DUMMYOECDER	0.069	0.253	0	32068	0.05	4 0.226	0	39100	0.015	0.000
ACE	47 252	38.678	34 000	29809	41.07	0 0.324 5 35.860	28,000	36468	6.177	0.000
LOGSIZE	7.752	1.667	7.782	32068	7.66	5 1.565	7.722	39100	0.086	0.000
LOGPPE	6.055	2.336	6.237	32068	5.79	4 2.298	5.980	39100	0.261	0.000
MB	2.373	2.676	1.588	32068	2.82	6 2.962	1.903	39100	-0.453	0.000
LEVERAGE	23.937	17.967	22.294	32068	23.24	9 18.279	21.290	39100	0.688	0.000
ROE	10.749	26.144	10.388	32068	11.87	2 23.995	11.544	39100	-1.123	0.000
SALES3YRCHG	-0.094	0.524	-0.024	32004	0.32	7 0.512	0.249	39034	-0.421	0.000
Panel A.2: Firm-years with at le	ast one EP	patent & grea	test emissio	n decreases,	resp. incre	ases				
GREENRATIOEP	11.944	23.526	0	4973	11.58	9 24.309	0	5478	0.355	0.449
BROWNEFFRATIOEP	3.776	13.151	0	4973	3.54	2 13.569	0	5478	0.234	0.371
OECDRATIOEP	13.354	24.952	0	4973	11.53	0 23.606	0	5478	1.823	0.000
GREENCITMAXEP	65.316	561.564	0	4973	56.95	5 532.163	0	5478	8.361	0.436
CREENCOUNTRREP	14.912	210.829	0	4973	8.50	2 51.493	0	5478	6.410	0.037
BROWNIEFECOUNTBRED	0.260	1.128	0	4973	0.19	5 1.007 7 0.472	0	5478	0.066	0.002
ACE	55 569	41 713	44,000	4973	46.44	2 39.625	32,000	54/8	0.049	0.000
LOGSIZE	8 365	1 589	8 363	4929	813	4 1 593	8 1 3 3	5445	0.231	0.000
LOGPPE	6 719	2 017	6 813	4973	6.16	9 2 151	6.312	5478	0.550	0.000
MB	2.609	2.714	1.837	4973	3.31	2 3.291	2.285	5478	-0.703	0.000
LEVERAGE	22.636	15.588	21.787	4973	22.14	3 16.984	21.209	5478	0.493	0.122
ROE	9.536	27.992	10.644	4973	9.08	8 28.816	11.344	5478	0.447	0.421
SALES3YRCHG	-0.110	0.553	-0.020	4968	0.42	9 0.599	0.350	5474	-0.539	0.000
Panel B: 3-year changes in sc	ope 2 emi	issions								
Panel B.1: Patenting and non-pa	atenting fii	rms								
DUMMYANYEP	0.296	0.457	0	29199	0.29	2 0.455	0	42027	0.004	0.228
DUMMYGREENEP	0.138	0.345	0	29199	0.12	6 0.332	0	42027	0.012	0.000
DUMMYBROWNEFFEP	0.065	0.247	0	29199	0.05	7 0.232	0	42027	0.008	0.000
DUMMYOECDEP	0.144	0.351	24.000	29199	0.12	9 0.335	28,000	42027	0.015	0.000
AGE LOCSIZE	47.200	36.775	7 723	2/2/1	41.43	0 55.990 4 1.548	26.000	39034	-0.023	0.000
LOGDIZE	5 962	2 376	6 162	29199	5.87	1 2 278	6.051	42027	0.023	0.002
MB	2 402	2 706	1 606	29199	2 77	4 2 927	1 859	42027	-0.373	0.000
LEVERAGE	24.072	18.132	22.416	29199	23.18	7 18.131	21.237	42027	0.885	0.000
ROE	10.519	27.006	10.359	29199	11.96	0 23.463	11.477	42027	-1.441	0.000
SALES3YRCHG	-0.117	0.537	-0.038	29138	0.31	4 0.501	0.241	41957	-0.431	0.000
Panel B 2: Firm-years with at le	ast one EP	natent & oreat	est emission	n decreases	resn incre	1505				
GREENRATIOEP	12.646	24.618	0	4325	12.11	9 24.608	0	6136	0.527	0.281
BROWNEFFRATIOEP	4.305	14.269	0	4325	3.40	6 13.053	0	6136	0.898	0.001
OECDRATIOEP	13.876	25.314	0	4325	12.23	3 24.368	0	6136	1.643	0.001
GREENCITMAXEP	44.640	187.160	0	4325	65.21	1 573.680	0	6136	-20.571	0.009
BROWNEFFCITMAXEP	13.322	223.038	0	4325	9.42	1 47.241	0	6136	3.901	0.257
GREENCOUNTBBEP	0.230	1.042	0	4325	0.21	2 1.018	0	6136	0.018	0.373
BROWNEFFCOUNTBBEP	0.093	0.794	0	4325	0.06	3 0.431	0	6136	0.030	0.024
AGE	56.880	42.765	45.000	4281	47.38	3 39.415	33.000	6094	9.496	0.000
LOGSIZE	8.353	1.688	8.361	4325	8.29	1 1.575	8.271	6136	0.062	0.058
LOGPPE	6.747	2.209	6.847	4325	6.44	6 2.143	6.508	6136	0.300	0.000
MB	2.551	2.717	1.778	4325	3.17	4 3.171	2.211	6136	-0.623	0.000
LEVEKAGE	23.615	15.744	22.637	4325	22.29	1 16.697	21.329	0130 (12)	1.325	0.000
NUE SALES3VRCHC	0.585	29.419	10.2/1	4323	9.60	4 28.328	11.476	6130	-1.019	0.076
JALLOJI KCI IG	-0.103	0.579	-0.075	-1021	0.40	1 0.367	0.524	0154	-0.504	0.000

