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Abstract

The tightening of climate policies may cause technologies based on fossil fuels to lose value compared to "green" technologies. For firms with significant fossil-based knowledge, this implies that their firm (market) value is at risk. This technological risk is also relevant for financial market actors, in particular institutional investors following long-term investment strategies. Measuring technological knowledge using patent data at the firm level, this paper uses a dynamic patent count data model and explores whether institutional investors address technological transition risk via engagement activities. Despite robust evidence for a positive influence of institutional investors on overall innovation, no evidence can be found that institutional ownership is associated with a change in the direction of innovation.

JEL Code: Q55, G23, O34
Keywords: Green innovation; green finance; climate policy; climate risk; institutional investors

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1 Introduction

The tightening of climate policies may cause technologies related to fossil fuel use to lose value compared to "green" technologies. (Future) climate policy then entails a "technological risk" for firms whose business model relies on fossil-based knowledge. This risk translates into a risk for investors. According to a recent survey, 75% of institutional investors – i.e. organizations that invest on behalf of their members or clients – consider technological risk to be a financial risk already today or within the next five years (Krueger et al. 2020). With large and increasing shares of worldwide equity under management, institutional investors will have an important role to play in the transition to a green economy. Due to their size, they can use voting power and direct conversations with management to affect firm-level outcomes. Building on evidence that institutional investors have an impact on firm-level innovation (Aghion et al. 2013) as well as environmental, social and governance (ESG) scores (Dyck et al. 2019; Dimson et al. 2015) and CO_2 emissions (Azar et al. 2020), this paper aims to find out whether institutional investors mitigate technological risk by influencing the direction of innovation in firms.

Institutional investors are playing an increasingly large role in financial markets, holding on average 40% of the equity of the firms in this paper's sample. More importantly still, a large number of institutional investors have voiced concern about climate risk. Typically, climate risk is understood as an aggregate of two types of risk: *physical risk* from climate change itself (see, e.g., Dietz et al. 2016), and *transition risk* (sometimes also called *regulatory risk*) due to stricter climate policies affecting asset values (McGlade and Ekins 2015; Battiston et al. 2017; Batten et al. 2016). Institutional investors are reported to be particularly concerned about transition risk, and many institutional investors have signed initiatives such as the "United Nations Principles for Responsible Investment" (UN PRI) or "Climate Action 100+", committing to (climate) responsible investment. This paper focuses on a particular case of transition risk: the risk that technologies related to fossil fuel use lose value due to climate policies. Car manufacturers, for instance, will meet climate policy goals less by reducing own emissions, but by changing the type of technology they sell.

The financial sector has traditionally not been equipped for dealing with uncertainties due to climate change or climate policy: models for risk management in portfolios are based on past, quantifiable risks and are not designed to reflect future uncertainties (Battiston et al. 2019; Silver 2016).[1] Using data for 2015, Battiston et al. (2017) have shown how institutional investors are still exposed to firms and sectors which face a high transition risk. They also demonstrate how the financial system, due to second-round effects from indirect holdings adding to the first-round effects, would get under stress in case of a strict climate policy scenario. This appears to reflect a very limited success of initiatives for sustainable investment.

[1] Risk and uncertainties in the context of climate change damages as well as climate policy are discussed in the literature on climate and energy economics, see e.g. Crost and Traeger (2014), Rudik (2020), Sinn (2008), Fried et al. (2020), Wesseler and Zhao (2019), Pommeret and Schubert (2018), Barradale (2014), Yang et al. (2008), Torani et al. (2016), and IEA (2007).

However, institutional investors can choose different strategies to act (climate) responsibly, of which portfolio adjustment plays a minor role. In a survey among international institutional investors on climate risk, 84% of respondents reported that they had taken climate-related engagement actions in the last five years – compared to 29% attempting to reduce carbon footprints through portfolio shifts (Krueger et al. 2020). Engagement can take various forms: the most visible channel is proxy voting in shareholder meetings. Analysts have noted that institutional investors are increasingly voting in favor of climate-related shareholder proposals, although there is quite some heterogeneity between them (Berridge and Nurjadin 2020). However, less visible channels also play a role: engagement can take place "via letters, emails, telephone conversations, and direct conversations with senior management" (Dimson et al. 2015). The actual influence of institutional investors can work via different mechanisms. They can use public pressure, threaten to divest, vote against proposals in shareholder meetings, or vote against re-election of managers. In a more positive sense, they can also back managers who initiate changes which only pay back later. With success measured by changes implemented after the engagement activities, such activities in the field of ESG themes have been shown to be effective and to create positive stock market reactions (Dimson et al. 2015; Dyck et al. 2019; Nguyen et al. 2020).

The relationship between the investor and the firm is that between a principal and an agent. In equity markets, agency problems between managers and shareholders have traditionally been a concern due to the disperson of ownership. The increasing number and size of institutional investors have changed this relationship (Bebchuk et al. 2017). In the case of climate transition risk, it is not a priori clear whether the principal or the agent should have a stronger incentive to become active. Essentially, it can be seen as a question of the time horizon (and the ability to deal with uncertainty) of managers vs. investors. The available literature suggests that managers of listed firms tend to be driven by short-term performance goals; institutional owners can back them with a long-term commitment, allowing to take risks in the short term for a more profitable future (Dimson et al. 2015; Aghion et al. 2013; Bushee 1998). This is relevant in the context of R&D and technological change.

This paper uses firm-level panel data to test for the influence of institutional ownership on the direction of innovation. The main data source is the Orbis database. It includes yearly information on the shares of each owner in total market capitalization and distinguishes between different investor types. This allows to calculate the share of total institutional ownership per firm and year, or shares of different investor types. For instance, signatories of the UN PRI or investors with a long time horizon (e.g. pension funds) would be expected to have a larger interest in future climate risks than the average institutional investor. Further firm-year specific control variables are also sourced from Orbis, as well as other data suppliers.

Data on patents comes from the Orbis Intellectual Property (Orbis IP) database and can be directly linked to firms. This paper classifies patents into *green* and *fossil* categories, based on their technological classification codes, applying a modified classification based on Dechezleprêtre et al. (2017). It then separately looks at the influence of institutional ownership on green and fossil patenting to draw conclusions on investors' preferences regarding the direction of innovation. Patents are a useful measure when discussing the (potentially) long-term horizon of institutional investors: they are the result of lengthy R&D efforts which bear fruit in the future. When successful, they grant the exclusive right to use an invention (in the jurisdiction of the patent office). Information on patents is publicly available. In particular, typical investor newsfeeds include information on patent applications and grants.[2] Moreover, institutional ownership has been shown to increase patenting activities (Aghion et al. 2013).

Studying green and fossil patents as an outcome variable of owners' engagement offers the advantage of being more clearly about climate issues than aggregate ESG scores.[3] Moreover, patents are rarely discussed in the broader media. This makes them an ideal measure to study institutional investors' motives beyond reputational issues, which are often the underlying concern behind ESG "risks". At the same time, the use of patents allows for more middle ground than approaches that divide firms into "clean" and "dirty" ones. Based on their innovation activities, companies can be *green* and *fossil* at the same time; they can also gradually shift their activities over time. This kind of gradual pattern fits with those institutional investors that use engagement rather than divestment.

To account for the count property of patent data and the path dependency of innovation, I use a dynamic count data model in the spirit of Aghion et al. (2016), where patenting depends on previous knowledge, knowledge spillovers, and R&D efforts. The share of institutional ownership is added as an additional explanatory variable. The model includes firm fixed effects using the pre-sample mean method (Blundell et al. 1999). To control for patent quality, I focus on patents filed at one of the main patenting offices (EU, US, Japan) which are ultimately granted. To account for potential bias through endogenous selection of investors, I apply a control function approach. A firm's institutional ownership share is instrumented by the inclusion of the firm in a large stock index.

Tracking more than 1,200 firms worldwide over the years 2009-2018, I find no evidence for investors' engagement for directed innovation. Overall, the number of patent applications increases with more institutional ownership. However, when looking at patents classified as green or fossil, no effect can be detected. This is true for more disaggregate measures of innovation (such as green/fossil transport and energy, respectively) and for more disaggregate types of investors (e.g. signatories of the UN PRI or pension funds). There is a positive association between climate-related opportunities mentioned in investor conference calls and subsequent green patenting; it is difficult, however, to ascertain that this

[2]Kogan et al. (2017) have recently used the attention of financial markets to patent grant events to derive a measure for patent values.

[3]Berg et al. (2019) show how the different methodologies of measuring and combining different issues in ESG scores by different providers leads to very heterogeneous scores within the same firm, giving rise to "aggregate confusion".

effect is causal. If institutional investors try to influence firms to become less susceptible to climate risk, then these efforts are not (yet) detectable in the innovation activities of firms.

Related literature This paper contributes to the literature on institutional investors and environmental concerns. Dyck et al. (2019) and Gibson and Krueger (2017) find that institutional investors improve firms' environmental and social performance; they do not look at climate policy risk specifically, though. Azar et al. (2020) show that firms tend to reduce their carbon emissions when the ownership share of the "Big Three" index funds (BlackRock, Vanguard, State Street) increases, consistent with data on these firms' engagement activities. Krueger et al. (2020) report survey results showing that institutional investors are concerned with climate risk, in particular regulatory risk; and that one of their preferred modes of action is engagement. Sautner et al. (2020b) use transcripts of investor conference calls to develop a measure for firm-level exposure to climate risk, thus making use of statements by managers as well as investors' concerns. The paper at hand tests whether these stated concerns and actions yield results in the technological sphere, using innovation activities as revealed engagement outcomes. In this context, the paper draws on previous work on institutional investors and innovation (Aghion et al. 2013; Borochin et al. 2020; Jiang and Yuan 2018; Rong et al. 2017; Bushee 1998). It is also related to the literature on ownership structure and financing innovation (Bernstein 2015; Chemmanur et al. 2014; Atanassov 2013; Lerner et al. 2011; Kerr and Nanda 2015; Hall and Lerner 2010; Munari et al. 2010).[4]

It also connects with the literature on environmental policy and green innovation. Theoretical work on climate policy and green innovation is mostly concerned with positive spillovers from green innovation, path dependencies, and their interaction with climate policies (Acemoglu et al. 2012; Fried 2018; Bretschger and Schaefer 2017; Di Maria and Smulders 2017; Lambertini et al. 2017). Empirical studies confirm the relevance of knowledge spillovers in the context of clean technologies (Dechezleprêtre et al. 2017; Verdolini and Bosetti 2017; Verdolini and Galeotti 2011; Lanzi et al. 2011) and for overall innovation (Peri 2005), with heterogeneity between sectors. Although path dependencies and spillovers are not the main focus of this paper, these considerations have inspired the path-dependency model used in this paper's empirical estimations. In the empirical literature on policy impacts, several studies find a positive effect of climate policies on green innovation (Kiso 2019; Calel and Dechezleprêtre 2016; Aghion et al. 2016; Nesta et al. 2014). This paper is methodologically closely related to Aghion et al. (2016). It is the first to link the direction of innovation to institutional investors' engagement activities.

[4] There is also a literature on "overlapping ownership" (also *cross-ownership* or *common ownership*), referring to the fact that the same institutional investors tend to own shares in all or most of an industry's competitors. Overlapping ownership may affect competition (Vives 2020; He and Huang 2017; Borochin et al. 2020), also via R&D spillovers (López and Vives 2019). This effect, or the generally established link between innovation and competition (Aghion et al. 2005; Dasgupta and Stiglitz 1980), is not the focus of this paper.

