Market Valuation of Climate Patents: What are the Most Valuable Innovations ?

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Abstract

This paper analyzes the market valuation of climate innovations through a detailed examination of patent data. We explore the relationship between Tobin's Q —a measure of firm valuation— and the stock of patents across various climate technology categories. Our findings indicate that, generally, investors do not value climate innovations. However, our exploratory analysis reveals two notable exceptions. First, patents related to improving the efficiency of carbon-intensive technologies (carbon intensive climate innovation) show a positive correlation with firm valuation. Second, a select group of patents in non-carbon-intensive climate technologies, which contribute to both adaptation and mitigation efforts, are also positively valued. Our results suggest that a one standard deviation increase in the stock of patents relative to R&D expenses, measuring firms' research efficiency in these climate innovation categories, is associated with an increase between 0.5 % and 1.5 % in Tobin's Q.

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1 Introduction

Reducing carbon emissions may either come from behavioral changes or technological improvements and innovation. Focusing on technological innovation is attractive for investors and policymakers alike since it offers a pathway to limit climate change without sacrificing economic progress. Technological development is also an integral part of the strategies to reach a net zero economy. IEA (2021) reports that most climate scenarios aimed at reaching net zero by 2050 assume the widespread use of technologies that have not been developed yet. Economic studies model policy-induced technical change as a possible solution to achieving sustainable growth that does not lead to an environmental catastrophe (Acemoglu et al., 2012).

The last two decades have indeed seen significant advances in alternative energy production and other low-carbon technological solutions. Climate technologies are considered an emerging field that touches on many different technological areas (

angelucciSupportingGlobalInitiatives2018). The number of climate related patents have seen a marked increase in many countries around the world, and new methods have been developed to identify them (Haščič and Migotto, 2015). Among the European start-ups, Carbon and Energy related firms have become dominant in recent years (The Economist, 2023).

Accordingly, climate innovation has also received increased attention from finance researchers. However, empirical evidence on the stock market reaction to climate innovation remains mixed, with many studies showing an under-performance of climate innovators in stock markets. Cohen et al. (2020) argue that most of the high-quality green innovation in the patent space is carried out by the energy sector, which is shunned by ESG funds because of its high carbon footprint, and does not get rewarded by ESG score providers for its innovative output. Atta-Darkua et al. (2022) show that institutional investors tend to tilt away from main climate innovator firms, that are deemed to be polluting. Furthermore, recent studies also do not find a positive market reaction to green innovation, even when looking beyond patents at the firm's broad innovation activities (Leippold and Yu, 2023), or controlling for various factors such as institutional ownership, investors' attention or firms' CEO characteristics (Andriosopoulos et al., 2022).

A particular advantage of patent data is that it carries information on the type of innovation a given organization is engaged in, unlike their R&D expenses. As explained in Reza and Wu (2024) patents carry information on technology classes, which can be utilized to follow firms' green investment activities. Recent advances in patent classification schemes of climate technologies have opened an array of research opportunities for economists, such as tracking down trends in climate technology (Dechezlepretre, Fankhauser, et al., 2020), analyzing determinants of green innovation (Aghion et al., 2016) and studying characteristics of green patents. Patents are also a verifiable investment activity, since they are issued by a third party - United States Patent and Trademark Office (USPTO) (Reza and Wu, 2024). In our sample, we observe a five-fold increase in the number of climate patents issued between 1995 and 2020. This points to their increased relevancy in the recent years.

In this paper, we make use of the granularity of patent classifications to compare not just climate innovation against the overall non-climate innovation, but also climate innovation and non-climate innovation within the carbon intensive technologies, i.e. the brown technological space. We also distinguish different types of innovation within climate patents according to climate goals they adress. Namely, we compare patents related to mitigation and adaptation and their relative market valuation.

We rely on Y02 scheme launched by European Patenting Office to identify innovation that contribute to climate change mitigation and adaptation and then use International Patent Classification (IPC) main section codes to identify whether a given patent relates to a carbon intensive technological class. Table A1 describes the sub-classes of Y02 patents, while Table A2 shows the list of technological classifications used in determining carbon intensive patents. While the majority of Y02 patent subclasses identify climate change mitigation in different sectors, there is a special subclass for adaptation patents. Carbon intensive technologies refer to technologies in fossil fuel electricity generation, as defined in Lanzi et al. (2011) or transportation engines relying on fossil fuel.

Using the market valuation framework by Hall et al. (2005), we regress Tobin's Q on US firm's patent stock in different categories of climate and non-climate innovation between 1995 and 2020. This hedonistic approach allows us to uncover investor valuation associated with different types of innovation (Goyal and Wahal, 2023).