	(1) I	(2) Emission dec	(3) crease samj	(4) ple	(5) Ei	(6) mission incr	(7) rease samj	(8) ple	(9) Differe	(10) ence
	Mean	Std. Dev.	Median	Count	Mean	Std. Dev.	Median	Count	Difference	p-value
<b>Panel C: 3-year changes in u</b> Panel C.1: Patenting and non-	<b>ipstream</b> patenting	n scope 3 em	issions							•
DUMMYANYEP	0.298	0.458	0	28408	0.290	0.454	0	42885	0.008	0.026
DUMMYGREENEP	0.140	0.347	0	28408	0.125	0.330	0	42885	0.015	0.000
DUMMYBROWNEFFEP	0.069	0.253	0	28408	0.055	0.228	0	42885	0.013	0.000
DUMMYOECDEP	0.146	0.353	0	28408	0.128	0.334	0	42885	0.018	0.000
AGE	46.931	38.457	34.000	26627	41.749	36.293	29.000	39765	5.182	0.000
LOGSIZE	7.631	1.672	7.690	28408	7.754	1.569	7.785	42885	-0.124	0.000
LOGPPE	6.062	2.356	6.255	28408	5.808	2.290	6.000	42885	0.254	0.000
MB	2.248	2.547	1.528	28408	2.869	3.000	1.931	42885	-0.621	0.000
LEVERAGE	24.414	18.091	22.840	28408	22.983	18.146	20.968	42885	1.430	0.000
KUE SALESZVRCHC	9.732	26.444	9.981	28408	12.452	23.891	0.266	42885	-2.720	0.000
Panel C 2: Firm-years with at 1	-0.190	EP natent & c	-0.102	20347 ssion decre	vases resp iv	0.475	0.200	42013	-0.558	0.000
GREENRATIOEP	13.261	25.164	0	4237	11.883	24.392	0	6229	1.377	0.005
BROWNEFFRATIOEP	4.592	14.783	0	4237	3.370	13.040	Õ	6229	1.222	0.000
OECDRATIOEP	14.522	26.082	0	4237	11.960	24.008	0	6229	2.561	0.000
GREENCITMAXEP	47.269	187.291	0	4237	54.588	327.325	0	6229	-7.320	0.147
BROWNEFFCITMAXEP	19.165	317.144	0	4237	8.678	42.631	0	6229	10.487	0.032
GREENCOUNTBBEP	0.243	1.098	0	4237	0.216	0.925	0	6229	0.026	0.198
BROWNEFFCOUNTBBEP	0.123	0.928	0	4237	0.067	0.496	0	6229	0.056	0.000
AGE	57.208	43.746	46.000	4215	45.397	39.138	31.000	6168	11.812	0.000
LOGSIZE	8.234	1.696	8.227	4237	8.294	1.611	8.285	6229	-0.060	0.070
LOGPPE	6.889	2.256	7.039	4237	6.222	2.139	6.266	6229	0.667	0.000
MB	2.215	2.428	1.601	4237	3.526	3.384	2.512	6229	-1.310	0.000
LEVERAGE	24.170	16.037	23.076	4237	21.742	16.918	20.308	6229	2.428	0.000
ROE	7.362	29.766	9.306	4237	10.395	29.696	11.984	6229	-3.033	0.000
SALES3YRCHG	-0.315	0.528	-0.217	4232	0.497	0.533	0.392	6226	-0.812	0.000
<b>Panel D: 3-year changes in o</b> Panel D.1: Patenting and non-	downstro patenting	eam scope 3	emissions							
DUMMYANYEP	0.244	0.430	0	6412	0.210	0.407	0	4628	0.034	0.000
DUMMYGREENEP	0.094	0.292	0	6412	0.082	0.275	0	4628	0.012	0.026
DUMMYBROWNEFFEP	0.041	0.198	0	6412	0.033	0.179	0	4628	0.008	0.036
DUMMYOECDEP	0.094	0.292	0	6412	0.079	0.270	0	4628	0.015	0.005
AGE	42.999	33.724	32.000	3863 (412	37.366	32.005	26.000	4219	5.433	0.000
LOGSIZE	7.120	1.550	7.055	6412 6412	7.210	1.031	7.115	4020	-0.090	0.005
MB	2 600	2.232	1 725	6412	4.933	2.374	1 870	4020	0.262	0.000
LEVERACE	2.009	18 573	19 725	6412	2.971	18 804	20 577	4020	-0.302	0.000
ROF	9.932	22 883	9.682	6412	9 211	25.840	9 994	4628	0 721	0.200
SALES3YRCHG	-0.012	0.526	0.061	6408	0.268	0.603	0.184	4624	-0.280	0.000
Panel D.2: Firm-years with at	least one	EP patent &	greatest emi	ssion decre	eases, resp. in	icreases				
GREENRATIOĚP	11.955	23.128	0	784	13.742	26.184	0	486	-1.787	0.217
BROWNEFFRATIOEP	2.861	11.181	0	784	2.346	9.927	0	486	0.516	0.392
OECDRATIOEP	12.019	23.823	0	784	9.269	21.192	0	486	2.750	0.032
GREENCITMAXEP	16.356	103.591	0	784	72.142	1115.594	0	486	-55.786	0.272
BROWNEFFCITMAXEP	3.171	14.083	0	784	2.891	13.033	0	486	0.280	0.718
GREENCOUNTBBEP	0.255	1.489	0	784	0.226	0.853	0	486	0.029	0.662
BROWNEFFCOUNTBBEP	0.101	1.160	0	784	0.109	1.062	0	486	-0.008	0.896
AGE	54.055	39.770	45.000	781	46.300	39.119	31.000	477	7.755	0.001
LOGSIZE	7.760	1.680	7.706	784	8.113	1.850	8.094	486	-0.354	0.001
LOGPPE	5.916	2.111	5.913	784	5.629	2.519	5.744	486	0.287	0.036
MB	2.916	2.942	2.071	784	3.981	3.858	2.817	486	-1.065	0.000
LEVERAGE	21.707	16.440	21.170	784	21.921	18.852	19.407	486	-0.214	0.837
KOE	8.980	26.828	9.502	784	5.596	38.696	10.700	486	3.384	0.091
SALES3YRCHG	-0.038	0.552	0.045	784	0.440	0.830	0.203	486	-0.478	0.000