The paper further contributes to the field of climate transition risk and financial markets. Central banks and other financial institutions have voiced concerns that these risks may not be adequately priced in yet in financial markets. Following an unexpected tightening of policies or sudden changes in expectations, the re-pricing might occur suddenly and with implications for financial stability (van der Ploeg and Rezai 2020; Monasterolo 2020; Batten et al. 2016; European Systemic Risk Board 2016). There is some empirical evidence that stock market investors are aware of these risks and price them in when they receive new information about regulation (Sen and von Schickfus 2020; Carattini and Sen 2019; Griffin et al. 2015; Ramiah et al. 2013). Especially the election of Donald Trump and the conclusion of the Paris Agreement have been used as events which changed policy expectations (Kruse, Mohnen, and Sato 2020; Monasterolo and de Angelis 2020; Ramelli et al. 2019; Mukanjari and Sterner 2018).

However, the mentioned event studies focus on immediate stock market reactions, excluding the engagement channel; moreover, firms are mostly selected as being “fossil” or not, leaving no ground for gradual change within firms. A notable exception is Kruse, Mohnen, Pope, et al. (2020), who use data on firms’ green revenues and find that firms providing more environmental goods and services have, on average, a higher market valuation (measured by Tobin’s q). Other strands of literature look at regulatory risk and the pricing of bank loans and corporate bonds (Seltzer et al. 2020; Delis et al. 2019), and at the exposure of interconnected financial markets to climate risk (Battiston et al. 2017). This paper is the first to examine technological transition risk, and to focus on institutional investors.

The remainder of the paper is organized as follows: Section 2 provides some background on patents and patent data characteristics. The methodological approach is presented in section 3, and section 4 describes the data sources and the construction of the dataset. Section 5 presents and discusses the results. Section 6 concludes.

2 Patents: background and classification

This section describes relevant patent data characteristics and how to classify patents by technology. Section 4 gives details on the data sources and provides summary statistics. Patents protect intellectual property rights: Individuals and firms apply for patenting in order to receive the exclusive right to use their invention. An example of a patent (its first page) can be found in Figure 1 in Appendix A.1. Patent applications are examined by patent office examiners, whose task is to ensure that only novel innovations are protected. Patents are often applied for at several patent offices to ensure protection in the relevant markets. All patent applications with the same content at different offices are referred to as one “patent family”. Patents also cite other patents, i.e. previous knowledge; they are themselves cited by other patents (forward citations).

Applications, examinations and generating citations all takes time. Table 1 shows the development of numbers for different patent measures in this paper’s sample over time.

Due to the nature of the patenting process, the number of patent applications in the data appears to decrease in recent years (see the column "Patents"): the closer we are to today, the fewer patent applications have actually been published and are available in the data - although it is very likely that applications have been filed.[5]

Table 1 – Mean number of patents, family size and citations over time

Year	Patents	Family size	Citations
2010	109.68	399.60	281.11
2011	109.02	389.46	273.82
2012	119.81	413.71	273.22
2013	116.61	390.00	197.16
2014	106.75	345.31	148.77
2015	107.25	320.00	124.30
2016	75.05	205.93	77.61
2017	51.10	120.74	28.39
2018	24.28	49.24	4.45
Average	89.93	287.35	150.85

Notes: Numbers are shown for patents (all technology types) applied for in the given year. Patent numbers are based on a sample of publicly listed firms which filed at least one patent classified as green or fossil in the sample period. Due to the lagged structure of the estimation, the sample period for patents is 2010-2018.

Like previous work on green innovation, this paper exploits the fact that examiners classify patents by technological field. There are two main classification schemes: The International Patent Classification (IPC) and the Cooperative Patent Classification (CPC). The latter is the result of efforts of the European Patent Office (EPO) and the US Patent Office (USPTO) to harmonize their systems. Each patent is usually assigned several technology classes. Within the CPC, a special Y category has been introduced to mark climate-friendly innovations. This is helpful, but not sufficient, to identify in particular fossil-based patents.

To classify patents as *green* and *fossil*, I use a slightly modified version of the classification by Dechezleprêtre et al. (2017) into clean and dirty patents.[6] Examples for fossil transport categories are F02F, *Cylinders, pistons, or casing for combustion engines; arrangements of sealings in combustion engines*, or F02N, *Starting of combustion engines*. Green transport includes, for instance, B60K 1, *Arrangement or mounting of electrical propulsion units*, or B60L 8, *Electric propulsion with power supply from force of nature, e.g. sun, wind.* For energy, corresponding categories would be Y02E 10 (*Energy generation through renewable*

[5] Table 13 shows the development of the counts over time separately for patents classified as green and fossil.

[6] I am using the term *fossil* instead of *dirty* due to the focus on climate change and climate risk: CO_2, the result of burning fossil fuels, is not a pollutant, but a greenhouse gas. Climate risk affects fossil-based technologies, but does not affect all "dirty" technologies with any environmental externalities. In the same vein, not all technologies replacing fossil fuels are automatically "clean" (biomass-fired power plants, for instance, do contribute to air pollution). The term *green* is therefore used to describe technologies which replace fossil-based technologies.

energy sources) and F23 (*Combustion apparatus; combustion processes*).

In reality, it is sometimes hard to identify climate-friendly innovation. For instance, there are inventions that make the use of fossil fuels more efficient and reduce emissions (Lanzi et al. 2011). Following Dechezleprêtre et al. (2017), I introduce a third category (in robustness checks): *grey* patents. Most of these technologies make combustion (in engines or power plants) more efficient, and they are thus a subset of the fossil technologies. In the case of energy, the *grey* category also includes the production of fuels of non-fossil origin, e.g. biofuels. However, all of these technologies have only limited potential to address technological risk, which is mainly about the phase-out of fossil-based technologies. Improving existing technologies at the margin may be successful in the short and medium run, but does not help on the way to new, carbon-free systems. An overview of the classifications for transport and energy-related patents can be found in Tables 9 and 10 in Appendix A.1.

The literature agrees that plain patent counts are a very imprecise measure, since patent quality (or value) is highly skewed (see Aghion et al. 2013, for example). It is therefore important to account for patent quality. As a first step, I filter patents based on the offices where they were filed. Only patents applied for at the US, EU, or Japanese patent office are considered. In a second step, patents were filtered to only include granted patents.

In robustness checks, family size and citations are used instead of patent counts. Family size measures the number of patent offices where the patent has been applied for: it is a measure for the importance the inventor attaches herself to the patent. If the inventor considers the invention to be of high value, she will opt to protect (and use) it in many jurisdictions. Protection at several offices incurs direct and administrative costs, so we can assume that it is a conscious decision of the inventing firm to increase a patent's family size. Citations, on the other hand, are a measure for the relevance that others attach to the patent: if the invention is cited by other patents, it is sufficiently novel and relevant to spur further innovation. Citations can be regarded as a measure for the scientific value of a patent; family size is closer to the commercial value of the patent.

The censoring issue discussed above is also relevant for the choice of patent measure. As Table 1 shows, the downward trend over time is particularly pronounced for citation counts. This is not surprising: citations accumulate over time, and patents applied for in 2018 did not have much time to collect citations. It is generally possible to take care of this issue by using year fixed effects. With count data, however, the amount of zeroes can become quite large towards the end of the sample, impeding estimations. Family size also decreases faster over time than plain patent counts - the process of applying for protection at different patent offices takes time as well, and this lag may differ between technologies and sectors. For this reason, the standard patent measure used in this paper is the patent count. Family size and citations are included as a robustness check.

3 Empirical approach

3.1 Path dependency model

The question of this paper is: do institutional investors influence green and/or fossil patenting, and if yes, in a different way? I therefore test for the impact of the ownership share of institutional investors on green and fossil patenting. The idea for the econometric specification is inspired by the dynamic path-dependency model by Aghion et al. (2016). In such a model, the amount of patenting depends on the firm's own stock of patents; on innovation spillovers from other firms in the country; and on R&D investments. Since most of the path-dependent explanatory variables can be derived for green and fossil patent classifications, the model can be used to separately assess the impact of institutional ownership on green and fossil patenting. In the following, the subscripts G and F are used to refer to green and fossil patents, respectively. For the exposition, green patents are used as the default example for the dependent variable.[7]

Following the literature standard, a Poisson specification is used to account for the count nature of the dependent variable. The model including institutional ownership reads

$$\begin{aligned} PAT_{G,it} = &\exp(\alpha_G + \beta_{G,IO} IO_{it-1} + \beta_{G,1} \ln K_{G,it-1} + \beta_{G,2} \ln K_{F,it-1} \\ &+ \beta_{G,3} \ln SPILL_{G,it-1} + \beta_{G,4} \ln SPILL_{F,it-1} \\ &+ \beta_{G,5} R\&D_{it-1} + \tau_{G,t} + \eta_{G,i} + \epsilon_{G,it}), \end{aligned} \tag{1}$$

where

- $PAT_{G,it}$ is the count of green patents applied for by firm i in year t;
- IO_{it} is the percentage of institutional ownership in firm i in year $t-1$;
- $K_{G,it-1}$ is the firm's pre-period green patent stock;
- $K_{F,it-1}$ is the firm's pre-period fossil patent stock;
- $SPILL_{G,it-1}$ are country-level green spillovers to firm i in period $t-1$;
- $SPILL_{F,it-1}$ are country-level fossil spillovers to firm i in period $t-1$;
- $R\&D_{it-1}$ are R&D expenditures of firm i in year $t-1$;
- $\tau_{G,t}$ is a year fixed effect;
- $\eta_{G,i}$ is a firm fixed effect; and
- $\epsilon_{G,it}$ is an error term.

Institutional ownership is a continuous variable reflecting the relative quantity of institutional ownership compared to other owners. The literature on institutional owners suggests

[7] Further categories are possible, such as green transport patents, grey patents, or total patents; these are introduced later in the text.

that this quantity makes a qualitative difference: (Many) large investors have more (joint) influence in proxy votes, conference calls, etc.

Essentially, the idea of Equation 1 is to single out the influence of institutional ownership while controlling for already existing knowledge stocks (due to own patenting and spillovers) and the inherent path dependency. Previous own knowledge on green technologies, $K_{G,it-1}$ can explain further innovative activities in this direction. $SPILL_{G,it-1}$ are country-level green innovation spillovers, based on the assumption that an environment of domestic firms with knowledge on green technologies is conducive to each firm's innovation in this direction. Following Aghion et al. (2016), previous knowledge on fossil technologies and fossil spillovers are also included ($K_{F,it-1}$, $SPILL_{F,it-1}$). This specification is derived from the observation that many firms with a track record in fossil innovation become active in green innovation: the technologies are used to serve similar markets, e.g. in the car industry. The construction of knowledge stocks and spillovers is discussed in detail in section 4.

However, patents of course are not generated simply out of previously existing patents. Research and Development is a further obvious part of the firm's production function of patents (see also Hall et al. 2005). The inclusion of R&D is particularly useful in the context of this paper's research question. R&D expenditure controls for the overall R&D efforts, so any change in green or fossil patents we observe can be more clearly interpreted as a directional change, as opposed to a pure increase.[8] In addition, investors may observe R&D efforts and select into firms with higher R&D expenditures, expecting larger innovation output; this would cause an omitted variable bias and an overestimation of investors' influence.

In robustness checks, two more control variables are used: Tobin's q and firm-specific climate exposure (see section 3.5 for details). One might think of other firm-specific variables that are associated with innovation, like financing constraints or firm size. Including measures for tangibility, leverage, operating revenue, capital-labor ratio, or profits did not significantly alter the outcome, so the corresponding results are not included in this paper.

