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ABSTRACT

No firm or sector of the global economy is untouched by innovation. In equilibrium, innovators will flock to (and innovation will occur where) the returns to innovative capital are the highest. In this paper, we document a strong empirical pattern in green patent production. Specifically, we find that oil, gas, and energy producing firms – firms with lower Environmental, Social, and Governance (ESG) scores, and who are often explicitly excluded from ESG funds' investment universe – are key innovators in the United States' green patent landscape. These energy producers produce more, and significantly higher quality, green innovation. Our findings raise important questions as to whether the current exclusions of many ESG-focused policies – along with the increasing incidence of explicit divestiture campaigns – are optimal, or whether reward-based incentives would lead to more efficient innovative outcomes.

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As of 2019, sustainable investing represents more than 20 percent of the $46 trillion in the U.S. assets under management. Compared to 2015, sustainable and impact investing has increased by more than 40% (USSIF 2018). A large contributor to this growth has been the 2015 guidance issued by the Department of Labor which allowed fiduciaries to incorporate environmental, social, and governance (ESG) factors into their investment decision.[1] Given this push, flows to ESG increased substantially.[2]

The most straightforward motivation for ESG investing comes from a preference function that loads positively on the goals of a given ESG fund. An investor with these preferences might be willing to sacrifice an amount of risk-adjusted return in order to allow the fund to achieve those returns with aligned ESG focus; or alternatively, pay more for a fund that promises the same ex-ante risk-return dynamics while delivering aligned ESG investment.

However, a number of other views could motivate ESG investing. For instance, a micro-founded, belief-based view of ESG investing could exist irrespective of the investor's actual preferences for ESG. If consumers value products that are ESG compliant, they

[1] https://www.federalregister.gov/documents/2015/10/26/2015-27146/interpretive-bulletin-relating-to-the-fiduciary-standard-under-erisa-in-considering-economically. In 2018, the agency further clarified their ESG factor stance: https://www.dol.gov/agencies/ebsa/employers-and-advisers/guidance/field-assistance-bulletins/2018-01

[2] According to a 2019 survey by Callen Institute, of the 89 U.S. institutional investors that were asked about their approach to environmental, social, and governance (ESG) factors when evaluating investments, 42% of them incorporated ESG factors into the investment decision-making. The corresponding figure in 2012 was 22%. The implementation of ESG is often done by either avoiding certain categories categorically (such as Tobacco (27%), Weapons (16%), Fossil Fuel (11%), Gambling (11%)), or embracing certain industries (such as Local Economic Benefit (22%), Clean Tech (14%), Environment (11%), etc.). Norges Bank, as an illustration, decides on the exclusion of companies from the fund's investment universe, or to place companies on an observation list. In 2020, out of 167 excluded companies, 76 % of them were either involved in production of coal or coal-based energy, caused severe environmental damage, or emitted unacceptable amounts of green-house gasses (https://www.nbim.no/en/the-fund/responsible-investment/exclusion-of-companies/).

might be willing to pay a premium for these, or firms might collect a monopolistic rent on production if it were a salient product differentiation attribute. Moreover, if talented workers preferred companies following ESG principles, it could also be a mechanism to attract higher quality factors of production (such as human capital), or pay less for these factors. In these ways, good ESG behavior might be a source of comparative advantage that – if the market didn't fully impound – could result in favorable future return dynamics.

The clearest counterargument to these positive arguments is that the constrained portfolio maximization run by ESG-constrained fund managers is dominated by the unconstrained maximization run by other managers, resulting in likely underperformance in the risk-return space.

The academic evidence on the realized performance of ESG-focused funds is decidedly mixed (Eccles, Ioannous, and Serefaim (2014), Krüger (2015), Dimson and Karakas, and Li (2015), Khan, Serafaim, and Yoon (2016), Ferrell, Liang and Renneboog (2016), among others). Moreover, there is limited systematic evidence that firms receiving disproportional amounts of capital from ESG funds have outperformed in any measurable way. Given this, our understanding of whether ESG investment flows impact innovation which can help us solve environmental problems is incomplete.

In this paper, we aim to address this gap in the literature by being the first paper to systematically investigate *who* produces green patents, the most influential of these green patent producers, and whether the capital of investors who desire to allocate capital toward ESG objectives actually do end up investing in these producers. As a starting point, as ESG capital investment flows have been rising in the past decades, there has been a concurrent sharp increase in green innovation and patent production, as shown in

Figure 1.

We show that the majority of this recent green patenting is not driven by highly rated ESG firms, firms that are commonly favored by ESG funds, but instead by firms that are explicitly excluded from ESG funds investment universe. We use two large datasets that capture the complete universe of patents from 2008 through 2017 in order to identify the universe of green patenting activity.[3] Moreover, for much of our analysis on firm characteristics of patenting entities, we concentrate on publicly traded firms, due to there being rich, publicly available measures of firm characteristics, external activities, income, profitability, and patent holdings.

Specifically, we show that the energy sector has a large and growing percentage of their entirety of patenting activity dedicated to green research. Moreover, the incremental green patent is significantly more likely to come from energy firms than any other type of firm, in particular highly rated ESG firms that are producers of green patents. In addition, the green patents of energy producing firms are significantly higher quality, in terms of being more highly cited. Energy producing firms are also significantly more likely to produce "blockbuster" green patents than other firms. Yet, these energy firms are explicitly excluded from many ESG funds, and the targets of many divestiture campaigns whose stated aims often include push forward green energy innovation.[4] On the intensive margin, energy firms even get less "credit" in terms of incremental ESG score increase for each (higher quality) green patent they produce.

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[3] While our patent data exists back to 1980, our ESG ranking data only begin in 2008, which is why we begin our main testing sample then. However, for every test that does not rely on the ESG data, the sample is from 1980 to 2017. Our overall institutional ownership data goes back to 2005, and hence for every test that rely on institutional ownership, the sample is from 2005-2017.

[4] For instance, see https://divested.betterfutureproject.org/ and https://gofossilfree.org/divestment/what-is-fossil-fuel-divestment/, both of which include many large signatories globally.

The remainder of the paper proceeds as follows. Section II provides background for our study, while Section III describes the data we collect on patents and ESG metrics in order to run our analyses. Section IV presents our main results on green patenting, including the most frequent patenting entities, the quality of this patenting, and the reward the market seemingly places upon it, Section V concludes.