	(1) S1TOT, S	1) (2) (3) (4) OT, S2TOT and S3UPTOT decrease sample		(5) (6) Increase in at le		(7) (8) east one scope		(9) Differe	(10) ence				
	Mean	Std. Dev.	Median	Count	Mean	Std. Dev.	Median	Count	Difference	p-value			
Panel E: Ex-post characteristics of firms decreasing absolute emissions across scope 1, 2, and upstream 3													
Panel E.1: Patenting and non-patenting firms													
DUMMYANYEP	0.260	0.439	0	16298	0.304	0.460	0	54950	-0.044	0.000			
DUMMYGREENEP	0.115	0.319	0	16298	0.136	0.342	0	54950	-0.021	0.000			
DUMMYBROWNEFFEP	0.054	0.225	0	16298	0.063	0.242	0	54950	-0.009	0.000			
DUMMYOECDEP	0.119	0.324	0	16298	0.140	0.347	0	54950	-0.020	0.000			
AGE	44.742	37.286	32.000	15124	43.565	37.259	30	51227	1.177	0.001			
LOGSIZE	7.411	1.690	7.461	16298	7.792	1.578	7.826	54950	-0.381	0.000			
LOGPPE	5.697	2.406	5.863	16298	5.973	2.289	6.160	54950	-0.276	0.000			
MB	2.244	2.588	1.509	16298	2.734	2.907	1.829	54950	-0.490	0.000			
LEVERAGE	24.227	18.693	22.417	16298	23.357	17.968	21.546	54950	0.870	0.000			
ROE	8.589	28.284	9.361	16298	12.192	23.852	11.467	54950	-3.603	0.000			
SALES3YRCHG	-0.299	0.592	-0.168	16254	0.267	0.477	0.204	54864	-0.566	0.000			
Panel E.2: Firm-years with at l	east one El	P patent & g	reatest emiss	ion decreases, resp	. increases								
GREENRATIOEP	12.232	24.679	0	2256	11.822	23.423	0	8469	0.410	0.478			
BROWNEFFRATIOEP	4.187	14.338	0	2256	3.830	13.524	0	8469	0.357	0.288			
OECDRATIOEP	13.448	25.767	0	2256	12.285	23.507	0	8469	1.163	0.052			
GREENCITMAXEP	58.520	554.662	0	2256	69.971	789.631	0	8469	-11.451	0.429			
BROWNEFFCITMAXEP	17.191	306.872	0	2256	10.717	52.799	0	8469	6.474	0.318			
GREENCOUNTBBEP	0.236	1.090	0	2256	0.249	1.201	0	8469	-0.013	0.614			
BROWNEFFCOUNTBBEP	0.116	0.996	0	2256	0.084	0.637	0	8469	0.032	0.147			
AGE	54.519	42.417	43.000	2240	52.884	42.120	39.000	8406	1.634	0.105			
LOGSIZE	8.096	1.722	8.086	2256	8.366	1.642	8.333	8469	-0.270	0.000			
LOGPPE	6.470	2.300	6.690	2256	6.622	2.158	6.704	8469	-0.152	0.005			
MB	2.402	2.613	1.711	2256	3.028	3.113	2.065	8469	-0.625	0.000			
LEVERAGE	23.427	16.196	22.574	2256	22.937	16.493	22.141	8469	0.490	0.203			
ROE	5.718	32.059	9.094	2256	10.529	27.509	11.311	8469	-4.810	0.000			
SALES3YRCHG	-0.402	0.640	-0.258	2252	0.310	0.530	0.225	8465	-0.713	0.000			