3.2 Firm fixed effects

Equations 1 and 3 include firm-level fixed effects: Unobserved heterogeneity between firms needs to be controlled for. In Poisson estimations, the standard approach is to use the

[8]Contrary to e.g. Aghion et al. (2013) and Hall et al. (2005), this paper uses yearly R&D spendings instead of R&D stocks. There are two main reasons for this choice. First, the specification in equation 1 already accounts for knowledge stocks, measured by patents. The additional value of the R&D variable (which does not appear in the, otherwise very similar, specification of Aghion et al. 2016) lies in capturing additional innovation efforts which are on top of, and separate from, existing knowledge stocks. The second reason is a data concern. Many firms in the sample have incomplete R&D time series, making the construction of R&D stocks difficult and error-prone. Sticking with yearly expenditures - and excluding missing firm-years from the analysis - is thus the safer variant. Test regressions (not shown) were run using R&D stocks, without significantly affecting results.

conditional fixed effects estimator proposed by Hausman et al. (1984). Put simply, it conditions on the sample average of the observable variables. The conditional fixed effects estimator requires strict exogeneity of the explanatory variables. This assumption is violated in a dynamic panel data model such as Equation 1, which exhibits serial correlation between innovation stock measures.

Therefore, an alternative approach to modelling firm fixed effects is used: the pre-sample mean estimator proposed by Blundell et al. (1999) (BGVR), which has been used in the environmental context e.g. in Nesta et al. (2014). The idea is to condition on the pre-sample mean of the dependent variable to proxy out the fixed effect. This approach is particularly well suited to patent data, because patent data is typically available in pre-sample years. Blundell et al. (2002) show that this estimator leads to some bias, but increasing the number of pre-sample periods (and, to a lesser extent, the number of in-sample periods and the number of observation units) improves performance. The pre-sample mean enters the estimation in logged form.

For the research question at hand, the choice of pre-sample periods means dealing with a trade-off: more pre-sample information is generally desirable, but green technologies are a relatively "young" phenomenon. Pre-sample averages of green patenting going back a long time may not be useful to reflect current firm characteristics regarding green innovation.[9] In this analysis, the pre-sample average for the years 1995-2008 is used. This is a reasonable amount of years and at the same time, years with measurable patenting activity in both green and fossil areas are covered.[10]

3.3 Selection issues and control function

One concern when estimating Equation 1 is the selection of investors into firms. The coefficient on institutional ownership share may be biased if investors select into firms with more expected green (or more fossil) innovation. Most investors use a combination of strategies to deal with climate risk; so it is possible that some investors select the most promising green-innovation firms, others try to encourage green innovation, and others do both.

I therefore use a source of exogenous variation in institutional ownership: The inclusion of a firm in a large stock index. It has been widely used as an instrument for institutional ownership (Aghion et al. 2013; Crane et al. 2016; Appel et al. 2016). The idea is that many institutional investors either directly track such indices, or their managers are benchmarked against them. Therefore the instrument is expected to be correlated with institutional ownership. For it to fulfill the exclusion restriction, I need to rule out a relationship

[9] Aghion et al. (2016), who have a sample covering the years 1986 to 2005, argue against the use of the BGVR method for this reason: green patenting in the early 1980s was not a good indicator for green patenting in the early 2000s.

[10] In a robustness check (not shown), the average for the years 2000-2008 was used, since the data show higher green patenting activity after 2000. The estimation results are virtually the same.

between pre-period index membership on this year's (green / fossil / total) patenting, controlling for observables. It is therefore helpful to understand the selection of index members.

Index membership is decided on by Index Committees; none of their criteria explicitly mention innovation. One of the main criteria for inclusion in a large stock index is market capitalization. Also, firms need to fulfil basic eligibility criteria to be added to an index, such as certain thresholds for free-float market capitalization and earnings in the quarters prior to index admission. There may be a concern that a firm's market value increases in expectation of future patenting, and this leads to admission to the index. All estimations control for R&D expenditures and thus for the observable part of innovation activities that may result in patents. I also show in Table 20 that Tobin's q, a measure for above-fundamental market valuation, is not a significant predictor of innovation. In the first-stage regressions, the coefficient of Tobin's q is insignificant as well, implying that this measure of market valuation does not affect institutional ownership, controlling for other observables. It has also been shown that markets price in most of the value of patents at a later stage: when a patent is granted (Kogan et al. 2017).[11]

Moreover, Index Committees do not simply decide based on fixed criteria. For instance, it is the explicit goal of the S&P 500 Index to be representative of the US economy in terms of sector coverage. Also, if a current index member does not fulfil the eligibility criteria any more, this does not automatically lead to exclusion. Index managers are interested in a stable composition of the index. This discretion provides another source of variation that is not related to other firm variables.

I define the instrument $indexmember_{it}$ as a dummy equal to one if a firm was a member of the S&P 500, the STOXX Europe 600 and/or the S&P Global 1200 index in year t. These indices cover a wide range of countries, while still being exclusive enough to have explanatory power. Given the nonlinear model, the instrument enters the estimation in a control function approach (Wooldridge 2010). In the first stage (OLS), institutional ownership is regressed on the instrument and all control variables of the second stage. The residuals from this estimation - i.e., the part of institutional investors' ownership that cannot be explained by the instrument - are then included as a control variable in the second-stage regression. As a result, the coefficient on IO_{it} reflects the effect of the part of institutional ownership that is due to the index membership of the firm.

[11] Considering the eligibility criteria, the relationship between high free-float (with, e.g., low family or management ownership) and innovation is not a priori clear, and the evidence on family or management ownership and innovation is mixed (Munari et al. 2010; Schmid et al. 2014; Beyer et al. 2012; Ortega-Argilés et al. 2005). Looking at earnings, it is difficult to think of a reason why higher earnings would be followed by patent filings, given that the required R&D expenditures reduce earnings.

3.4 Heterogeneity of sectors and institutional owners

The measurement of green and fossil patents is noisy. Some of the noise can be addressed by differentiating between sectors. The transport and the energy sector are quite different, and it is well possible that innovation and patents play a different role in the two sectors. For capital-heavy energy firms, their fossil fuel reserves or power generating infrastructure are important assets which are directly affected by climate policy, whereas intangible assets such as patents are likely to play a smaller role. In the transport industry, by contrast, knowledge and innovation are relatively more important.

In separate regressions, Equation 1 is modified accordingly to reflect green/fossil transport and energy patents separately. The estimated equation for green transport patents, denoted by GT, thus reads

$$\begin{aligned} PAT_{GT,it} = & \exp(\alpha_G T + \beta_{GT,IO} IO_{it-1} + \beta_{GT,1} \ln K_{GT,it-1} + \beta_{GT,2} \ln K_{FT,it-1} \\ & + \beta_{GT,3} \ln SPILL_{GT,it-1} + \beta_{GT,4} \ln SPILL_{FT,it-1} \\ & + \beta_{GT,3} R\&D_{it-1} + \tau_{GT,t} + \eta_{GT,i} + \epsilon_{GT,it}). \end{aligned} \tag{2}$$

Models for fossil transport and green/fossil energy patents can be derived analogously.

Similarly, there is noise in the measurement of institutional ownership: there are many different types of institutional investors, and they may have quite different investment/ engagement strategies, time horizons, or environmental concerns. One way to deal with the noise is to look at these different types specifically. The literature on institutional owners' engagement suggests some time-invariant types which are expected to have long-term investment strategies (Hsu and Liang 2017; Borochin et al. 2020). Insurance companies and pension funds are prime examples. Government ownership is also typically long-term and stable; state-owned enterprises have been shown to perform better environmentally. Moreover, domestic investors (sharing the portfolio firm's headquarter country) may have better opportunities to engage.

In the context of sustainable finance, it is also possible to exploit a time-varying investor type, namely signatories of the UN Principles for Responsible Investment (UN PRI) initiative (see also Dyck et al. 2019). Principle 2, for instance, reads: "We will be active owners and incorporate ESG issues into our ownership policies and practices."[12] The UN PRI sees itself as "the world's leading proponent of responsible investment". The initiative was launched in 2006 and currently has more than 3,000 signatories. With their membership, investors declare their willingness to implement the six principles.

In the literature on institutional investors, the role of engagement has been very prominently discussed in the context of the big passive index funds. Instead of actively managing funds, these hold relatively fixed positions as they are mirroring certain stock indices. This means they cannot easily sell their positions, and some argue that this limits their shareholder power. On the other hand, they have an incentive to use engagement, since this is

[12] Stated on the PRI website, see `https://www.unpri.org/pri`.

the only way they can manage risk. A growing literature shows how the big indexers use their voting power in director (re-)elections and other governance choices (Fichtner et al. 2017; Appel et al. 2016), support activists (Appel et al. 2018), and have an influence on firms' emission reductions. In this light, direct engagement activities with management seem to be a successful strategy even, or particularly, for big "passive" investors. Therefore, the "Big Three" index fund investment companies (BlackRock, Vanguard, and State Street) are defined as another investor type.

To account for investor type heterogeneity, the variable IO from Equation 1 can be replaced by specific sub-groups of institutional owners: government (GOV), insurance and pension funds (INP), domestic owners (DOM), signatories of the UN Principles for Responsible Investment (UN PRI) initiative (PRI), and "Big Three" investment companies ($BIG3$).[13]

3.5 Informational value of nonsignificant results

As will be shown in detail in section 5 on Results, I do not find a statistically significant effect of institutional ownership on green or fossil innovation. I therefore conducted some additional estimations, which are not robustness checks in the typical sense. The usual robustness checks aim to rule out a type I error, i.e., falsely rejecting the null hypothesis. The additional estimations presented here are rather attempts to rule out a type II error: failure to reject the null despite an actually existing relationship. Abadie (2020) argues that insignificant estimates can be highly informative: it is interesting to learn that a previously expected relationship does not exist. The question is whether insignificant estimates are meaningful, i.e. can be interpreted as "no effect". Type II errors are most likely to result from data quality or research design issues. The two specifications presented in the following aim to answer the question whether research design or data quality are a concern.[14]

Institutional ownership and total innovation A first check concerns the overall setup of the model, and the sufficiency of data variation in the institutional ownership variable. The relationship between institutional ownership and patenting is an established result (Aghion et al. 2013). If the data and model used here cannot confirm this result, the research design and / or the measurement of the institutional ownership would need to be re-examined. Equation 3 tests whether institutional ownership affects total innovation (denoted by A):

$$\begin{aligned} PAT_{A,it} = &\exp(\alpha_G + \beta_{A,IO} IO_{it-1} + \beta_{A,1} \ln K_{A,it-1} + \beta_{A,2} \ln SPILL_{A,it-1} \\ &+ \beta_{A,3} R\&D_{it-1} + \tau_{A,t} + \eta_{A,i} + \epsilon_{A,it}). \end{aligned} \tag{3}$$

[13] Further investor type definitions are possible (see section A.2), but are less likely to be relevant in a climate context, and their results are not shown in the paper.

[14] In addition, section 5.1 provides results for some specification alterations that also partly address this question. Section 6 provides a general discussion of the plausibility of the results.

In this case, previous own knowledge and spillovers in terms of all technologies are included as explanatory variables. In a robustness check, Tobin's q is also included. Tobin's q is defined as $(marketcapitalization + totaldebt)/totalassets$ and is therefore a measure of the market's future expectations deviating from current fundamentals. As argued in Aghion et al. (2013), the market valuation of firms may be an omitted variable in a regression involving institutional ownership and innovation. It is correlated with the number of patents and could be correlated with institutional ownership, since institutional owners are more likely to invest in firms with high market valuation.