II. Background

In addition to the above-mentioned studies, recent empirical work investigating the implications of socially responsible investing on firms include Teoh et al. (1999), Hong and Kacperczyk (2009), Geczy et al. (2005), among others. Teoh et al. (1999) studies the effects of the South African boycott to end apartheid and shows the boycott had no discernible effect on the valuation of firms with ties to South Africa. Similarly, a New York Times (2014) article notes that Stanford's divestment from coal stocks had little effect on stock prices. Geczy et al. (2005) and Hong and Kacperczyk (2009) study the characteristics of stocks that are not usually favored by socially responsible investing and show that these stocks tend to have lower price-to-book ratios, less institutional ownership, and less analyst coverage.

Earlier studies on the theory of impact investing argue that firms that are excluded by socially responsible investors end up facing with higher costs of capital, suggesting clean projects need to clear a higher hurdle rate to be financed (Heinkel et al. 2001). Unlike Heinkel et al. (2001) which puts emphasis on the negative effects of screening by the socially responsible funds, Oehmke and Opp (2020) focus on the conditions under which socially responsible investors provide additional financing for clean technology relative to what profit-maximizing investors would be willing to provide. In that sense, Oehmke and Opp (2020) highlight the positive aspects of impact investing by focusing on the ability of socially responsible investors to impact firms by relaxing financial constraints for clean production. Chowdry, Davies, and Waters (2019) provide a model in which profit- and social- impact motivated investors provide financing for projects that produce both corporate profits and social good. They show that when a firm that cannot commit to pursuing social goals, impact investors should hold financial claims in the firm to incentivize profit-motivated owners to pursue social goals. Moreover, Hart and Zingales (2017) argue companies should consider maximize shareholder welfare, including environmental concerns, not just financial value, and explicitly calls for active fund engagement rather than divestment.[5]

The equilibrium asset pricing implications of divestment have been subject of Davies and Van Wesep (2018), and Pastor, Stambaugh, and Taylor (2019). Davies and Van Wesep (2018) study divestment campaigns which aim to depress share prices to induce managers to change firm behavior. They make the case that divestment campaigns are likely to be ineffective and may be counterproductive simply because managerial compensation contracts reward long-run profitability and stock returns, rather than short term prices. Pastor, Stambaugh, and Taylor (2019) propose a general equilibrium pricing model incorporating ESG investment preferences. In their model, ESG firms have negative CAPM alphas, the extent to which depend on preference heterogeneity and strength of ESG sensitivity in preferences.

[5] This has also generated considerable attention in the popular press. See for instance, Andrew Edgecliffe-Johnson and Billy Nauman, "Fossil fuel divestment has 'zero' climate impact, says Bill Gates" Financial Times, 9/17/2019; William MacAskill, "Does divestment work?", New Yorker, October 20 2015.

III. Data

Our analysis relies on two main streams of data: (1) Patent Citation and Patent Assignment databases, and (2) Environmental Score data from Sustainalytics ESG Ratings database. We collect data on all patents granted in the United States from the Patent Citation and Patent Assignment database for the years from 1980 through 2017.[6] We focus on publicly traded firms, for which there are rich, publicly available measures of firm characteristics, external activities, income, profitability, and patent holdings. We assign patents to Compustat firms by matching patents' assignee names with Compustat company names. In order to do this, we use a combination of natural language processing (NLP) techniques to implement exact and fuzzy matching, and then augment with hand matching (and checking).

We then further classify each patent into a technology class (essentially, the industry to which the patent applies) and also whether the patent has the potential to contribute to environmental problems, which we call "green patents" following the guidelines the Organization for Economic Co-operation and Development (OECD) created for the same purpose.[7] According to this classification, patents that are related to environmental technologies are classified into various broad environmental technology categories including environmental management, water related adaptation technologies, biodiversity protection and ecosystem health, climate change mitigation technologies related to energy

[6] https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-assignment-dataset

[7] USPTO technology classes:
https://www.uspto.gov/web/offices/ac/ido/oeip/taf/tecstc/classes_clstc_gd.htm.

generation, and waste-water treatment or waste management.[8] Hascic, and Migotto (2015) provide a detailed explanation of OECD's algorithm that identify patents that contain environment-related technologies related to environmental pollution, water scarcity, climate change mitigation.[9]

Additionally, we use Sustainalytics' Environmental, Social, and Governance (ESG) Ratings Database to measure a given firm's engagement in environmental issues. Sustainalytics' database aims to contain information on how well companies proactively manage the environmental, social, and governance issues that are the most material to their respective business. More specifically, Sustainalytics evaluates firms based on three categories: (a) Preparedness, (b) Disclosure, and (c) Performance. Preparedness refers to company management systems and policies designed to manage material environmental risks. Disclosure refers to whether the company meets international best practice-standards and is transparent with respect to the most material ESG issues. Finally, Performance refers to company environmental performance based on quantitative metrics such as carbon intensity and based on the analysis of controversial incidents in which the company may have been involved.

[8] https://www.oecd.org/environment/consumption-innovation/ENV-tech%20search%20strategies,%20version%20for%20OECDstat%20(2016).pdf

[9] https://www.oecd-ilibrary.org/environment/measuring-environmental-innovation-using-patent-data_5js009kf48xw-en

IV. Main Results on Green Patenting

a. *Top Green Patenting Firms and the Time Series of Green Patenting*

We begin our analysis by examining the top green patent holding firms as of 2017. This is shown in Table 1. Table 1 shows a number of initial interesting patterns. From Panel A, out of top 50 green patent producers, for instance, 14% of them are energy firms, which are *explicitly excluded* by many ESG favored funds, and a main segment of the firms focused-upon by divestiture campaigns. These firms are Exxon Mobil, Honeywell International, Royal Dutch Shell, BP, Conoco Phillips, Chevron, and US Oil. These seven firms collectively produced 6,969 green innovation patents. This can also be seen in Panel B, in which the Energy Sector has the second most green patents amongst the sector-classifiable green patents.

-- Insert Table 1 here --

In Table 2, we tabulate the number of granted patents that we use in our tests – both green and non-green - for public firms. Our final sample, containing all firms from 1980 to 2017 that produce at least one patent is 11,397 public firms. These firms produce 2,077,832 patents, of which we flag 5.61% as green patents. In looking at the time series, the percentage of green patents peaks in number and percentage in the last year of the sample, with 5,251 patents produced (6.32% of all patents produced by publicly traded firms in 2017).