#### **TABLE 16: PATENT RATIOS EXPLANATORY POWER**

In Panel A, the unit of observation is a firm. For each firm, we split horizons into halves based on existing emission data between 2005 and 2020. We calculate changes in average total emissions, patent ratios (calculated as sum over sums) and control variables over the two periods (except for the lagged MSCI dummy). The dependent variable is SITOTCHG, S2TOTCHG, S3DUPIOTCHG, S3DOWNTOTCHG or S123UPIOTCHG, which captures the change in total emissions in scope 1, scope 2, scope upstream 3, scope downstream 3, or the sum of scope 1, 2 and upstream 3. The key independent variable of interest is the change in green (PatChgKEENRATIOEP) patent ratio. Controls include changes in LOGSIZE, LOCPPE, LEVERAGE, KOE, M/B, INVEST/A, BIATA, VOLAT, MOM, RET and an average of the dummy MSCI dummy in the first horizon. In Panel B to III of discretion is firm-year. The sample period is 2005 to 2020. The dependent variable logs of cumulative sums of SITOT, S2DOWNTOT and S122UPIOT over 1, a 'or 5 years, respectively long-term averages of SINT, S2INT, S3UPINT and S3DOWNINT for 1, 3 or 5 years. The key independent variables is *CREENRATIOEP* pageed by 1, 3, or 5 years are similarly lagged by 1, 3, or 5 years are defined in Table 2. Controls include: LOGSIZE, LOCPPE, LEVERAGE, NGE, M/B, INVEST/A, BETA, VOLAT, MOM, RET and and SINT, S2INT, S3UPINT and S3DOWNINT for 1, 3 or 5 years, are defined in Table 2. Controls include: LOGSIZE, LOCPPE, LEVERAGE, NGE, M/B, INVEST/A, BETA, VOLAT, MOM, RET and and S2DOWNINT for 1, 3 or 5 years, are defined in Table 3. Controls include: LOGSIZE, LOCPPE, LEVERAGE, NGE, M/B, INVEST/A, BETA, VOLAT, MOM, RET and and S2DOWNINT for 1, 3 or 5 years, are defined in Table 3. Controls include: LOGSIZE, LOCPPE, LEVERAGE, NGE, M/B, INVEST/A, BETA, VOLAT, MOM, RET and MSCL All variables are similarly lagged by 1, 3, or 5 years are defined in Table 3. Controls include: LOGSIZE, LOCPPE, LEVERAGE, NGE, M/B, INVEST/A, MOM, RET and AMSCL All variables are similarly lagged by 1, 3, or 5 years are defined in Table 3. Control