Firm-specific climate concerns: "climate exposure" The second approach addresses the question whether there is sufficient statistical power in the dependent variable(s), i.e. in the counts of green and fossil patents; it also addresses the question whether the degree to which firms are affected by climate issues play a role in explaining innovation. The degree to which firms are affected by, or concerned about, climate issues varies between firms and over time. Previous research has shown that firms facing higher fuel taxes tend to patent more in green technologies, and less in fossil technologies (Aghion et al. 2016). It is logical to test whether the panel used in this paper can confirm the relationship between firm-level climate policy impacts and the direction of innovation.

In the context of the research question on institutional ownership and risk from future climate policies, a newly developed measure is particularly useful: "climate exposure", an indicator derived from conference calls between managers and investors. This indicator, developed by Sautner et al. (2020b), measures the relative frequency with which climate-related issues are mentioned in these conference calls.

As climate-related issues can be quite broad and diverse, four different sets of bigrams (expressions) are used: one for broadly defined climate change aspects ("climate change exposure" or "exposure to a climate change-related shock"), and three for more specific topics. These are physical, regulatory, and opportunity shocks, relating to physical climate change-induced events (such as heatwaves or sea-level rise), regulatory changes (such as CO_2 pricing), and opportunities (capturing opportunities related to climate change issues, mostly green technologies). Since physical shocks are unlikely to influence green or fossil patenting (the patent classifications do not include technologies for adaptation to climate change), the measures used in this paper are "climate change exposure", "regulatory exposure", and "opportunity exposure". Table 2 shows the top 10 bigrams contributing to general climate exposure, regulatory exposure, and opportunity exposure, respectively.

To interpret the exposure measures, it is helpful to think of them as "firm-level exposure to a particular shock", where the shock can be positive or negative. For opportunity shocks, on could think of clean technology subsidies or R%D incentive schemes. However, the "shocks" can also originate from within the firm, if it initiated or completed green technology development. Conference calls are held in conjunction with firms' quarterly earnings reports, and investors tend to be interested in the firm's future outlook. The exposure indicators therefore most likely include current climate policy impacts as well

Table 2 – Top 10 bigrams contributing to climate exposure measures

Climate exposure	**Regulatory exposure**	**Opportunity exposure**
renewable energy	greenhouse gas	renewable energy
electric vehicle	reduce emission	electric vehicle
clean energy	carbon emission	clean energy
new energy	carbon dioxide	new energy
wind power	gas emission	wind power
wind energy	air pollution	wind energy
energy efficient	reduce carbon	solar energy
climate change	energy regulatory	plug hybrid
greenhouse gas	carbon tax	heat power
solar energy	carbon price	renewable resource

Notes: These bigrams are the "top 10" since they enter the respective measures with the largest weights.
Source: Own representation based on Sautner et al. (2020b).

as expectations for future impacts. At the same time, they tell us something about the awareness of this among managers and investors.[15] Being firm- and year-specific, they go beyond a general notion of "transition risk" due to multilateral climate agreements; they are more likely to capture (expectations of) implemented policies.

To incorporate these measures of impacts, expectations and awareness, Equation 1 is adjusted to read

$$\begin{aligned} PAT_{G,it} = &\exp(\alpha_G + \beta_{G,IO} IO_{it-1} + \beta_{G,1} \ln K_{G,it-1} + \beta_{G,2} \ln K_{F,it-1} \\ &+ \beta_{G,3} \ln SPILL_{G,it-1} + \beta_{G,4} \ln SPILL_{F,it-1} \\ &+ \beta_{G,5} R\&D_{it-1} + \beta_{G,6} CCExp_{E,it-1} + \tau_{G,t} + \eta_{G,i} + \epsilon_{G,it}), \end{aligned} \tag{4}$$

where $CCExp_{E,it-1}$ is firm i's climate exposure in year $t-1$, and E stands for the type of exposure: overall, regulatory, or opportunity. Note that the share of institutional ownership in the firm is still included in the regression. $CCExp$ is a measure that combines firm-specific exposure to climate-related shocks with the intensity of their discussion between management and investors.

If no effect of climate exposure on green or fossil innovation can be detected, this would be an indication that there is not enough meaningful variation in the dependent variable. The coefficient on $CCExp$ is also an interesting outcome in itself: it shows whether a more forward-looking firm-level climate indicator, reflecting awareness at manager and investor level, can explain firm-level innovation.[16]

[15] Unfortunately, the available data does not distinguish whether issues are mentioned by managers or investors.

[16] More details on the construction of the climate exposure variable can be found in Appendix A.3.

4 Data

The main sample consists of $1,261$ publicly listed firms over 10 years (2009-2018), with an average of 90 patents per firm per year. Table 3 provides summary statistics for the main variables. Typical for patent data, all patent counts are highly skewed, with the maximum far away from the mean. The same is true for R%D expenditures. The institutional owner share of 40.6% on average is comparable to data reported in the literature (Dyck et al. 2019; Bebchuk et al. 2017).

Table 3 – Summary statistics

	Mean	Standard deviation	Minimum	Maximum
All patents	89.93	316.17	0	7,975
Fossil patents	3.08	20.22	0	708
Green patents	2.47	16.93	0	794
Patent stock	633.6	1,960.3	0	36,324.3
Fossil patent stock	20.4	118.3	0	4,404.1
Green patent stock	16.3	99.9	0	3,845.9
Spillover	259,268.6	218,863.6	0	584,411.2
Fossil spillover	9,183.1	9,491.4	0	24,151.9
Green spillover	7,577.0	8,560.5	0	21,157.4
R & D exp., in thousand USD	1,117,383	$6.96{\cdot}10^{6}$	0	$6.43{\cdot}10^{12}$
IO share, in percent	40.64	27.10	0	100

Climate-relevant – i.e. fossil or green – patents account for about 6% of total patents. Note that the sample is restricted to firms which have filed at least one climate-relevant patent in the sample period. Green and fossil patents are quite similar in terms of patent counts, patent stocks and spillovers, with green innovation always slightly below fossil. Table 12 in Appendix A.4 shows the respective averages for family size and citations.

The main data source for patents, firms and ownership is Orbis and Orbis Intellectual Property, offered by Bureau van Dijk (BvD). Orbis provides information on more than 300 million companies worldwide, with the data including standardized financials, ownership links, and more.

Ownership data Data on ownership is recorded in the Orbis Historical Database. It provides links between firms and their shareholders, listing the respective ownership shares. The ownership data is collected from various sources, leading to over-reporting in the dataset. Extensive manual checks were done to rule out duplicates. In case a duplicate was identified, preference was given to the most recent reporting, to the most comprehensive (and thus consistent) data sources,[17] or to the parent company in case of holding reportings.

[17] The most prevalent data source, and therefore most consistent across firms and years, is Factset. Factset is an independent data provider collecting data on large investors' holdings, based on filings with

The ownership data allows to distinguish between different investor types based on their NACE codes and BvD classifications. Details on the mapping can be found in section A.2 in Appendix A.2. In addition, the headquarter country of each investor is recorded in the dataset, allowing to identify domestic investors.

Information on the investors' signature dates in the United Nations Principles for Responsible Investment initiative is from the PRI's website.[18] The PRI signatories are only available by name. They were matched to the investor dataset using a fuzzy matching approach as a first step; this was augmented with a manual check of the matches. In some cases, it is difficult to find out from an investor's PRI reporting which parts of the company can be counted as PRI signatories. The matches were checked with the greatest care possible, but some mismatches can not be ruled out.

Summary statistics for the different owner types can be found in Table 14 in Appendix A.4. The average share of governments and Big Three investors is lowest; the ownership share of domestic owners is the highest of all types used (27.7% on average, more than half of total institutional ownership, and with a maximum value of 100%). In the shares of governments as well as insurance and pension fund companies, the variation is somewhat larger than for the other groups.

Patent data Orbis Intellectual Property is the result of a matching between PATSTAT (a worldwide patent database run by the European Patent Office) and Orbis. Linked to company IDs, it provides rich information on each patent, including its classification, date of publication, and application offices. The dataset in this paper consists of all patents which were filed at the European Patent Office (EPO), the US Patent and Trademark Office (USPTO), the Japanese Patent Office (JPO), or the World Intellectual Property Organization (WIPO) in the relevant period; which were ultimately granted; and which can be linked to a listed firm (either through direct or indirect ownership, currently or formerly).

The database offers information of the applicant firm(s), current direct owner(s), and current indirect owner(s) of the patents. The patents were thus assigned to firms based on the original applicant (or several original applicants), if this original applicant is a listed firm. If the original applicant is not listed, but the current indirect owner is (and if there has been no ownership change), then the patent is assigned to the indirect owner. Since the database does not easily allow to track indirect ownership of firms over time, cases with changes in ownership are not assigned an indirect owner. Changes in ownership are determined by a) using the label "with ownership change" from Orbis, and b) by ensuring that the data lists the applicant also as the direct owner.

national stock exchange supervision authorities. The most well-known are the so-called "13F" filings, which are mandatory for investors in US-listed firms when their share crosses a certain threshold. Unfortunately, the sample could not be restricted to Factset alone, since in many cases important investors appeared under different sources in different years in the same firm.

[18] `https://www.unpri.org/signatories/signatory-directory`

The estimations use patent applications (a flow) as the dependent variable, but patent stocks as explanatory variables. In line with the literature, these patent stocks are calculated using the perpetual inventory method. Firm i's green patent stock in year t, $K_{G,it}$, is equal to the discounted flow of green patents in the previous years:

$$K_{G,it} = PAT_{G,it} + (1-\rho)K_{G,it-1}, \tag{5}$$

and symmetrically for fossil ($K_{F,it}$) or all patents ($K_{A,it}$), respectively. A discount rate of $\rho = 0.15$ is used, which is in the medium range of depreciation rates for intellectual capital used in the literature.[19]

Spillovers are accounted for in a relatively straightforward way. A firm's green spillover at time t is equal to the sum of green patents applied for in the firm's country c at time t, minus the firm's own green patent applications in that year:

$$SPILL_{G,it} = \sum_{j \in c} PAT_{G,jt} - PAT_{G,it}. \tag{6}$$

In all expressions involving the log of a number of patents (i.e. $\ln K$, $\ln SPILL$, as well as the pre-sample mean), I follow the literature standard of replacing zeroes by an arbitrary small constant and including dummies for the number of patents being zero (Aghion et al. 2016; Blundell et al. 1999).

Firm data Firm-level data on R&D expenditures and Tobin's q is from the Orbis Historical Database. BvD firm-level data is mainly sourced from companies' mandatory filings. For companies with subsidiaries, sometimes both unconsolidated and consolidated (including subsidiaries) reporting is available. Whenever a company appears as an indirect patent applicant (or as both direct and indirect), and both filing versions are available, then the consolidated reporting version is used. In further regressions, more firm-level characteristics were used as control variables (such as operating revenue, capital-labor ratio), but as they did not alter the results, the respective regressions are not shown in the paper.

Firm-level data is augmented by other sources: Thomson Reuters Datastream was used to extract time series of index constituents of the STOXX Europe 600 and S&P Global 1200 indices. The time series of the S&P 500 is from Wharton Research Data Services (WRDS).

In addition, the Sautner et al. (2020a) data was merged to the firms to cover firm-level climate exposure and its recognition with managers and investors. Since all firms in the sample are publicly listed, ISINs (International Securities Identification Numbers) of their traded shares could be used to match the firms. The climate change exposure data is limited in terms of firm coverage and in terms of time series coverage per firm, reducing the sample size of the dataset to roughly half of the original dataset. Summary statistics

[19] For example, Aghion et al. (2016) use 20%; Peri (2005) uses 10%, Hall et al. (2005) and Cockburn and Griliches (1988) use 15%.

for the reduced sample can be found in Table 15 in Appendix A.4. Firms in the climate exposure sample have filed more patents (in all categories), have higher R&D expenditures, and a higher institutional owner share than the average of the full sample.