-- Insert Table 2 here --

b. *Green Patenting at the Industry Level*

We next move on to our main regression analyses in order to explore the above patterns in a more formal setting where we can control for numerous determinants of R&D and patenting. In particular, we explore the role that the energy sector is playing in the landscape of green innovation vis-à-vis other firms undertaking R&D programs and patenting in the same space. We begin by examining green patenting at the industry level.

Turning to this industry-level analysis, we first explore whether green patent production in the energy sector differs from that of green patent production in other industries. To perform the analysis, we estimate the following OLS fixed-effects model:

$$\textit{Green Patent Ratio}_{it} = b0 + b1 \text{ x } \textit{Energy Sector}_{it} + \textit{Year Fixed Effects} \qquad (1)$$

The unit of observation in this analysis is industry-year, where we define an industry with its 2-digit SIC code. In this analysis, reported in Table 3, we only include industries if at least one firm produced one green patent in a particular year, ensuring that we compare only industries that engage actively in green patent production. Our sample spans from 1980 to 2017 and we have roughly 56 industries per year on average. *Energy Sector* is a dummy variable if the first two digits of its Standard Industrial Classification (SIC) is 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), or 49 (Electric, Gas, & Sanitary Services). Out of 2,143 industry-year observations, 197 observations belong to the energy sector.

-- Insert Table 3 here --

Our main dependent variable of interest is the *Green Patent Ratio*. We compute this ratio simply by dividing the number of granted green patents in a given industry by the total number of granted patents in that industry in that particular year. This measure is meant to capture the relative importance of green innovation in that industry (vs. all other innovation), through this green share. In this sample, 8.30 % of the patents are green patents. We find that the coefficient of the *Energy Sector Dummy* is 13.95% (t = 15.28). This implies that the energy sector has nearly three times the relative focus on green innovation in their innovation portfolio as the average industry, at 22.25%. Moreover, at the sector-wide level, the energy sector appears to have a sizable percentage of its innovation efforts going toward green research – with nearly a quarter of its patent innovation in this space. From Table 3, our conclusions remain similar when we control for several important factors that could potentially contribute to the industry level green patent production. These factors include average industry level investment, R&D spending level, average firm age in the industry, average firm size in the industry, average firm cash level, and average industry book leverage. Moreover, nearly all of these on their own are not significantly related to the *Green Patent Ratio* on their own. This is to say that it is not industries that on average have higher overall investment, specifically higher R&D investment industries, industries with older firms, larger firms, or firms with more cash reserves that focus disproportionately on green innovation. The only industry-level variable that appears related is average book leverage, with industries focusing on green patenting being slightly more highly levered on average.

One might worry that the patenting we are measuring in Table 3 has to do broader green patenting outside of specific climate-mitigation technology with respect to energy sources. This might be especially true if energy firms were attempting to strategically appear engaged in green patenting, but not wanting to materially impact the fossil-fuel components of their businesses. In order to explore this, we subset our green patent universe to examine solely those green patents in the universe that directly address "*Climate change mitigation technologies related to energy generation, transmission, or distribution.*"

The results of the analysis are reported in Appendix Table A1. Specifically, in Appendix Table A1 we run an identical regression to Table 3, but focusing solely on these alternative energy patents. From Appendix Table A1, the *Energy Sector* appears to have a significantly larger percentage of its innovation efforts going specifically toward alternative energy innovation relative to all other industries. Specifically, the coefficient in Column 3 of 0.0221 (t=5.022) implies that the energy sector has, similar to Table 3, an almost three times larger focus specifically on climate change mitigation technology innovation relative to all other industries.

c. Which Environmental Score firms are Green Patenting?

We now turn our focus to the link between incremental green patent production and environmental metrics many investors focus on to allocate their capital in this space. We begin by asking the simple question of whether firms with better *Environmental Scores* contribute more to green patent production in general; i.e., we ask if the incremental green patent is more likely to come from better or worse scored ESG firms. Relatedly, we also examine whether the incremental green patent is more likely to come from companies in the energy sector to check whether the Table 3's industry-level analysis - which suggested energy industries dedicate a significantly larger percentage of their patenting activity to green research - is also echoed at a more granular, firm-level. We conduct this analysis using the patent level data and use the following linear probability models:

$$Green\ Patent\ Dummy_{i} = b0 + b1\ x\ Environmental\ Score_{it} + Year\ Fixed\ Effects \quad (2)$$

and

$$Green\ Patent\ Dummy_{i} = b0 + b1\ x\ Energy\ Sector_{it} + Year\ Fixed\ Effects \quad (3)$$

Our initial findings, summarized in Table 4, demonstrate two strong patterns. First, the coefficient of *Environmental Score* in Column 1 is negative, indicating that the incremental green patent is more likely to come from more poorly scored ESG firms. More specifically, the negative coefficient of *Environmental Score* (-0.011, t =3.704). In particular, the -0.0011 coefficient implies that a firm which has a one standard deviation higher *Environmental Score* (13.807) is 24% *less* likely to green patent (1.52% less likely from a mean of 6.38%). In Column 2, we then explore to what extent this might be driven by the relation from Table 3 – that energy firms have both significantly lower *Environmental Scores*, but also are large and important producers of green patents.

-- Insert Table 4 here --

Column 2 of Table 4 suggests that the incremental green patent is more likely to come from firms in the energy sector. More specifically, the positive coefficient on *Energy Sector* of 0.1364 (t = 5.50) implies that green patents are over three times more likely to be produced by energy firms than by firms in other industries (20.02% vs. 6.38%).

Lastly, one might argue that given that we know energy firms are active in green patenting, perhaps this is simply a mechanical relationship – and would hold with any industry we know is active in the green patenting space. In order to test this thesis, we run the identical specification in Table 4, but instead include a categorical variable for whether the firm is from one of the Top 3 Industries in green patenting activity (excluding the Energy Sector):

Green Patent Dummy $_{i}$ *= b0 + b1 x Top 3 Sectors (outside of Energy)*$_{it}$ *+ Year Fixed Effects* (4)

The results are shown in Column 3 of Table 4. In sharp contrast to the *Energy Sector*, the coefficient on other active sectors is negative and highly significant. This suggests that these industries, while active in green patenting, are even more active in patenting in *other* types of technologies. Thus, these industries are simply higher frequency patentors across all technologies, and in fact appear to actually proportionately concentrate on activities outside of green innovation. Again, this is the opposite of the relative concentration in this activity for energy firms.