Panel A: Long-term changes over changes										
	(1) S1TOTCHG	(2) S2TOTCHG	(3) S3UPTOTCHG	(4) S3DOWNTOTCH	(5) IG S123UPTOTCH	(6) IG S1TOTCHG	(7) S2TOTCHG	(8) S3UPTOTCHG	(9) S3DOWNTOTCHG	(10) S123UPTOTCHG
PatChgGREENRATIOEP	0.017	0.014	0.014	0.057	0.011					
PatChgBROWNEFFRATIOEP	(0.019)	(0.027)	(0.012)	(0.095)	(0.014)	$-0.068^{***}$ (0.025)	-0.021 (0.030)	-0.016 (0.010)	-0.071 (0.119)	-0.027** (0.013)
Observations R2	1715 0.349	1715 0.386	1715 0.570	1189 0.319	1715 0.544	802 0.365	802 0.381	802 0.584	532 0.467	802 0.556
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E. Industry F.E.	yes ves	yes ves	yes ves	yes ves	yes ves	yes ves	yes ves	yes ves	yes ves	yes ves
			,	, ···	,	, ···		,		
Panel B: Partial R2 of patent rati	os									
Davel P.1. Crean inversion	LO	(1) GS1TOT	(2) LOGS2TOT	(3) LOGS3UPTOT	(4) LOGS3DOWNTOT	(5) LOGS123UPTOT	(6) S1INT	(7) S2INT	(8) S3UPINT	(9) S3DOWNINT
L1 CREENRATIOEP		0 514***	_0.199***	-0.059**	0.153	0.111***	1 385***	0.042**	* 0.146***	4 168***
EI GREENRAHOEI		(0.041)	(0.033)	(0.029)	(0.097)	(0.028)	(0.128)	(0.013)	(0.036)	(0.610)
Partial R2	0	.00596	0.00167	0.000172	0.000219	0.000628	0.00760	0.000378	0.000552	0.00579
R2 Full Model R2 Reduced Model		0.668	0.742	0.785	0.459	0.810	0.149	0.171	0.226	0.106
Observations	:	31049	31049	31048	11600	31049	31049	31049	31049	11600
L3 GREENRATIOEP		0.592*** (0.048)	-0.199*** (0.039)	-0.022 (0.034)	0.172 (0.145)	0.172*** (0.032)	1.553*** (0.157)	0.040*	0.145*** (0.043)	4.720*** (0.956)
Partial R2	0	.00748	0.00163	0.0000243	0.000293	0.00151	0.00868	0.000320	0.000518	0.00712
R2 Full Model		0.659	0.731	0.765	0.493	0.795	0.159	0.187	0.218	0.113
Observations	:	23485	23485	23485	5419	23485	23485	23485	23485	5428
L5 GREENRATIOEP		0.695***	-0.253*** (0.048)	0.017 (0.040)		0.234*** (0.039)	1.789*** (0.200)	0.009	0.146*** (0.054)	
Partial R2	0	.00954	0.00251	0.0000144		0.00270	0.0100	0.0000167	0.000484	
R2 Full Model		0.635	0.701	0.730		0.768	0.168	0.196	0.209	
Observations		16892	16892	16892		16892	16892	16892	16892	
L1 3YEARAVGGREENRATIOEP		0.552*** (0.038)	-0.226*** (0.032)	-0.069** (0.027)	0.239*** (0.091)	0.129*** (0.027)	1.561*** (0.126)	0.057* (0.013)	** 0.185*** (0.035)	5.290*** (0.603)