5 Results

5.1 Institutional owners and climate-relevant innovation

Table 4 show the main results for Equation 1, separately for green and fossil patents. For each estimation, the first stage of the control function approach is shown in an extra column. As can be seen from columns 2 and 4, the *indexmember* instrument is positive and significant: Institutional investors own about 2.3 percentage points more stocks in members of large stock indices than we would expect from other observables.

Table 4 – Green and fossil patents

	(1)	(2)	(3)	(4)
Model	Poisson	OLS (first stage)	Poisson	OLS (first stage)
Dep. var.	Green patents	L.IO share	Fossil patents	L.IO share
L.IO share	0.0227		0.0103	
	(0.0561)		(0.0387)	
L.Own stock green	1.464***	-1.341***	0.0224	-2.550***
	(0.104)	(0.493)	(0.107)	(0.268)
L.Own stock fossil	0.134**	-1.076***	1.321***	-2.556***
	(0.0617)	(0.264)	(0.122)	(0.524)
L.Green spillover	0.544	-20.05***	0.212	-20.01***
	(1.141)	(0.788)	(0.783)	(0.781)
L.Fossil spillover	-0.515	20.24***	-0.223	20.15***
	(1.147)	(0.791)	(0.787)	(0.783)
L.R and D exp.	0.0131	3.962***	0.0943	4.012***
	(0.238)	(0.170)	(0.171)	(0.171)
L.Index member		2.286***		2.291***
		(0.705)		(0.705)
Observations	8621		8621	

Notes: Robust standard errors in parentheses. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

After controlling for their endogeneity, the influence of institutional investors on both green and fossil patenting is positive, but statistically indistinguishable from zero. Based on the aggregate measures of green and fossil patents as well as institutional ownership used here, I cannot say that there is any causal relationship between institutional ownership and green or fossil patenting.

The results do, however, qualitatively confirm the findings from Aghion et al. (2016) on path dependency: A higher fossil (green) patent stock significantly increases the probability of filing another fossil (green) patent. The data also confirm another result, namely that a firm's fossil knowledge stock is also associated with more green patenting, whereas the green knowledge stock does not affect fossil patent applications. Overall, the path dependency model seems to fit the data quite well. The very simple spillover measure applied in this estimation is not significant though, neither for green nor for fossil patenting.

Accounting for sector heterogeneity As mentioned in section 3.4, the aggregate measures on green and fossil patenting may hide some important differences between the energy and the transport sector. Most likely, (green) innovations play a larger role in the transport sector than in the capital-heavy energy sector. Moreover, product market competition likely differs between these sectors, with implications for the innovation process and ownership.[20] Table 5 therefore shows results for green and fossil patents in the transport (columns 1 and 2) and energy sector (columns 3 and 4) separately. In all cases, the coefficient on institutional ownership is small or even negative, and the null hypothesis of it being zero cannot be rejected.

Again, the general path dependency model performs well: Both green and fossil transport knowledge stocks influence green transport patenting positively, while green transport knowledge is not associated with an increase in fossil transport patenting – this is in line with the results in Aghion et al. (2016), which are in fact focused on the transport sector. In the case of energy-related patents, the same pattern can be observed with very similar coefficients. This suggests that the specification in Equation 2 works well for both sectors.

Accounting for investor heterogeneity The insignificant influence of institutional owners on the direction of innovation may also be due to the underlying heterogeneity of investors, as mentioned in section 3.4.[21] Not all institutional owners invest with a long time horizon, not all of them have voiced an interest in climate change issues, and not all of them are prone to engage. The results for the effect of different types of investors on green innovation can be found in Table 6. This table only shows the coefficient for investor type ownership; the full tables for green as well as fossil innovation can be found in Appendix A.5 (Tables 18 and 19).

For governments, PRI signatories, and insurers and pension funds, one might expect a particular interest in long-term investments and a preference for low transition risk. The results for the three groups can be seen in columns 1-3. The coefficient on government ownership and PRI signatory ownership is large and positive (a one percentage point increase in PRI signatory ownership is associated with 3 percent more green patents in the following year), but insignificant. For insurance and pension fund companies, no significant influence on the direction of innovation of their portfolio companies can be detected either;

[20]For the relevance of competition in the context of (green) innovation and ownership, see e.g. Aghion et al. (2005), Atanassov (2013), Borochin et al. (2020), Lambertini et al. (2017), and Nesta et al. (2014).

[21]For summary statistics for the respective owner types, please refer to Table 14.

Table 5 – Patents split into transport and energy sectors

Sector	Transport		Energy	
	(1)	(2)	(3)	(4)
Dep. var.	Green patents	Fossil patents	Green patents	Fossil patents
L.IO share	0.0104	-0.116	-0.0462	0.0352
	(0.0599)	(0.106)	(0.0448)	(0.0229)
L.Own stock gr. tr.	1.656***	-0.198		
	(0.188)	(0.379)		
L.Own stock fo. tr.	0.169***	1.952***		
	(0.0457)	(0.224)		
L.Green tr. spillover	0.308	-1.776		
	(1.016)	(1.839)		
L.Fossil tr. spillover	-0.251	1.567		
	(0.940)	(1.710)		
L.Own stock gr. en.			1.561***	0.0978
			(0.122)	(0.0687)
L.Own stock fo. en.			0.193*	1.416***
			(0.109)	(0.0889)
L.Green en. spillover			-0.648	0.541
			(0.715)	(0.356)
L.Fossil en. spillover			0.645	-0.550
			(0.721)	(0.357)
L.R and D exp.	0.0497	0.584	0.331	-0.0237
	(0.238)	(0.434)	(0.212)	(0.110)
Observations	8622	8622	8622	8622

Notes: All columns: Poisson control function estimation (first stage not shown). Robust standard errors in parentheses. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. First stage of control function not shown. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

the coefficient even turns negative. This result may be due to the necessary aggregation of this investor type (see section A.2 for details).

Table 6 – Special investor types and green patenting

	(1)	(2)	(3)	(4)	(5)
L.Gov. share	0.0342				
	(0.0882)				
L.PRI sig. share		0.0343			
		(0.0796)			
L.Ins.& pens. fd. share			-0.121		
			(0.298)		
L.Domestic owner share				-0.0210	
				(0.0505)	
L.Big 3 share					0.0257
					(0.0610)
Observations	8622	8622	8622	8622	8622

Notes: Dependent variable: Green patents. All columns: Poisson control function estimation (first stage not shown). Robust standard errors in parentheses. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Further regressors not shown. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Domestic investors (column 4) are not necessarily more interested in climate issues, but may have better capacities to engage in firms close to them. However, this ability is not reflected in the results, where the coefficient on domestic investors is insignificant and even negative. Column 5 reports results with the share of the “Big Three” index fund managers (BlackRock, Vanguard, and State Street) as the dependent variable. All of them have voiced concern about climate risk.[22] Given their limited ability to influence their risk via selection, the engagement channel might be particularly important for them. Although the Big Three have been shown to contribute to emission reductions of firms (Azar et al. 2020), the insignificant coefficient suggests that their engagement activities do not yet address technological risk in a measurable way.

In summary, the findings for all of these investor types are the same as for the aggregate: no statistically significant effect of a larger ownership share of any particular investor type on green or fossil patenting can be detected.

Some further specification alterations Tables 16 and 17 in Appendix A.5 show results for some basic changes in the specification.

One could argue that institutional investors have a particular interest to direct innovation towards *high-quality* green patenting. Despite focusing on patents which are ultimately granted, patent counts may not capture patent quality sufficiently. As described in section

[22]In fact, they are all PRI signatories, implying some overlap between the Big Three type and the PRI signatory type.

2, family size could be a useful measure in the context of this analysis: it captures the firm's expected commercial value of the patent, and it suffers less from sample censoring than citations. Columns 1 and 2 of Table 16 show the impact of institutional ownership on the family size of green and fossil patents, respectively. The coefficients decrease in size and remain insignificant. Owners' concern with innovative quality does not seem to be the main issue.

Another concern could be that the dichotomy of *green* and *fossil* technologies does not fully capture climate-relevant innovation. There is also the interim case of *grey* patents, which make fossil technologies more efficient and thus reduce emissions. It is possible that investors value the (potentially) low cost and low risk character of these types of incremental innovations. As column 3 in Table 16 shows, this hypothesis is not supported by the data.

One of the main arguments why institutional owners can exert influence on firms is that their large stakes imply more concentrated ownership. It might therefore only be the largest owners that drive successful engagement. In columns 1 and 2 of Table 17, the share of institutional ownership is replaced by the share of the five largest owners. The coefficient is negative in both cases, and insignificant.

It is also possible that the influence of institutional investors takes longer to materialize than one year.[23] Columns 3 and 4 of Table 17 therefore show results for a two-year lag of institutional ownership, IO_{it-2}. The coefficient on green patenting gets larger compared to the baseline, and the coefficient on fossil patenting gets smaller, indicating that there might be some truth in this argument; however, the coefficients are still insignificant.

5.2 Institutional owners and total innovation

From the results presented so far, the interim conclusion is that there is no evidence of institutional owners influencing the direction of innovation in firms. However, this lack of significant effects on climate-related patenting might be due to specification or data issues that have nothing to do with the green and fossil patents themselves. Can the data and model identify any effect of institutional ownership on innovation? To answer this question, equation 3 is estimated, covering all patents.

The main results from these regressions (omitting all explanatory variables except institutional ownership from the table[24]) are presented in Table 7. In this case, institutional ownership has a positive and significant effect on total innovation: A ten percentage point increase in institutional ownership leads to 11.4% more patent filings. At the mean, this would mean a shift from 40.6 to 50.6% in institutional ownership resulting in an increase from 89.9 to 100.2 patents. Despite a different model equation, this result is quite close to the findings in Aghion et al. (2013), where the Poisson specification delivers coefficients

[23] Atanassov (2013), for instance, uses a time lag of two years.
[24] The complete results are available in Appendix A.5, Table 20.

between 0.007 and 0.010. It is surprisingly robust over a wide range of specifications. Column 1 shows the baseline Poisson control function regression of equation 3, which is comparable to the estimations in Tables 4 and 5. Column 2 introduces two-way clustering of standard errors at the 4-digit NACE code and country level.

In column 3, an additional control variable is introduced: Tobin's q, a measure of the market's future expectations deviating from current fundamentals. It could bias the results, since it might be correlated with patents as well as institutional ownership. However, controlling for Tobin's q hardly changes the coefficient on institutional ownership; as shown in Table 20, the coefficient on Tobin's q is also insignificant.

In columns 4 and 5, robustness with respect to the choice of patent count measure is tested. Column 4 uses family-weighted patents in all patent variables, and column 5 uses citations. The citation-based regression is the only one without a significant effect of institutional ownership. As explained in section 2, citations suffer particularly from sample attrition due to the time line of the patenting and citation process. Also, the number of citations can be zero, which leads to an excessive amount of zeroes especially towards the end of the sample (whereas the family size of each patent is always at least 1, the patent itself). Finally, column 6 changes the estimation model from Poisson to negative binomial, which is sometimes recommended in case of overdispersion of the data.[25] The coefficient on institutional ownership gets smaller, but is still significant.