These results collectively reinforce those from Table 3, suggesting that the incremental green patent is significantly more likely to come from energy firms than other green patentors.

d. Who gets Rewarded for Green Patenting?

In this section, we turn out focus to the determinants of ESG scores. Specifically, we ask whether the widely used environmental metrics reflect the green patent production of firms. Put differently, the evidence thus far suggests that: i.) the energy sector firms (which have lower ESG scores, along with being explicitly restricted by many ESG-focused vehicles and campaigns) appear to be large players in the universe of the entirety of green patenting; and ii.) that firms with higher environmental scoring seem to produce fewer green patents, on average. Given these two facts, we next ask whether energy firms are driving the negative relationship in general between ESG scores and green patents we document in Table 4; and relatedly, whether energy firms get less "credit" in terms of incremental ESG scores for each green patent they produce.

To examine these questions, we estimate the following OLS model,

$$
\begin{aligned}
\textit{Environmental Score}_{it} = \; & b0 + b1 \text{ x } \textit{Energy Sector}_{i} \\
& + b2 \text{ x } \textit{Green Effort}_{it} \\
& + b3 \text{ x } (\textit{Energy Sector} \text{ x } \textit{Green Effort}_{it}) \\
& + b4 \text{ x } \textit{Firm Size}_{it} \\
& + \textit{Year Fixed Effects}_{t} \qquad (4)
\end{aligned}
$$

In this analysis, we work with firm level data as public firm disclosures allow us to measure several research inputs, such as research and development expenses, at the firm level. The data also allow us to control for important firm characteristics potentially related to green patent production. For instance, if the energy sector were dominated by large firms and green patents require a certain minimum-scale, we could be attributing the higher green patent production result documented in Tables 3 and 4 to being involved in energy, when in fact firm size is driving the results. We include firm size in this last specification to explicitly control for such factors contaminating our results.

-- Insert Table 5 here --

Our main variable of interest in Table 5 is *Green Effort*, which measures a firm's effort to produce green patents. We use three metrics for this purpose: (1) number of green patents granted in a given year, (2) number of green patent applications in a given year, and (3) number of citations per green patent, in that particular year. With the first two metrics, number of patent applications and patents granted, we seek to capture the green patent production activity at different points of the patenting process. The last metric, number of citations per green patent, proxies for some measure of green patent quality produced. For all the measures, to look at their relative percentage differences across firms and years, we take the log of one plus the metrics (1)-(3).

From Table 5, a number of empirical patterns emerge. First, once *Energy Sector* firms are stripped out, for all other firms there is a positive relationship between *Environmental Score* and green effort metrics. For instance, the coefficient of number of green patents granted from Column 1 suggests that a firm with one-standard deviation higher green patenting receives a 2.10 point higher *Environmental Score* ($t = 2.026$). This same positive and significant relationship with *Environmental Score* holds across the other measures of green effort for firms outside of the *Energy Sector*: number of green patents applied for and number of citations per green patent.

Second, that the energy sector seems to be an exception to this general positive reward that is given for green patenting efforts by firms. In particular, both the main effect coefficient on a firm being in the *Energy Sector* is negative, along with the interaction term, *Energy Sector x Green Effort*, being negative across specifications. While marginally statistically significant, the coefficients imply large economic magnitudes across each of the respective *Green Effort* metrics. For instance, the results in Column 1 suggest that an energy firm with a one-standard deviation larger amount of green patents granted in a given year compared to average firm in the sample, is associated with -5.26 (t = 1.926) lower *Environmental Score*. Compared to the mean Environmental Score of 56, this magnitude corresponds to a roughly 10% lower score. Put differently, energy firms get less credit in terms of incremental ESG scores for each green patent they are granted, apply for, or even citation per green patent awarded.

Panel B of Table 5 performs the identical analysis as Panel A, but again with the placebo grouping of other frequent green patenting sectors. In sharp contrast to energy sector firms, other top green patenting firms both have significantly higher ESG scores on average, and are rewarded more for green patenting activity, than the average firm. Thus, it appears again to be a special characteristic of energy firms with regard to the association of their green patenting vs. all other firms (even other frequent green patentors).

e. Quality of Green Innovation

One explanation that could potentially explain the results in Tables 3-5 is that energy producing firms simply produce lower quality (or less meaningful) innovation within the green innovation space. If this were true, we might expect to see exactly what is observed – that while the energy sector produces a large quantity of green patents (in number), the value of these patents are low, and thus *Environmental Scores* appropriately take this into account by not rewarding for this relatively low-quality innovation.

In Table 6 we test this by investigating the quality of green innovation by the energy sector vs. other green innovation. For this purpose, we define two variables. Our first metric is the number of citations the green patents of a firm receives. The second one is a dummy variable that takes a value of one if the percentage of green patent citations is above the 95^{th} percentile of all green patents for that year (which we term *Blockbuster Patent*). Results presented in Table 6 show that energy firms do not appear to produce green patents of lower quality. In fact, the opposite appears to be true. Green patents produced by the energy sector are significantly more highly cited than the average green patent, and are significantly more likely to be *Blockbuster Patents*. The coefficient in Column 3 of Panel A on *Energy sector* suggests that the green patents of energy firms have 9.14% (t = 4.281) more citations on average than other green patents. Relatedly, Column 3 of Panel B suggests that energy firms are 12.36% (t = 4.898) more likely to produce a blockbuster green patent.

In Panels C and D we test this same alternative for other industries that produce large amounts of green patents. Again, these industries appear to be producing different kinds of green patents. For these other industries, even though they are large producers of green patents, the green patents seem to be of significantly lower quality on average (Panel C). Moreover, they are also significantly less likely to be blockbuster green patents (Panel D).

Stepping back, the results of Tables 3-6 then suggest that energy producers in our sample appear to produce more, and significantly higher quality, green innovation. Further, this is not a function of them being simply producers of a large share of green patents, as other aggregate large share producers of green patents exhibit quite different empirical dynamics.

-- Insert Table 6 here --

f. *Fund Flow Analysis*

In our final analysis, we investigate whether energy firms – who empirically appear to be large producers of high quality green innovation in relative terms - are getting disproportionally more (or less) capital from ESG funds. For this purpose, we conduct two tests. First, we investigate whether green funds are investing less in energy firms in comparison to other funds. In other words, after conditioning on a firm being in the energy sector, do we observe ESG funds invest *less* in energy than other types of (otherwise equivalent) funds. Secondly, we ask whether energy firms constitute a lower weight of the portfolio of ESG funds compared to their other investments; i.e. if we solely focus on ESG or green funds, do we observe a less weight is given to firms that operate in energy sector.