Partial R2	0	.00620	0.00192	0.000205	0.000480	0.000748	0.00836	0.000626	0.000793	0.00808
R2 Full Model R2 Reduced Model		0.670	0.740	0.782	0.460	0.807	0.150	0.168	0.214	0.111 0.104
Observations	:	38934	38934	38933	15245	38934	38934	38934	38934	15245
Panel B.2: Brown efficiency innovat	ion									
L1 BROWNEFFRATIOEP		0.511***	$-0.374^{***}$	0.578***	1.656***	0.584***	1.604***	$-0.210^{*}$	** 0.637*** (0.064)	9.014*** (1.383)
Partial R2	0	00185	0.00185	0.00519	0.00709	0.00548	0.00320	0.00294	0.00331	0.00744
R2 Full Model	0	0.667	0.742	0.786	0.463	0.811	0.146	0.173	0.228	0.108
R2 Reduced Model Observations		0.666 31049	0.742	0.785 31048	0.459	0.809	0.143	0.171 31049	0.225	0.101
		0 804333	01010	01010	1.000	01010		01010		. 1 (0****
L3 BROWNEFFRATIOEP		(0.085)	-0.474*** (0.072)	(0.056)	(0.259)	(0.052)	(0.352)	(0.025)	(0.073)	(1.969)
Partial R2 R2 Full Model	0	0.00201	0.00309	0.00534	0.00714	0.00606	0.00494	0.00354	0.00322	0.00588
R2 Reduced Model		0.656	0.730	0.765	0.497	0.795	0.156	0.189	0.220	0.106
Observations	:	23485	23485	23485	5419	23485	23485	23485	23485	5428
L5 BROWNEFFRATIOEP		0.584*** (0.102)	$-0.576^{***}$ (0.084)	0.589*** (0.064)		0.629*** (0.062)	2.338*** (0.426)	-0.273* (0.029)	** 0.659**** (0.086)	
Partial R2	0	.00245	0.00474	0.00599		0.00705	0.00620	0.00504	0.00359	
R2 Full Model R2 Reduced Model		0.632	0.701	0.732		0.769	0.165	0.200	0.211	
Observations		16892	16892	16892		16892	16892	16892	16892	
L1 3YEARAVGBROWNEFFRATI	OEP	0.587*** (0.068)	$-0.488^{***}$ (0.060)	0.599*** (0.045)	1.528*** (0.176)	0.622*** (0.042)	2.065*** (0.283)	-0.215* (0.021)	** 0.720**** (0.060)	8.439*** (1.279)
Partial R2	0	.00212	0.00270	0.00469	0.00575	0.00521	0.00442	0.00274	0.00362	0.00603
K2 Full Model R2 Reduced Model		0.669	0.740	0.783	0.463 0.460	0.808	0.146	0.169	0.216	0.109 0.104
Observations		38934	38934	38933	15245	38934	38934	38934	38934	15245
Controls		yes	yes	yes	yes	yes	yes	yes	yes	yes
Country F.E. Year F.E.		yes ves	yes ves	yes ves	yes ves	yes ves	yes	yes ves	yes	yes ves
		1.1	,	,	,	,	,	,	,	,