Table 7 – Institutional investors and total patents

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Neg. bin.
Dep. var.	Patents	Patents	Patents	Family size	Citations	Patents
L.IO share	0.0114***	0.0114**	0.0110*	0.0129**	-0.0258	0.00671**
	(0.00348)	(0.00481)	(0.00603)	(0.00624)	(0.0177)	(0.00310)
Clustered SEs	no	yes	yes	yes	yes	yes
Add. control	no	no	yes	no	no	no
Observations	8622	8622	8040	8622	8622	8622

Notes: All estimations use a control function approach (first stage not shown). "Add. control" refers to the inclusion of Tobin's q as an additional control variable. Robust standard errors in parentheses. In the Poisson control function estimations starting in column 2, standard errors are two-way clustered at the 4-digit NACE code and country level. In the negative binomial control function estimation, standard errors are clustered at the 4-digit NACE code level. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include further controls, year fixed effects, and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

From Table 7, we can conclude that a connection between institutional ownership and innovation can be established with the given data and model. Looking at the combined results

[25] Note that the GMM-based ivpoisson estimator implemented in Stata works for any exponential model with multiplicative error and is robust to overdispersion. The negative binomial estimator, on the other hand, is less robust to misspecification.

on carbon-relevant and total patenting, investors appear to encourage overall innovation, while not exerting any influence on climate-relevant innovation. However, the estimates on total patenting may simply be more precise because of higher counts of total patents in the data. As can be seen in the summary statistics in Table 3, climate-relevant patents account for only about 6% of the patents in the sample (which, notably, is a sample of companies which have filed at least one green or fossil patent during the sample period).

5.3 Climate exposure and climate-relevant innovation

This section presents results for testing Equation 4, including climate exposure as an explanatory variable. This specification is a check for statistical power in the dependent variable, looking for any measurable influence between patents and a variable that is not directly innovation-related. It also helps to find out whether firm-specific concerns with climate issues explain green or fossil patenting.

As described in detail in section 3.5, the Sautner et al. (2020a) dataset measures different types of "climate exposure" at firm level based on transcripts of firms' quarterly earnings conference calls with investors. The data reflect both managers' and investors' awareness of these issues. "Climate exposure" can be understood as "exposure to a climate-related shock" specific to the firm. The general "climate exposure" variable can refer to any climate-related shock. The Sautner et al. (2020a) dataset also offers more specific indicators, which are of interest here: "Regulatory exposure" reflects the discussion of climate policies affecting the firm; "opportunity exposure" reflects the discussion of opportunities the firm faces in conjunction with climate issues. Sautner et al. (2020b) show that both of these measures are correlated with other available indicators for climate regulation at country or firm level. Aghion et al. (2016) find a clear relationship between policy-driven fuel prices and a redirection of innovation away from dirty and into clean technologies. We would expect regulatory exposure to have a similar effect.

Table 8 shows the effects of different measures of climate change exposure on green (columns 1-3) and fossil (columns 4-6) patenting.[26] Overall climate change exposure is significantly positively associated with green patenting. Exposure to regulatory shocks, however, does not have any significant impact on green or fossil patenting. Regulatory exposure as measured by Sautner et al. (2020a) differs from policy exposure as measured by fuel prices (Aghion et al. 2016) in one key aspect: Fuel prices are measures of existing climate policies. They are observable, and firms can easily build expectations regarding future fuel prices (at least the tax component of it) based on past fuel prices. This is what might make lagged fuel prices a good predictor of green patenting.[27] The regulatory climate change

[26]The inclusion of the climate change exposure measures significantly reduces sample size. For the sake of completeness, Table 21 reproduces the baseline results (comparable to Table 4) for the reduced sample. Table 15 reports summary statistics for the reduced sample.

[27]The fact that tax-driven fuel price changes can lead to larger fuel demand changes is an established result in the literature on environmental and energy economics, see e.g. Li et al. (2014) and Davis and Kilian (2011). It is usually attributed to the predictability of the tax component.

Table 8 – Climate exposure and carbon-relevant patenting

Dep. var.	(1) Green patents	(2) Green patents	(3) Green patents	(4) Fossil patents	(5) Fossil patents	(6) Fossil patents
L.IO share	-0.00790	-0.000916	-0.0126	0.00964	0.00749	0.00927
	(0.0266)	(0.0268)	(0.0274)	(0.0220)	(0.0234)	(0.0228)
L.CC Exposure	0.0617**			-0.0188		
	(0.0301)			(0.0203)		
L.CC Regulatory Exp.		-0.0893			-0.00158	
		(0.454)			(0.156)	
L.CC Opportunity Exp.			0.134***			-0.0249
			(0.0471)			(0.0346)
L.Own stock fossil	0.0638	0.0640	0.0652	1.364***	1.337***	1.346***
	(0.0645)	(0.0524)	(0.0683)	(0.117)	(0.113)	(0.120)
L.Own stock green	1.443***	1.498***	1.424***	0.0256	0.00423	0.0235
	(0.106)	(0.114)	(0.111)	(0.117)	(0.132)	(0.125)
L.Green spillover	-0.147	-0.0359	-0.190	0.0631	0.0502	0.0679
	(0.288)	(0.293)	(0.297)	(0.219)	(0.236)	(0.227)
L.Fossil spillover	0.183	0.0384	0.246	-0.0656	-0.0439	-0.0683
	(0.354)	(0.362)	(0.365)	(0.284)	(0.306)	(0.296)
L.R and D exp.	0.165***	0.110***	0.175***	0.118***	0.132***	0.125***
	(0.0348)	(0.0314)	(0.0389)	(0.0456)	(0.0452)	(0.0467)
Observations	3972	3972	3972	3972	3972	3972

Notes: All estimations: Poisson control function estimation (first stage not shown). Robust standard errors in parentheses, two-way clustered at the 4-digit NACE code and country level. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

exposure measure probably reflects more long-term expectations voiced by investors. In line with the insignificant results on institutional owner shares, it seems that the concerns about expected regulation do not (yet) translate into a change in the direction of innovation within firms.[28]

Exposure to opportunity shocks, on the other hand, is significantly positively associated with green patenting. According to these results, a one standard deviation increase in climate opportunity exposure leads to a staggering 25% increase in green patents (0.134*1.887). As shown in Table 2, the top bigrams for opportunity and overall exposure are very similar, indicating that the frequency of opportunity-related keywords is driving the results for overall climate change exposure.

Given the way in which the "climate change opportunity" measure is constructed, it is difficult to interpret the effect as causal. The question is what "exposure to opportunity shocks" actually means. Only very few of the underlying bigrams relate to opportunity-creating policies, which would reflect an exogenous opportunity shock. Looking at the bigrams, it is possible that investors are making management aware of green opportunities in a more general sense, and push for more innovation. It is, however, also likely that managers mention particular green R&D successes in earnings conference calls – resulting in high "climate change opportunity" measures –, which are followed by green patent applications in the next year. Therefore, the results from table 8 suggest that "climate change opportunity exposure" is a good predictor of green patenting activity, but not necessarily reflecting a causal relationship.

Nevertheless, the clear results on climate change opportunity exposure (with the expected sign) indicate that the patent data exhibit sufficient variation over time to detect effects of firm-specific characteristics related to climate risk and institutional ownership. This is an indication that the nonsignificant results can be interpreted as "no effect". In this light, it is interesting that fossil patenting is not affected by any climate-related exposure. There is no evidence that green technologies crowd out fossil ones, or that technological risk is addressed by actively moving out of fossil technologies.

6 Conclusion

The tightening of climate policies entails transition risk not only for fossil fuel producers and emitters, but also for innovators in related technologies: their knowledge is at risk of losing value due to climate policy. This translates into a risk for investors of the affected technology firms. This paper explores whether institutional investors have recognized this risk, and whether their engagement directs firms' innovation into green technologies.

The analysis draws on the growing literature on the role of institutional investors in equity markets. Via direct conversations and voting in shareholder meetings, large asset managers

[28]Regressions using the second lag of regulatory exposure yield insignificant coefficients as well. Results are available upon request.

and funds can influence the behavior of firms (Appel et al. 2016, 2018; Dimson et al. 2015) and have been shown to encourage innovation (Aghion et al. 2013; Bushee 1998). The underlying idea is that many institutional investors have a more long-term perspective than "myopic" managers who are incentivized by short-term performance goals.

In this paper, I construct a worldwide firm-level panel on patents and institutional ownership. A classification of patents into *green* and *fossil* technology categories is applied to measure firm-specific technological knowledge and innovation. I then estimate a dynamic patent count data model building on Aghion et al. (2016), where patenting depends on previous knowledge, spillovers, R&D efforts, and the share of institutional ownership. The endogeneity of institutional ownership is addressed by a control function approach.

I find robust evidence for the positive influence of institutional ownership on overall patenting activity. However, there is no evidence for any effect on fossil or green technologies, not even for investors with long-term perspective or signatories of the UN Principles for Responsible Investment (UN PRI). The results also hold when looking specifically at the transport sector, where technological knowledge likely plays a larger role. These results are in contrast to previous studies which show a positive relationship between climate policy and green innovation (Aghion et al. 2016), and between institutional ownership and environmental outcomes (Dyck et al. 2019; Dimson et al. 2015; Azar et al. 2020). Institutional investors seem to perceive and address technological risk differently from overall environmental or transition risks.

To find out whether climate-relevant patenting can be explained by firm-specific climate-related risks, I use a newly developed dataset on firm-level climate exposure (Sautner et al. 2020a). It is based on firms' conference calls with investors and measures the relative frequency at which climate-related terms are mentioned. I find a significant positive relationship between "climate opportunity exposure" and subsequent green variation. I cannot ascertain that this is a causal effect of an exogenous opportunity shock, e.g., green technology support schemes. What the indicator rather seems to reflect is that managers talk about green innovation activity that is filed as a patent in the following year.

The results on climate exposure can be used to address another issue. If the insignificant effects I find for institutional ownership just result from a dataset with insufficient variation, they do not have any informational value. The climate exposure results show that there is sufficient statistical power in the data to detect a relationship between green patents and a variable that is not directly related to innovation. The insignificant effect of institutional ownership on green and fossil innovation can therefore likely be interpreted as a zero effect.

It is remarkable that neither institutional ownership, nor firm-specific regulatory or opportunity shocks have any effect on fossil patenting. Moving out of fossil technology development does not (yet) seem an answer to (expected) policies. Possibly, the use of fossil technologies still generates too much income today to be given up in favor of more future-oriented technologies; neither investors nor regulation appear to generate sufficient pressure to draw managers away from their "cash cows". For the large, publicly listed firms which constitute my sample, such a turnaround may be particularly difficult.[29]

One reason for the missing influence of institutional ownership on fossil as well as green technologies could be related to reputational concerns, or the lack thereof. "ESG risks" are often reputation risks: a firm may be affected by negative headlines in case of oil spills or worker protests, for example. Innovation is less visible. It is possible that investors' main concern is about reputational risk, and they are therefore less interested in the direction of innovation.

Policy uncertainty has been shown to reduce innovation (Bhattacharya et al. 2017) and could be another explanation for the absence of an effect of institutional ownership on climate-relevant patenting. With climate policy uncertainty, investors' strategy might be to support innovation in other fields rather than betting on green or fossil technologies. An important next step in this line of research would be to examine events that reduce policy uncertainty and the resulting market valuation of green and fossil patenting.

This also points to a related issue: the timing of this analysis. Event studies have shown that the conclusion of the Paris Agreement changed investors' expectations regarding climate policy stringency (Ramelli et al. 2019; Kruse, Mohnen, and Sato 2020). Despite early actions such as the launch of the UN PRI in 2006, investors may have only started to recognize and address transition risk more recently. It is possible that too few years have passed since Paris to detect an effect of institutional ownership on the direction of innovation – but repeating the analysis in a couple of years may provide a different picture.

[29] In the management literature, we can find the idea that established companies focus more on incremental improvements, whereas small start-ups create "disruptive innovation" (Christensen et al. 2015). As most green innovations can still be regarded as more "novel" (Dechezleprêtre et al. 2017), a typical strategy for an incumbent firm would be to continue with their traditional business areas, and to acquire new-technology startups. In future research, it would be interesting to see whether an increase in indirect green knowledge acquisition can be observed in the data, and whether institutional investors support this.