To conduct these two tests, we need to identify the funds that are likely to be considered as "green funds," or "ESG funds," by investors. We identify these green funds using two methods. First, we look at the fund names. We label a fund as a green fund if its name contains "ESG" or "green". We manually go through this list and eliminate names that are likely to give us a type 2 errors, i.e. we do not call "Evergreen Money Market Fund" as a green fund. Second, we look at the lists that are publicized by two well-known market participants in this space - The Forum for Sustainable and Responsible Investment (USSIF) and Charles Schwab.

Table 7 contains our analysis. From Table 7, the answers to the questions posed above appear to be "yes" in both instances. Specifically, across Panel A of Table 7, the coefficients on *Green Fund* indicate that controlling for other determinants of holding, energy firms are: i.) significantly less likely to be held at all; ii.) are held in significantly smaller amounts; and iii.) are held in significantly smaller weights relative to their index-weight; by *Green Funds* vs. all other funds. Each of these effects are large in magnitude (25% to 100% differences), and highly statistically significant.

Panel B then shows that the exact opposite is true of other highly active green patenting firms outside of the energy sector. Finally, Panel C shows that from the perspective of conditioning on a *Green Fund*, and reinforces these findings: controlling for other firm-level determinants of holdings, *Green Funds* significantly underweight energy sector firms, and overweight other green patenting firms.

Stepping back, Table 7 shows a real, capital markets flow implication of being an energy firm in terms of investment underweighting (and avoidance) by *Green Funds*. This is despite the evidence in Tables 3-6 regarding their extensive role in green patenting, and the relative quality of this green patenting activity.

-- Insert Table 7 here --

V. Conclusion

We find consistent and robust markers that the quantity and quality of green patenting is higher for energy firms. Paradoxically, these firms are precisely those to which capital is often restricted by mandates and campaigns whose directive is to solve the important problems linked to green innovation. Our analysis thus suggests there is a, perhaps surprisingly, negative relationship between the generators of innovation that can help us confront environmental challenges and where capital is being directed. That said, there is still work to be done as to whether capital allocation indeed follows the ESG scores, and to what extent this ESG score-motivated investment can be calibrated to achieve better capital allocation by the investors.

Stepping back, we believe investigation of these issues will provide critical insight into the shifting landscape of innovation, allowing us to capture and assess the full welfare impact of ESG capital on the economy. Moreover, our findings raise important questions as to whether the current exclusions of many ESG-focused policies – along with the increasing incidence of explicit divestiture campaigns - are optimal, or whether reward-based incentives would lead to more efficient innovative outcomes.

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Table 1: Companies and Industry Sectors with the Most Green Patents.

Panel A shows the list of top 50 public companies by green patent holders in 2017. Panel B shows the number of green patents held by industry sectors in 2017. A firm is in the Energy Sector when its two digit Standard Industrial Classification (SIC) is 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), or 49 (Electric, Gas, & Sanitary Services). Green patents are patents that are in environment-related technologies. We identify green patents using OECD's IPC classification, i.e. green patents are the ones that contain one of the following environmental technologies: environmental management, water-related adaptation technologies, biodiversity protection and ecosystem health, climate change mitigation technologies related to energy generation, transmission or distribution, transportation, buildings, waste-water treatment or waste management, and production or processing of goods. Green patent classification is constructed and developed by the European Patent Office using algorithm by the OECD.[10]

[10] A more detailed description of green patent classification can be found on OECD's website: https://www.oecd.org/env/indicators-modelling-outlooks/green-patents.htm

Panel A

Company Name	Total green patents	Rank
GENERAL ELECTRIC CO	7,520	1
HONDA MOTOR CO LTD	4,685	2
PANASONIC CORP	4,576	3
HITACHI LTD	3,921	4
FORD MOTOR CO	2,633	5
DUPONT DE NEMOURS INC	2,617	6
UNITED TECHNOLOGIES CORP	2,302	7
GENERAL MOTORS CO	2,118	8
NISSAN MOTOR CO LTD	2,084	9
CATERPILLAR INC	1,712	10
EXXON MOBIL CORP	**1,670**	**11**
SONY CORP	1,640	12
HONEYWELL INTERNATIONAL INC	**1,631**	**13**
SIEMENS AG	1,486	14
INTL BUSINESS MACHINES CORP	1,469	15
SANYO ELECTRIC CO LTD	1,315	16
VIACOMCBS INC	1,240	17
ROYAL DUTCH SHELL PLC	**1,199**	**18**
DAIMLER AG	1,038	19
PARKER-HANNIFIN CORP	990	20
CANON INC	974	21
KONINKLIJKE PHILIPS NV	903	22
AIR PRODUCTS & CHEMICALS INC	863	23
CUMMINS INC	804	24
BOEING CO	743	25
MOTOROLA SOLUTIONS INC	712	26
BP PLC	**631**	**27**
CONOCOPHILLIPS	**629**	**28**
IONIS PHARMACEUTICALS INC	621	29
CHEVRON CORP	**614**	**30**
BASF SE	604	31
US OIL CO	**595**	**32**
DELPHI TECHNOLOGIES PLC	585	33
NEC CORP	549	34
APPLIED INDUSTRIAL TECH INC	548	35
PFIZER INC	546	36
APTIV PLC	542	37
BAYER AG	527	38
FUJIFILM HLDGS CORP	418	39
INTEL CORP	417	40
CHRYSLER CORP	401	41
MICRON TECHNOLOGY INC	398	42
LOCKHEED MARTIN CORP	395	43
LINDE PLC	392	44
EASTMAN KODAK CO	364	45
APPLIED MATERIALS INC	359	46
ROCKWELL AUTOMATION	355	47
LG DISPLAY CO LTD	346	48
DEERE & CO	337	49
VERIZON COMMUNICATIONS INC	336	50

Panel B

Industry Sectors	Total Green Patents
Manufacturing	83,172
Energy and Mining	8,838
Services	4,551
Transportation & Public Utilities	2,473
Finance, Insurance, & Real Estate	1,519
Agriculture, Forestry, & Fishing	1,231
Wholesale Trade	464
Construction	463
Retail Trade	217

Table 2. Green and Non-green Patents by Year.