In our first regression, we distinguish only two types of innovation: climate and non-climate. In line with previous findings (Andriosopoulos et al., 2022, Leippold and Yu, 2023), we do not find a positive reaction of firms' value to climate patents overall, either by considering current and one-year forward Tobin's Q. Similarly, we find no link between overall Non Climate patents and market valuation. We argue that climate innovation (and innovation, in general) may be in most cases too risky or uncertain to be reflected in market valuation.

Next, we focus on a specific type of climate innovation those improving the efficiencies of existing brown technologies, which we label as Climate Carbon Intensive. To do that, we distinguish patents not only on whether they contribute to climate (i.e. whether they have a Y02 tag), but also whether they belong to a carbon intensive technology class (based on main IPC codes). This leads to four mutually exclusive categories of patents: Climate Carbon Intensive, Climate Non Carbon Intensive, Non Climate Carbon Intensive, and Non Climate Non Carbon Intensive. The large majority of carbon intensive climate patents belong to transportation subclass (Y02T), followed by energy (Y02E), and production (Y02P). An example of a carbon intensive climate patent is shown in Figure A1, which describes a skip-cycle strategy to operate a four cycle engine - a type of internal combustion engine (ICE) that requires four piston strokes (intake, compression, power, and exhaust). The patent is labeled as Y02T (climate mitigation related to Transportation), because of its potential to help with ICE efficiencies.

We show that only Climate Carbon Intensive among the four categories is positively correlated with Tobin's Q. One standard deviation increase in the stock of Climate CI patents scaled by R & D stock is associated with around 0.9% and 1.5 % increase in current market valuation and around 0.5% increase in one year-forward market valuation. This relationship survives, even if we use industry dummies or other firm-level control variables. The coefficient on similar innovations without a climate label (Non Climate Carbon Intensive patents) is negative and statically not different from zero. We interpret these results as markets valuing firms' innovative efforts as a response to climate change transition. However, this response is limited to climate innovation in fossil fuel technologies. It may be that markets value directly applicable (and thus less risky) innovation responses to the transition. These innovations may also directly help the patent-issuing firms to attain superior financial performance by switching to less expensive factors of production (Reza and Wu, 2024).

Next, we distinguish Climate Non-Carbon Intensive patents further based on whether they contribute to mitigation or adaptation efforts. Our initial results are confirmed to a large extent. Namely, coefficients on Climate Adaptation and Mitigation patents remain largely insignificant. However, we report a positive correlation between market valuation and dual-purpose patents that help both with mitigation and adaptation after accounting for industry-fixed effects. We report an economic magnitude of between 0.5% and 0.7% increase in current market valuation following one standard deviation increase in research efficiency (patent stock divided by R&D) in this innovation category [1]. This relationship may stem from investors taking a multiplicative perspective on the value obtained from climate risk strategies.

Our paper is related to a growing number of studies that explore the relationship between firms' value and their green innovative activities. Dechezlepretre, Mucklay, and Neelakantan (2020) report on an international sample of firms that green innovation is positively correlated with market value as proxied by Tobin's Q, while dirty innovation is not. Our study differs from theirs in terms of the sample, period covered and the definition of climate innovations. On the other hand, Andriosopoulos et al. (2022) find that in the US, green patents is not associated with higher firm value, firm's environmental score or level of institutional ownership. Our paper adds to these papers by examining a more refined classification of climate patents. We show that non all climate patents are born equal and that specific climate innovations: (1) those improving carbon intensive technologies and (2) those pertaining to both mitigation and adaptation are positively valued by financial markets.

[1] In all specifications, the relationship between Tobin's Q and innovation variables remain consistent until t +3, when the relationship becomes non-significant. However, with each horizon, our sample size is also reduced.

Some studies also concentrate on the immediate stock market reaction to patent issuance and use it as a proxy for the patent economic value, as proposed by Kogan et al. (2017)). Andriosopoulos et al. (2022) show that stock price reacted negatively on dates when green patents are granted. Hege et al. (2023) show that firms that get *lucky* climate patents (those randomly assigned to a more lenient patent examiner for approval) enjoy higher abnormal cumulative returns, especially if there is a heightened attention to climate at the time of the patent's issue. Reza and Wu (2024) compare the short term market reaction to green patents vs non-green patents issuance and show that this reaction is higher for green patents, and that it increases with more stringent environmental regulations or higher energy prices. Higher societal attention to climate change (proxied by climate news concerns from the media) also drives a larger reaction to green patents (Kuang and Liang, 2024).

Finally, Leippold and Yu (2023) look at more general innovations than just patented ones, analyzing the firms' communication about their innovation activity as reported in earning calls transcripts and conclude that firms that discuss more about climate innovation in their earning calls have lower expected returns. Bolton et al. (2022) show that innovating companies with higher carbon emissions engage more in brown R&D and less in green R&D but that green innovation does not predict higher future reductions in carbon emissions of innovating firms.