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A Appendix

A.1 Patent example and patent classification codes

Figure 1 – Patent example

US010018145B2

(12) **United States Patent**
Hussain

(10) **Patent No.: US 10,018,145 B2**
(45) **Date of Patent: Jul. 10, 2018**

(54) **SYSTEM AND METHOD FOR IN-CYLINDER THERMAL ENERGY RECOVERY AND CONTROLLING CYLINDER TEMPERATURE**

(71) Applicant: **Ford Global Technologies, LLC**, Dearborn, MI (US)

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(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 158 days.

(21) Appl. No.: **15/013,786**

(22) Filed: **Feb. 2, 2016**

(65) **Prior Publication Data**

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F02B 7/00	(2006.01)
F01K 23/06	(2006.01)
F02F 1/40	(2006.01)
F01N 5/02	(2006.01)
F02B 37/00	(2006.01)
F02G 5/02	(2006.01)
F02G 5/04	(2006.01)

(52) **U.S. Cl.**
CPC ***F02F 1/10*** (2013.01); ***F01K 23/065*** (2013.01); ***F01N 5/02*** (2013.01); ***F02B 37/00*** (2013.01); ***F02F 1/40*** (2013.01); ***F02G 5/02*** (2013.01); ***F02G 5/04*** (2013.01); *F02G 2262/00* (2013.01); *Y02T 10/166* (2013.01)

(58) **Field of Classification Search**
CPC F02F 1/10; F02F 1/40; F02B 37/00; F02G 5/02; F02G 5/04; F02G 2262/00; F01K 23/065; F01N 5/02; Y02T 10/166
USPC 60/605.1, 605.2, 614, 616, 618
See application file for complete search history.

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(57) **ABSTRACT**

Methods and systems are provided for an in-cylinder thermal energy recovery device that utilizes the Rankine Cycle to recover energy from exhaust gasses that may be used to produce additional work in the vehicle. In one example, a method may include outfitting the head area of each cylinder of an engine with a tube array comprising one or more tubes passing through the combustion chamber of the corresponding cylinder. Each tube array may receive an injection of working fluid that is based, in part, on the temperature of the tube array's corresponding cylinder, which may then be utilized to recover heat energy.

20 Claims, 4 Drawing Sheets

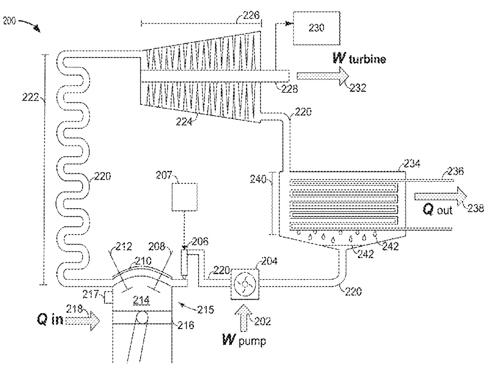

Table 9 – Patent classification codes: transport

GREEN	
B60K 1	Arrangement or mounting of electrical propulsion units
B60K 6	Arrangement or mounting of hybrid propulsion systems comprising electric motors and internal combustion
B60K 16	Arrangements in connection with power supply of propulsion units in vehicles from force of nature, e.g. sun or wind
B60L 3	Electric devices on electrically-propelled vehicles
B60L 7	Dynamic electric regenerative braking
B60L 8	Electric propulsion with power supply from force of nature, e.g. sun, wind
B60L 9	Electric propulsion with power supply external to vehicle
B60L 11*	Electric propulsion with power supplied within the vehicle
B60L 13	Electric propulsion for monorail vehicles, suspension vehicles or rack railways; Magnetic suspension or levitation for vehicles
B60M	Power supply lines, or devices along rails, for electrically-propelled vehicles
B60L 15	Methods, circuits, or devices for controlling the traction-motor speed of electrically-propelled vehicles
B60R 16	Electric or fluid circuits specially adapted for vehicles and not otherwise provided for
B60S 5/06	Supplying batteries to, or removing batteries from, vehicles
B60W 10**	Conjoint control of vehicles sub-units of different type or different function (for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle B60L0011)
B60W 20**	Control systems specially adapted for hybrid vehicles
H01 M8	Fuel cells
GREY***	
F02M 39, F02M 71	Fuel injection apparatus
F02M 3/02-05	Idling devices for carburettors preventing flow of idling fuel
F02M 23	Apparatus for adding secondary air to fuel-air mixture
F02M 25	Engine-pertinent apparatus for adding non-fuel substances or small quantities of secondary fuel to combustion-air, main fuel, or fuel-air mixture
F02D 41	Electric control of supply of combustion mixture or its constituents
F02B 47/06	Methods of operating engines involving adding non-fuel substances or anti-knock agents to combustion air, fuel, or fuel-air mixtures of engines, the substances including non-airborne oxygen
FOSSIL	
F02B*	Internal-combustion piston engines; combustion engines in general
F02D**	Controlling combustion engines
F02F	Cylinders, pistons, or casing for combustion engines; arrangements of sealings in combustion engines
F02M	Supplying combustion engines with combustiles mixtures or constituents thereof
F02N	Starting of combustion engines
F02P	Ignition (other than compression ignition) for internal-combustion engines

[*] : A patent with code B60L 11 is not considered clean when it is also classified as F02B (e.g., a diesel locomotive).
[**] : Patents with code B60W 10 and B60W 20 are not considered as clean when they are also classified as F02D.
[***] : Note that codes classified as grey are a subset of codes classified as fossil in the transport case.
Source: Adapted from Dechezleprêtre et al. (2017), using information from the International Patent Classification. In this table, all codes are from the International Patent Classification (IPC).

Table 10 – Patent classification codes: energy

GREEN	
Y02E 10	Energy generation through renewable energy sources
Y02E 30	Energy generation of nuclear origin
E02B 8/08	Tide or wave power plants
F03B 13/10-26	Submerged units incorporating electric generators or motors characterized by using wave or tide energy
F03D	Wind motors
F03G 4	Devices for producing mechanical power from geothermal energy
F03G 6	Devices for producing mechanical power from solar energy
F03G 7/05	Ocean thermal energy conversion
F24J 2	Use of solar heat
F24J 3	Other production or use of heat, not derived from combustion
F24S	Solar heat collectors; solar heat systems
F24T	Geothermal collectors; geothermal systems
F26B 3/28	Drying solid materials or objects by processes involving the application of heat by radiation, e.g. from the sun
GREY	
Y02 E20	Combustion technologies with mitigation potential
Y02 E50	Technologies for the production of fuel of non-fossil origin
FOSSIL	
C10 G1	Production of liquid hydrocarbon mixtures from oil-shale, oil-sand, or non-melting solid carbonaceous or similar materials, e.g. wood, coal
C10 L1	Fuel
C10 J	Production of fuel gases by carburetting air or other gases
F01 K	Steam engine plants; steam accumulators; engine plants not otherwise provided for; engines using special working fluids or cycles
F02 C	Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants
F22	Steam generation
F23	Combustion apparatus; combustion processes
F27	Furnaces; kilns; ovens; retorts

Source: Adapted from Dechezleprêtre et al. (2017), using information from the International Patent Classification and Cooperative Patent Classification.
In this table, the patent classes starting with Y are from the Cooperative Patent Classification (CPC), all other codes are from the International Patent Classification (IPC).

A.2 Mapping of investor types

Table 11 provides an overview of the mapping of shareholder types. The shareholders are identified by their own BvD ID (if available). In order to classify them into different shareholder types, both their NACE code and the "entity type" asigned by BvD are used. Each of the classifications have their own advantages and disadvantages. NACE codes generally allow for a good distinction between private financial services institutions, such as banks, investment funds, or insurance and pension funds. However, outside of the financial services classification, NACE codes become less useful: many foundations, private funds or even cooperative banks are classified as "Activities of membership organizations". The shareholder types provided by BvD, on the other hand, identify these institutions more clearly. Moreover, they are generally useful to distinguish between individuals and institutional investors, and to differentiate between government investors and private ones. Within private investment organizations, the attribution of types in the BvD classification seems somewhat arbitrary (e.g. pension funds are sometimes coded as "insurance companies", and BlackRock is labelled "Bank"). Therefore, the financial sector classification follows, and slightly adapts, the approach from Battiston et al. (2017):

- The Orbis classification is used in case of "Government" and "Foundation".
- In all other cases, the NACE classification is used, if it is available and if it is equal to some financial services-related sector (for the mapping, see Table 11).
- If no NACE code is available or if it is not related to financial services, the Orbis classification is used (for the mapping, see Table 11).
- Investors which do not belong to the institutional ownership category are dropped from the analysis:
  - In case the Orbis classification lists them as "Industrial Company", "self-owned", or "One or more known individuals or families", observations are excluded.
  - In case the Orbis classification lists them as "Other unnamed private shareholders" or "Other unnamed shareholders", they are excluded if there is no NACE code available (these often appear to be unclassified funds or investment vehicles).

Firms are assigned dummies whenever a Global Ultimate Owner for them is reported who controls more than 50% or more than 25%, respectively, and if this Global Ultimate Owner is different from the firm itself. Another dummy indicates that a firm is self-owned.

Table 11 – Mapping of shareholder types

Type	NACE Rev. 2 4-digit codes	BvD Entity types
Bank	6410-6419	Bank
Insurance and Pension funds	6510-6539, 6620-6629	Insurance company; Mutual & Pension Fund/ Nominee/ Trust/ Trustee
Investment fund	6420-6439, 6491, 6612, 6630-6639	Hedge fund; Private equity
Other Credit Institutions	6492, 6499	Venture Capital
(Other) Financial Services	6611, 6619, 6400	Financial Company
Government		Government
Foundation		Foundation

Notes: For types in normal font, the NACE code was given precedence; only if it was missing or equal to none of the listed codes, the BvD classification was used.
For types in italics, the BvD classification was used regardless of the NACE classification code.

A.3 Background on climate exposure variable

Publicly listed firms are required to report their quarterly earnings; in conjunction with these reportings, firm managers hold conference calls with investors and analysts. Sautner et al. (2020b) have developed a method – and corresponding dataset – to measure firm-specific climate change exposure by the use of transcripts of these conference calls. The conference calls are considered to play an important role in reducing information asymmetry between managers and investors, and have been described as "more or less routine" (Hollander et al. 2010) for already quite a while. Transcripts of the conference calls are available from financial data providers such as Thomson Reuters.

Importantly, a conference call consists of two parts: a presentation by management is followed by a question-and-answer round. In the first part, managers can choose what information to disclose; in the second part, call participants can ask questions also about issues which were not disclosed previously. Therefore, conference calls provide an important source of information beyond voluntary disclosure such as in sustainability reports.

The conference calls can cover virtually any topic of relevance to the firm at the time. With the help of the transcripts and machine learning algorithms, certain words or expressions can be identified and assigned to a topic of interest. Sautner et al. (2020b) develop and use a set of signal word combinations (termed "bigrams") related to climate change and climate policy to derive a measure of "climate change exposure" at firm-year level.