This table shows the total number of green and non-green patents granted to public firms by year. Green patents are patents that are in environment-related technologies. We identify green patents using OECD's IPC classification, i.e. green patents are the ones that contain one of the following environmental technologies: environmental management, water-related adaptation technologies, biodiversity protection and ecosystem health, climate change mitigation technologies related to energy generation, transmission or distribution, transportation, buildings, waste-water treatment or waste management, and production or processing of goods. Green patent classification is constructed and developed by the European Patent Office using algorithm by the OECD.

Year	Green Patents	Non-Green Patents	Total Granted Patents
1980	288	4,496	4,784
1981	975	13,257	14,232
1982	1,323	17,033	18,356
1983	1,724	21,613	23,337
1984	1,958	25,940	27,898
1985	1,878	27,532	29,410
1986	1,646	27,036	28,682
1987	1,900	30,747	32,647
1988	1,813	28,129	29,942
1989	1,936	33,071	35,007
1990	1,809	30,084	31,893
1991	1,837	32,364	34,201
1992	2,085	33,210	35,295
1993	2,130	34,156	36,286
1994	2,306	35,637	37,943
1995	2,204	35,205	37,409
1996	2,448	37,850	40,298
1997	2,565	38,293	40,858
1998	3,133	53,121	56,254
1999	3,338	58,124	61,462
2000	3,523	62,289	65,812
2001	4,041	66,924	70,965
2002	4,269	67,920	72,189
2003	4,261	70,240	74,501
2004	3,983	69,268	73,251
2005	4,067	66,453	70,520
2006	4,701	80,709	85,410
2007	4,224	72,295	76,519
2008	3,942	72,418	76,360
2009	4,024	76,956	80,980
2010	5,050	93,215	98,265
2011	3,446	67,938	71,384
2012	3,847	74,659	78,506
2013	3,907	79,469	83,376
2014	4,536	84,938	89,474
2015	5,119	81,165	86,284
2016	5,066	79,751	84,817
2017	5,251	77,774	83,025
	116,553	1,961,279	2,077,832

Table 3: Green Patent Production and Energy Sector.

This table reports the results of OLS regressions where the dependent variable is the Industry Green Patent Ratio, which is the percentage of green patents granted in a given industry, defined by 2-digit SIC code, in that particular year. Energy Sector is a dummy variable if the first two digit of Standard Industrial Classification (SIC) is 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), or 49 (Electric, Gas, & Sanitary Services). We identify green patents using OECD's IPC classification, i.e. green patents are the ones that contain one of the following environmental technologies: environmental management, water-related adaptation technologies, biodiversity protection and ecosystem health, climate change mitigation technologies related to energy generation, transmission or distribution, transportation, buildings, waste-water treatment or waste management, and production or processing of goods. Unit of observation is industry (2-digit SIC code) and year. The sample covers 1980 to 2017. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by year.

	(1)	(2)	(3)
	Industry Green Patent Ratio		
Energy Sector	0.1337***	0.1349***	0.1395***
	(14.392)	(14.225)	(15.283)
Average Industry Investment		-0.0013	-0.0164
		(-0.083)	(-1.116)
Average Industry R&D Investment		0.0126	0.0186
		(0.514)	(0.745)
Average Industry Log Firm Age		-0.0164	-0.0153
		(-1.625)	(-1.445)
Average Industry Log MVE		0.0021	0.0019
		(0.840)	(0.774)
Average Industry Cash			0.0001
			(0.271)
Average Industry Book Leverage			0.0021**
			(2.361)
Observations	2,143	2,105	2,059
R-squared	0.094	0.097	0.102
Year FE	YES	YES	YES

Table 4. Green Patent Production, Environmental Score and Energy Sector – Patent level analysis. This table reports the results of OLS regressions where the dependent variable is a dummy variable that takes a value of one if the granted patent is a green patent, as defined in the description of Table 1. The independent variable is Environmental Score (out of 100) which shows how well companies proactively manage the environmental issues that are the most material to their business. Energy Sector is a dummy variable that equals to one if the first two digit of Standard Industrial Classification (SIC) is 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), or 49 (Electric, Gas, & Sanitary Services). *Top 3 Sector (outside of Energy)* is a dummy variable that equals to one if the sector is among the top 3 sectors in terms of green patent production, excluding the Energy Sector: Manufacturing, Services, and Transportation & Public Utilities. The sample period is from 2008 to 2018. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by year. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by year.

	(1)	(2)	(3)
VARIABLES	Green Patent	Green Patent	Green Patent
Environmental Score	-0.0011***		
	(-3.704)		
Energy Sector		0.1364***	
		(5.498)	
Top 3 Sectors (outside of Energy)			-0.1620***
			(-13.764)
Observations	217,083	199,557	199,557
R-squared	0.006	0.007	0.053
Year FE	YES	YES	YES

Table 5. Environmental Score and Green Effort – Firm level analysis.

This table reports the results of OLS regressions where the dependent variable is the Environmental Score (out of 100). We identify green patents using OECD's IPC classification, i.e. green patents are the ones that contain one of the following environmental technologies: environmental management, water-related adaptation technologies, biodiversity protection and ecosystem health, climate change mitigation technologies related to energy generation, transmission or distribution, transportation, buildings, waste-water treatment or waste management, and production or processing of goods. Energy Sector is a dummy variable that equals to one if the first two digit of Standard Industrial Classification (SIC) is 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), or 49 (Electric, Gas, & Sanitary Services). *Top 3 Sectors (outside of Energy)* is a dummy variable that equals to one if the sector is among the top 3 sectors in terms of green patent production, excluding the Energy Sector: Manufacturing, Services, and Transportation & Public Utilities. The sample period is from 2008 to 2018. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by year.