One possible reason for the limited impact of climate innovations on firms' market value may be that climate innovation (or even innovation in general) is perceived as too risky or difficult to value by investors, given the large uncertainty around the financial revenues that these innovations could generate for the company. Hirshleifer et al. (2013) argue that investors find it difficult to process information that is less tangible and whose future prospects are highly uncertain, such as technological innovations, whose significance depends upon major shifts in industrial organizational structure. In line with these interpretations, we show that investors value more the efforts to improve the carbon efficiency of the "old" dirty technological processes, probably because these innovations are more immediately applicable. Cohen et al. (2013) further argue that the stock market may be unable to distinguish between "good" and "bad" innovations, despite the fact that successful innovation is in theory predictable based on past firms' success at R&D. Patent statistics may be crowded out by many low-quality patents (De Rassenfosse et al., 2021). And given the complexity of patent description available at issuance for non technical experts, investors may find it difficult to judge patents' quality.

Our paper is organized as follows. Section 2 presents our methodology, Section 3 our data, Section 4 our empirical results and Section 5 concludes.

2 Methodology

2.1 Measuring Climate Innovation

Amid the increased attention on climate technologies, a collaborative project was set up between European Patenting Office (EPO) and United Nations Environmental Program (UNEP) to harmonise the patent landscape for technologies with a climate mitigation potential. Later, adaptation technologies were also added to the classification. Making such efforts is not an easy task, however, since climate mitigation potential can be found in different technological fields from chemistry to electronics, and relying on technology field classifications such as International Patent Classification (IPC) in empirical analyses may lead to Type I and Type II errors (Veefkind et al., 2012). Therefore, patent examiners in EPO worked on creating a "tagging" of patent documents - Y02 classification scheme in climate technologies (Veefkind et al., 2012). This classification scheme has grown considerably to include technologies that can mitigate climate change by reducing sources of greenhouse gas emissions in energy production, but also in buildings, transportation, and production or through ITC technologies, or by creating carbon sinks in the case of Carbon Capture technologies. It also includes patents in medicine and agriculture that can help with climate adaptation goals.

We rely on Y02 classification tags to extract patents in climate technologies, and use the main IPC section codes to identify carbon intensive technologies (we explain the structure of IPC codes, in more detail, in the appendix) . Since Y02 codes do not replace existing codes but are complementary to main technology fields (IPC sections) patents belong to, we can make use of this multidimensionality to identify patents not only along the climate dimension but also along their carbon intensity. Namely in order to identify broad developments in the so-called “carbon intensive” technologies, and later track this brown innovation at the firm level, we use the list of IPC codes provided in Dechezlepretre, Mucklay, and Neelakantan, 2020. The authors use previous work from two main sources to identify patent documents in fossil fuel electricity generation (Lanzi et al., 2011) and the automobile sector (Aghion et al., 2016). The selected codes help researchers with non-field knowledge to easily access innovation trends in different technological fields. Lanzi et al., 2011 , for example, work with patent experts in order to produce a list of IPC codes that identifies overall patents in fossil fuel electricity generation. Aghion et al., 2016 follows a similar strategy for patents in the automobile sector. We provide these IPC codes and Y02 codes in the Appendix.

In the first regression, we simply distinguish between climate and non-climate innovation. A given patent is defined as climate innovation, if it has a Y02 tag.

Second, we define four categories of innovation, as expressed in the below matrix. For a given patent, we first look at whether it has received an IPC code that appears in the list of carbon intensive technologies. Then, we look along the vertical direction to see if the same patent has a climate (Y02) tag. Every patent is classified into one of the four categories: CI Climate - climate mitigating innovation (due to efficiency improvements) in carbon intensive technologies such as internal combustion engines, Climate Non CI - climate innovation in non carbon intensive technologies, Non Climate CI - non climate innovation in carbon intensive technologies, and Non Climate Non CI - non climate and non carbon intensive innovation, which groups the rest of the patents that do not fall into any of the first three categories. Some studies such as von Schickfus, 2021 or Dechezleprêtre et al., 2017 group Climate CI patents into *grey innovation* due to them being situated between pure green and pure brown innovation

	Carbon Intensive	Non Carbon Intensive
Climate	Climate CI	Climate Non-CI
Non-Climate	Non Climate CI	Non Climate Non CI