# 8 Figures

# FIGURE 1: COMPARING GREEN AND OECD TITLES

The sample is all patents granted by the European Patent Office from 2005 to 2020 that belong to the Trucost sample. Wordclouds display the top 100 words (unigrams) based on the TF-IDF comparing patent titles of GREEN patents to OECD env-tech patents, respectively OECD env-tech to GREEN patents.



(A) "GREEN" AGAINST "OECD"

#### (B) "OECD" AGAINST "GREEN"



## FIGURE 2: GREEN AND BROWN EFFICIENCY EPO PATENT COUNTS ACROSS REGIONS

The sample period is 2005 to 2020. We report the total number of granted or purchased green and brown efficiency EPO patents across all regions and by region, namely North America, Europe, Asia, and other (rest of the world), per year. In Panel A the sample covers the full sample, i.e all public and private firms. In Panel B the sample covers only public firms with emission data from Trucost and in Panel C we restrict the sample inclusion further to those firms that Trucost covers in its database before 2016.



(A) FULL (PUBLIC/PRIVATE) SAMPLE



#### (B) TRUCOST SAMPLE





### FIGURE 3: GREEN AND BROWN EFFICIENCY EPO PATENT RATIOS ACROSS REGIONS

The sample period is 2005 to 2020. We report the average GREENRATIOEP, BROWNEFFRATIOEP and OECDRATIOEP across all regions and for the regions North America, Europe and Asia per year. Patent ratios are defined in Table 3. In Panel A the sample covers the full sample, i.e all public and private firms. In Panel B the sample covers only public firms with emission data from Trucost and in Panel C we restrict the sample inclusion further to those firms that Trucost covers in its database before 2016.



(A) FULL (PUBLIC/PRIVATE) SAMPLE



(B) TRUCOST SAMPLE

---- OECD env-tech

Patent type 🔶 brown efficiency 📥 green

Patent type 🔸 brown efficiency 📥 green 💷 OECD env-tech

(C) TRUCOST (PRE 2016) LEGACY SAMPLE



Patent type 🔶 brown efficiency 📥 green 💷 OECD env-tech

## FIGURE 4: EMISSION DISTRIBUTION FOR DIFFERENT QUINTILES

The sample period is 2005 to 2020. We report histograms for LOGS1TOT for unconditional top and bottom quintiles based on "AGE" in Panel A, "ASSETS" in Panel B, and "M/B" in Panel C. All variables are defined in Table 2 and 4.



(A) PANEL A: AGE QUINTILES





(C) PANEL C: M/B QUINTILES