Panel A. Environmental Score and Energy Sector

	(1)	(2)	(3)
VARIABLES		Environment Score	
Energy Sector	-3.1051*	-2.9417	-3.9103**
	(-1.682)	(-1.625)	(-2.134)
Number of Green Patents Granted	1.0720**		
	(2.026)		
Energy Sector x Number of Green Patents Granted	-3.0077*		
	(-1.926)		
Number of Green Patents Appl.		1.7659***	
		(3.037)	
Energy Sector x Number of Green Patents Appl.		-3.3171*	
		(-1.774)	
Number of Cite per Green Patent			0.7814***
			(2.710)
Energy Sector x Number of Cite per Green Patent			-0.6674
			(-1.235)
Log MVE	1.9351***	1.8274***	1.9102***
	(4.862)	(4.668)	(4.935)
Log Age	2.6707***	2.7095***	2.6964***
	(3.745)	(3.838)	(3.770)
Cash	-0.7874	-0.7494	-0.7431
	(-0.531)	(-0.513)	(-0.503)
Book Leverage	-1.8511	-1.7258	-1.7458
	(-0.758)	(-0.731)	(-0.726)
Investment	-4.2532	-4.9355	-4.5034
	(-0.301)	(-0.351)	(-0.319)
Observations	2,332	2,332	2,332
R-squared	0.172	0.179	0.173
Year FE	YES	YES	YES

Panel B. Environmental Score and Top 3 Sectors *(outside of Energy)*

VARIABLES	(1)	(2)	(3)
		Environment Score	
Top 3 Sectors (outside of Energy)	2.9442**	2.7686*	3.2243**
	(1.977)	(1.887)	(2.117)
Number of Green Patents Granted	-0.9585		
	(-1.169)		
Top 3 Sectors (outside of Energy) x Number of Green Patents Granted	2.3771**		
	(2.507)		
Number of Green Patents Appl.		-0.3154	
		(-0.338)	
Top 3 Sectors (outside of Energy) x Number of Green Patents Appl.		2.3969**	
		(2.235)	
Number of Cite per Green Patent			-0.1836
			(-0.388)
Top 3 Sectors (outside of Energy) x Number of Cite per Green Patent			0.9289*
			(1.691)
Log MVE	2.0458***	1.9303***	2.0426***
	(5.075)	(4.820)	(5.199)
Log Age	2.6363***	2.7119***	2.6397***
	(3.724)	(3.852)	(3.721)
Cash	-0.8538	-0.7585	-0.9080
	(-0.583)	(-0.523)	(-0.623)
Book Leverage	-1.7496	-1.5649	-1.9131
	(-0.720)	(-0.668)	(-0.794)
Investment	-11.4386	-12.1102	-10.5919
	(-0.909)	(-0.964)	(-0.847)
Observations	2,332	2,332	2,332
R-squared	0.182	0.186	0.179
Year FE	YES	YES	YES

Table 6. Green Patent Citations and Energy Sector.

This table reports the results of OLS regressions where the dependent variable in Panel A is the log of green patent citations normalized by all patent citations by a firm, and the dependent variable in Panel B is an indicator variable that equals to one if the percentage of green patent citation is the the top 95 percentile. We identify green patents using OECD's IPC classification, i.e. green patents are the ones that contain one of the following environmental technologies: environmental management, water-related adaptation technologies, biodiversity protection and ecosystem health, climate change mitigation technologies related to energy generation, transmission or distribution, transportation, buildings, waste-water treatment or waste management, and production or processing of goods. Energy Sector is a dummy variable that equals to one if the first two digit of Standard Industrial Classification (SIC) is 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), or 49 (Electric, Gas, & Sanitary Services). Top 3 Sectors (outside of Energy) is a dummy variable that equals to one if the sector is among the top 3 sectors in terms of green patent production, excluding the Energy Sector: Manufacturing, Services, and Transportation & Public Utilities. The sample covers 1980 to 2017. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by year.

Panel A. Green Patent Citations and Energy Sector

	(1)	(2)	(3)
		Log Green Patent Citations	
Energy Sector	0.0915***	0.0881***	0.0914***
	(4.410)	(4.159)	(4.281)
Investment		0.0551	0.0636
		(1.252)	(1.393)
R&D Investment		0.0007	0.0034
		(0.288)	(0.443)
Log Age			0.0036
			(1.527)
Log MVE			-0.0031***
			(-2.772)
Cash			-0.0007
			(-0.655)
Book Leverage			0.0080
			(0.602)
Observations	15,134	15,134	14,927
R-squared	0.010	0.010	0.012
Year FE	YES	YES	YES

Panel B. Blockbuster Green Patents and Energy Sector

	(1)	(2)	(3)
VARIABLES		Blockbuster Green Patents	
Energy Sector	0.1198***	0.1172***	0.1236***
	(4.871)	(4.681)	(4.898)
Investment		0.0464	0.0593
		(0.890)	(1.120)
R&D Investment		0.0029	0.0082
		(0.824)	(0.775)
Log Age			0.0017
			(0.582)
Log MVE			-0.0042***
			(-3.660)
Cash			-0.0016
			(-1.011)
Book Leverage			0.0046
			(0.375)
Observations	15,134	15,134	14,927
R-squared	0.013	0.014	0.016
Year FE	YES	YES	YES

Panel C. Green Patent Citations and Top 3 Sectors *(outside of Energy)*

	(1)	(2)	(3)
		Log Green Patent Citations	
Top 3 Sectors (outside of Energy)	-0.0318***	-0.0306***	-0.0345***
	(-3.068)	(-2.961)	(-3.209)
Investment		0.0992**	0.1087**
		(2.041)	(2.118)
R&D Investment		0.0003	0.0054
		(0.137)	(0.713)
Log Age			0.0047*
			(1.953)
Log MVE			-0.0029**
			(-2.486)
Cash			-0.0011
			(-0.959)
Book Leverage			0.0078
			(0.587)
Observations	15,134	15,134	14,927
R-squared	0.004	0.005	0.007
Year FE	YES	YES	YES

Panel D. Blockbuster Green Patents and Top 3 Sectors *(outside of Energy)*

	(1)	(2)	(3)
VARIABLES		Blockbuster Green Patents	
Top 3 Sectors (outside of Energy)	-0.0440***	-0.0428***	-0.0484***
	(-3.435)	(-3.367)	(-3.701)
Investment		0.1027*	0.1182*
		(1.780)	(1.954)
R&D Investment		0.0011	0.0088
		(0.324)	(0.814)
Log Age			0.0049
			(1.499)
Log MVE			-0.0041***
			(-3.145)
Cash			-0.0018
			(-1.095)
Book Leverage			0.0060
			(0.475)
Observations	15,134	15,134	14,927
R-squared	0.005	0.006	0.008
Year FE	YES	YES	YES

Table 7. Green Funds Investment in Energy Sector

Panel A reports OLS regression of fund ownership in a firm on whether the fund is a green fund, conditioning on a firm being in the Energy Sector. Panel B reports OlS regression of fund ownership in a firm on whether the firm is in the Energy Sector, conditioning on the fund being a green fund. A fund is considered green if is has "ESG" or "green" in its name, or is in in the list of USSIF (The Forum of Sustainable and Responsible Investment), or it is in the list of Charles Schwab's Green Funds. Energy Sector is a dummy variable that equals to one if the first two digit of Standard Industrial Classification (SIC) is 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), or 49 (Electric, Gas, & Sanitary Services). Top 3 Sectors is a dummy variable that equals to one if the industry is among the top 3 sectors in terms of green patent production, excluding the Energy Sector: Manufacturing, Services, and Transportation & Public Utilities. The sample covers 2005 to 2018.[11] All regressions include year-quarter fixed effects. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by fund x firm.