Similar methods have been used to identify risks and opportunities that firms face in various dimensions, such as political risk (Hassan et al. 2019), uncertainty about Brexit

(Hassan et al. 2020b), or even Covid-19 (Hassan et al. 2020a). In this literature, the term "exposure" is used to describe "the proportion of the conversation during the conference call that is centered on a particular topic" (Sautner et al. 2020b).[30]

A.4 Further summary statistics

Table 12 – Average patent numbers per firm and year

	Green	Fossil	All patents
Raw patent count	2.47	3.08	89.93
Family-size-weighted patent count	8.85	10.97	287.35
Average family size per patent	3.58	3.56	3.20
Citation-weighted patent count	1.25	1.50	150.85
Average citations per patent	0.51	0.49	1.68

Notes: The table shows averages over all sample years. Due to the lagged structure of the estimation, the sample period for patents is 2010-2018. Note that in this paper's definition, family size is at least equal to 1 (each patent is applied for at least once in one country). Citations, on the other hand, can be zero.

[30]This use of the term exposure differs from how the term "risk exposure" is defined in the asset pricing literature, see Hassan et al. (2019) for a discussion.

Table 13 – Mean number of fossil, green and all patents, family size and citations over time

Year	Green patent count	Green patent family size	Green patent citations	Fossil patent count	Fossil patent family size	Fossil patent citations	All patents count	All patents family size	All patents citations
2010	3.58	14.84	2.04	3.49	13.99	2.23	109.68	399.60	281.11
2011	3.90	14.92	2.38	3.80	15.13	2.96	109.02	389.46	273.82
2012	4.07	15.33	2.27	4.02	15.04	2.90	119.81	413.71	273.22
2013	3.12	10.95	1.92	4.08	15.76	2.26	116.61	390.00	197.16
2014	2.65	9.45	1.48	4.01	13.62	1.74	106.75	345.31	148.77
2015	2.45	7.81	0.79	3.94	12.84	1.14	107.25	320.00	124.30
2016	1.67	5.14	0.48	2.67	8.47	0.52	75.05	205.93	77.61
2017	0.97	2.83	0.22	1.53	4.33	0.15	51.10	120.74	28.39
2018	0.35	0.84	0.03	0.51	1.17	0.03	24.28	49.24	4.45
Average	2.47	8.85	1.25	3.08	10.97	1.50	89.93	287.35	150.85

Notes: Numbers are shown for patents applied for in the given year. Patent numbers are based on a sample of publicly listed firms which filed at least one patent classified as green or fossil in the sample period. Due to the lagged structure of the estimation, the sample period for patents is 2010-2019.

Table 14 – Summary statistics for different investor types

	Mean	Standard deviation	Minimum	Maximum
Gov. share	3.07	5.97	0	89.08
PRI sig. share	8.83	8.90	0	52.26
Ins. and PF share	6.45	7.18	0	81.35
Domestic share	27.73	24.99	0	100.00
Big 3 share	5.97	6.48	0	30.25
Observations	8.622			

Table 15 – Summary statistics for climate change exposure sample

	Mean	Standard deviation	Minimum	Maximum
CC Exposure	1.988	3.353	0	37.648
CC Regulatory Exp.	0.098	0.448	0	11.111
CC Opportunity Exp.	0.898	1.887	0	26.037
All patents	125.64	411.11	0	7,975
Fossil patents	3.91	24.45	0	708
Green patents	3.16	23.10	0	794
Patent stock	844.7	2471.1	0	36324.3
Fossil patent stock	25.6	156.9	0	4404.1
Green patent stock	20.2	137.0	0	3,845.9
Spillover	179,300.7	151,570.5	0	584,380.8
Fossil spillover	4,625.5	5,829.4	0	24,151.9
Green spillover	3,094.1	5,161.2	0	21,157.4
R & D expenditures, in thousand USD	2,307,401	$1.03 \cdot 10^{11}$	0	$6.43 \cdot 10^{12}$
IO share, in percent	56.21	24.57	0	100

Notes: CC Exposure is “Climate Change Exposure”, CC Regulatory Exp. is “Climate Change Regulatory Exposure”, and CC Opportunity Exp. is “Climate Change Opportunity Exposure” as constructed in Sautner et al. (2020a); all climate exposure variables are scaled by the factor 1000 compared to the Sautner et al. (2020a) dataset.

A.5 Further estimation results

Table 16 – Family size and grey patents

Dep. var.	(1) Green family size	(2) Fossil family size	(3) Grey patents
L.IO share	0.000346	-0.00364	-0.00489
	(0.0391)	(0.0276)	(0.140)
L.Own stock fossil, FS	0.105***	0.887***	
	(0.0385)	(0.0858)	
L.Own stock green, FS	1.034***	0.0332	
	(0.0838)	(0.0672)	
L.Green spillover, FS	0.0104	-0.0205	
	(0.598)	(0.417)	
L.Fossil spillover, FS	-0.0304	0.00764	
	(0.598)	(0.414)	
L.R and D exp.	0.128	0.165	0.330
	(0.166)	(0.123)	(0.602)
L.Own stock fossil			0.378
			(0.246)
L.Own stock green			-0.271
			(0.329)
L.Own stock grey			1.896***
			(0.231)
L.Green spillover			-0.153
			(2.935)
L.Fossil spillover			-0.730
			(2.328)
L.Grey spillover			0.810
			(0.756)
Observations	8622	8622	8622

Notes: All columns: Poisson control function estimations (first stage not shown). Robust standard errors in parentheses. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 17 – Ownership concentration and two-year lag

Dep. var.	(1) Green patents	(2) Fossil patents	(3) Green patents	(4) Fossil patents
L.Top 5 share	-0.0629	-0.0282		
	(0.148)	(0.102)		
L2.IO share			0.0673	-0.00383
			(0.0705)	(0.0414)
L.Own stock fossil	0.101*	1.283***	0.170**	1.295***
	(0.0536)	(0.0780)	(0.0768)	(0.124)
L.Own stock green	1.435***	0.00734	1.575***	-0.00861
	(0.0715)	(0.0502)	(0.154)	(0.128)
L.Green spillover	0.0742	-0.00195	1.488	-0.126
	(0.0834)	(0.0749)	(1.502)	(0.867)
L.Fossil spillover	-0.0590	-0.0150	-1.463	0.119
	(0.0813)	(0.0742)	(1.503)	(0.867)
L.R and D exp.	0.0763	0.123**	-0.170	0.162
	(0.0825)	(0.0624)	(0.309)	(0.189)
Observations	8622	8622	7345	7345

Notes: All columns: Poisson control function estimations (first stage not shown). Robust standard errors in parentheses. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 18 – Special investor types and green patenting, full table

	(1)	(2)	(3)	(4)	(5)
L.Gov. share	0.0342				
	(0.0882)				
L.PRI sig. share		0.0343			
		(0.0796)			
L.Ins.& pens. fd. share			-0.121		
			(0.298)		
L.Domestic owner share				-0.0210	
				(0.0505)	
L.Big 3 share					0.0257
					(0.0610)
L.Own stock green	1.431***	1.452***	1.445***	1.421***	1.444***
	(0.0720)	(0.0851)	(0.0908)	(0.0769)	(0.0775)
L.Own stock fossil	0.110**	0.113***	0.0909	0.0850	0.111**
	(0.0437)	(0.0425)	(0.0793)	(0.0851)	(0.0435)
L.Green spillover	0.0777	0.259	-0.270	-0.251	0.182
	(0.0805)	(0.416)	(0.877)	(0.807)	(0.246)
L.Fossil spillover	-0.0294	-0.235	0.320	0.322	-0.160
	(0.0954)	(0.434)	(0.923)	(0.902)	(0.268)
L.R and D exp.	0.0997***	0.0712	0.161	0.176	0.0755
	(0.0356)	(0.0937)	(0.119)	(0.162)	(0.0874)
Observations	8622	8622	8622	8622	8622

Notes: Dependent variable: Green patents. All columns: Poisson control function estimations (first stage not shown). Robust standard errors in parentheses. Knowledge stocks, spillovers and R&D expenditures are in logs. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 19 – Special investor types and fossil patenting

	(1)	(2)	(3)	(4)	(5)
L.Government share	0.0171				
	(0.0629)				
L.PRI sig. share		0.0135			
		(0.0539)			
L.Ins.& pens. fd. share			-0.0858		
			(0.186)		
L.Domestic owner share				-0.0101	
				(0.0362)	
L.Big 3 share					0.0120
					(0.0412)
L.Own stock green	-0.00700	0.00880	0.00566	-0.0218	0.00789
	(0.0340)	(0.0608)	(0.0374)	(0.0710)	(0.0528)
L.Own stock fossil	1.289***	1.289***	1.249***	1.278***	1.289***
	(0.0742)	(0.0700)	(0.124)	(0.0904)	(0.0699)
L.Green spillover	0.00426	0.0720	-0.249	-0.156	0.0513
	(0.0729)	(0.280)	(0.552)	(0.582)	(0.167)
L.Fossil spillover	-0.00563	-0.0854	0.250	0.164	-0.0662
	(0.0853)	(0.293)	(0.579)	(0.646)	(0.184)
L.R and D exp.	0.134***	0.123*	0.170**	0.170	0.122*
	(0.0296)	(0.0699)	(0.0721)	(0.113)	(0.0653)
Observations	8622	8622	8622	8622	8622

Notes: Dependent variable: Fossil patents. All columns: Poisson control function estimations (first stage not shown). Robust standard errors in parentheses. Estimation period is 2009-2018. All regressions include year fixed effects and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 20 – Total Patents, full table

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Poisson CF	Poisson CF with SE clust.	Poisson CF add. control	Poisson CF	Poisson CF	Neg. bin. CF
Dep. var.	Patents	Patents	Patents	Family size	Citations	Patents
L.IO share	0.0114***	0.0114**	0.0110*	0.0129**	-0.0258	0.00671**
	(0.00348)	(0.00481)	(0.00603)	(0.00624)	(0.0177)	(0.00310)
L.Own patent stock	1.274***	1.274***	1.270***			1.483***
	(0.0374)	(0.0313)	(0.0370)			(0.0340)
L.Own patent stock, FS				1.109***		
				(0.0540)		
L.Own patent stock, cit.					1.318***	
					(0.0758)	
L.Total spillover	-0.0174*	-0.0174	-0.0154			-0.0167
	(0.00902)	(0.0161)	(0.0172)			(0.0104)
L.Total spillover, FS				-0.00957		
				(0.0224)		
L.Total spillover, cit.					0.0989	
					(0.0633)	
L.Tobin's Q			0.0257			
			(0.0276)			
L.R and D exp.	0.0132	0.0132	0.0179	0.0447	0.128**	0.0358
	(0.0277)	(0.0374)	(0.0436)	(0.0467)	(0.0610)	(0.0228)
Observations	8622	8622	8040	8622	8622	8622

Notes: Robust standard errors in parentheses. In the Poisson control function (CF) estimations starting in column 2, standard errors are two-way clustered at the 4-digit NACE code and country level. In the negative binomial control function estimation, standard errors are clustered at the 4-digit NACE code level. Estimation period is 2009-2018. All regressions include year fixed effects, and firm fixed effects using the BGVR method. First stage not shown. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 21 – Baseline results with climate exposure sample

	(1) Green patents	(2) Fossil patents
L.IO share	-0.00157	0.00760
	(0.0272)	(0.0236)
L.Own stock fossil	0.0609	1.335**
	(0.0567)	(0.120)
L.Own stock green	1.496**	0.00494
	(0.114)	(0.134)
L.Green spillover	-0.0467	0.0551
	(0.293)	(0.237)
L.Fossil spillover	0.0525	-0.0488
	(0.363)	(0.309)
L.R and D exp.	0.114**	0.133**
	(0.0399)	(0.0469)
Observations	3972	3972

Notes: All columns: Poisson control function estimation (first stage not shown). Robust standard errors in parentheses, two-way clustered at the 4-digit NACE code and country level. Estimation period is 2009-2018. All regressions include year fixed effects, and firm fixed effects using the BGVR method. Significance levels are indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.