Panel A: Conditional on a firm being in the Energy Sector

	(1)	(2)	(3)
VARIABLES	%fund holding	I[%fund holding > 0]	I[%fund holding > %index]
Green Fund	-0.0706***	-0.0454***	-0.0131***
	(-9.250)	(-10.149)	(-3.973)
Log MVE	0.0947***	0.0372***	0.0103***
	(80.438)	(75.525)	(32.136)
Log Age	0.0238***	0.0071***	0.0027***
	(24.113)	(10.186)	(5.396)
Cash	0.0901***	0.0283***	0.0771***
	(6.345)	(3.857)	(14.169)
Book Leverage	-0.3754***	-0.0238***	0.0734***
	(-29.694)	(-3.995)	(17.241)
Investment	0.1016***	0.1083***	0.1236***
	(5.586)	(11.693)	(18.582)
Lag Return	0.0102***	0.0207***	0.0170***
	(5.132)	(17.746)	(17.622)
Observations	4,559,019	4,559,019	4,559,019
R-squared	0.050	0.031	0.006
Year-Quarter FE	YES	YES	YES

[11] Our patent data goes back to 1980, our ESG ranking data goes back to 2008, and our institutional ownership data goes back to 2005.

Panel B: Conditional on a firm being in the Top 3 Sectors (outside of Energy)

VARIABLES	(1) %fund holding	(2) I [%fund holding > 0]	(3) I [%fund holding > %index]
Green Fund	0.0282***	0.0219***	0.0321***
	(19.655)	(22.249)	(38.162)
Log MVE	0.0683***	0.0343***	0.0146***
	(238.610)	(264.053)	(165.541)
Log Age	-0.0034***	0.0039***	0.0012***
	(-16.931)	(24.814)	(10.259)
Cash	0.0787***	0.0428***	0.0314***
	(85.773)	(71.144)	(70.380)
Book Leverage	-0.0223***	-0.0020***	-0.0032***
	(-35.589)	(-4.366)	(-9.184)
Investment	0.0848***	0.0203***	-0.0043
	(15.236)	(5.523)	(-1.629)
Lag Return	0.0476***	0.0287***	0.0197***
	(144.284)	(136.294)	(111.318)
Observations	105,609,003	105,609,003	105,609,003
R-squared	0.036	0.021	0.008
Year-Quarter FE	YES	YES	YES

Panel C: Conditional on a fund being a Green fund

VARIABLES	(1) %fund holding	(2) I[%fund holding > 0]	(3) I[%fund holding > %index]	(4) %fund holding	(5) I[%fund holding > 0]	(6) I[%fund holding > %index]
Energy Sector	-0.0739***	-0.0600***	-0.0538***			
	(-9.549)	(-12.602)	(-14.672)			
Top 3 Sectors (outside of Energy)				0.0215***	0.0115***	0.0107***
				(7.093)	(5.469)	(6.106)
Log MVE	0.0755***	0.0286***	0.0159***	0.0747***	0.0278***	0.0151***
	(44.842)	(35.136)	(24.572)	(44.451)	(34.123)	(23.507)
Log Age	0.0059***	0.0123***	0.0096***	0.0042**	0.0113***	0.0087***
	(3.651)	(11.034)	(10.054)	(2.530)	(10.157)	(9.112)
Cash	0.0847***	0.0545***	0.0384***	0.0809***	0.0549***	0.0385***
	(12.118)	(12.163)	(10.112)	(11.291)	(11.950)	(9.856)
Book Leverage	-0.0335***	-0.0240***	-0.0209***	-0.0267***	-0.0187***	-0.0161***
	(-7.786)	(-8.154)	(-8.297)	(-6.280)	(-6.340)	(-6.405)
Investment	0.2578***	0.2447***	0.1821***	0.1878***	0.1737***	0.1197***
	(7.761)	(10.479)	(9.091)	(5.610)	(7.749)	(6.243)
Lag Return	0.0337***	0.0145***	0.0127***	0.0342***	0.0150***	0.0132***
	(15.086)	(10.128)	(9.883)	(15.245)	(10.444)	(10.190)
Observations	2,674,767	2,674,767	2,674,767	2,674,767	2,674,767	2,674,767
R-squared	0.037	0.017	0.008	0.037	0.016	0.007
Year-Quarter FE	YES	YES	YES	YES	YES	YES

Appendix Table A.1: Green Patent Production and Energy Sector – Looking only at patents that are "Climate change mitigation technologies related to energy generation, transmission or distribution".

This table reports the results of OLS regressions where the dependent variable is the Industry Green Patent Ratio, which is the percentage of green patents granted in a given industry, defined by 2-digit SIC code, in that particular year. Energy Sector is a dummy variable if the first two digit of Standard Industrial Classification (SIC) is 10 (Metal, Mining), 12 (Coal Mining), 13 (Oil & Gas Extraction), 14 (Nonmetallic Minerals, Except Fuels), 29 (Petroleum & Coal Products), or 49 (Electric, Gas, & Sanitary Services). We identify green patents using OECD's IPC classification, i.e. green patents climate change mitigation technologies related to energy generation, transmission or distribution. Unit of observation is industry (2-digit SIC code) and year. The sample covers 1980 to 2017. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by year.

	(1)	(2)	(3)
	Industry Green Patent Ratio		
Energy Sector	0.0227***	0.0214***	0.0221***
	(5.301)	(4.952)	(5.022)
Average Industry Investment		-0.0001***	0.0009
		(-16.286)	(1.643)
Average Industry R&D Investment		-0.0080*	-0.0083*
		(-1.822)	(-1.838)
Average Industry Log Firm Age		0.0014	0.0014
		(0.372)	(0.378)
Average Industry Log MVE		0.0019*	0.0018*
		(1.917)	(1.874)
Average Industry Cash			0.0002
			(1.537)
Average Industry Book Leverage			-0.0002*
			(-1.783)
Observations	2,143	2,105	2,059
R-squared	0.038	0.041	0.041
Year FE	YES	YES	YES