In later regressions, we further disintegrate Non CI Climate patents into those that help with adaptation, mitigation and adaptation and mitigation at the same time. We do not distinguish Climate CI patents based on whether or not they help with mitigation or adaptation for two reasons. First, in our sample, only few adaptation (around a dozen) patents also belong to the carbon intensive category. Creating a distinct category for Adaptation CI and Adaptation and Mitigation CI and making inferences about their coefficients based on this limited number of patents is not ideal. Second, conceptually, the intersection of Climate and Carbon Intensive Technologies refer to technologies that improve the efficiency of internal combustion engines and similar brown technologies, and lead to potential carbon emission reductions. By definition, these patents contribute to climate mitigation, and any crossover between adaptation and mitigation is most likely a byproduct of engines that have been improved to deal with pollution controls (Hötte and Jee, 2022). Adaptation technologies, for the most part, deal with drought-resistant seeds or pharmaceutical products against air-borne diseases, which are generally, not carbon intensive. Therefore, with a few exceptions, Climate CI patents in our sample should be seen more as CI mitigation patents.

Previous literature has used different methods to distinguish between non carbon intensive and carbon intensive climate innovation. Bolton et al., 2023 rely on four different sources to identify relevant IPC classes for climate innovation, and then analyse lower level codes associated with those IPC classes to group them into: green, general efficiency and brown efficiency innovation. Our approach to classify climate innovation is simpler, but also, at least for the climate part, does not rely on a human judgment about the selection of appropriate IPC codes. As an emerging field, climate change technologies are scattered across different IPC codes, and relying on them may lead to incomplete results or unnecessary noise (Angelucci et al., 2018). In the Appendix, we explain the advantages of the Y02 scheme in more detail, with the excerpts taken from EPO's guide to Y02 tagging scheme (EPO, 2021).

Cohen et al. (2020) also looks at the intersection of brown and green innovation. However, different from our study, they focus on green innovation by brown firms. They define brown firms as those operating in certain SIC industries, specifically related to fossil fuel and energy. Our classification stays at the patent level, and as such, we are able to identify both climate and carbon intensive innovation done by brown or green firms. As we observe in our sample, a lot of climate innovation - both carbon intensive and non carbon intensive - are conducted by transportation firms, which are not the first target, when we think about brown firms, and which are not included in Cohen et al. (2020) study.

2.2 Empirical Framework

Our main regression is based on a market valuation model by the seminal work of Hall et al., 2005, which builds on Griliches, 1981, one of the first papers that looks at the stock valuation of patents. The model links the firm's market value to its stock of knowledge - proxied by its capitalized R&D expenses, patents and citations. As an intangible asset, firm's knowledge stock should have a positive relationship with its valuation, in theory.

The model follows an additively separable linear function, in the spirit of Griliches, 1981, where the market value, $V_{i,t}$ for a firm i, is a function of the book value of assets, $A_{i,t}$ and replacement value of knowledge stocks $K_{i,t}$ at time t.

$$V_{i,t} = \beta(A_{i,t} + \gamma K_{i,t})^{\sigma} \tag{1}$$

β is the valuation coefficient of total assets.Grandi et al., 2009 interprets β as the monopoly position or differentiation risk of a firm. The parameter σ represents non-constant scale effects between market value and tangible and non-tangible assets, if $\sigma \neq 1$. However, to make the empirical estimation easier, we assume that the value function has constant returns to scale and take σ to be equal to 1, similar to Hall et al., 2005. Taking logarithms and moving $logA$ to the left of the equation, we estimate the following model, where ϵ is the error term.

$$logQ_{i,t} \equiv log(\frac{V_{i,t}}{A_{i,t}}) = logb + log(1 + \gamma\frac{K_{i,t}}{A_{i,t}}) + \epsilon_{i,t} \tag{2}$$

Q refers to the Tobin's Q of the firm, while $\frac{K}{A}$ is the knowledge assets scaled by total assets. γ measures the shadow value of knowledge assets relative to tangible assets, that is valuation derived from firm's market value. The advantage of this specification by Griliches, 1981 is that the marginal shadow value on asset is equalized across firms. We approximate $log(1 + \gamma\frac{K_{i,t}}{A_{i,t}})$ by $\gamma\frac{K_{i,t}}{A_{i,t}}$. Furthermore, based on Cohn et al., 2021, in the main regressions, we estimate the independent variables without taking their logarithm in order to not bias the coefficients. This estimation is consistent with Dechezlepretre, Mucklay, and Neelakantan, 2020.

Hall et al., 2005 mentions that there is no theoretical guidance on the choice of innovation variables. They assume the knowledge creation process as a continuum from R&D to citations (through patents), with each step revealing additional information to the market. While R&D reveals the firm's resource allocation to innovative activities, patents show its success in creating legally protected piece of knowledge, and citations proxy the quality or relevance of this knowledge. In practice, when R&D becomes public, the market should price the expected value of the knowledge creation process that will result from it, however, deviations from the expectation may occur, if for example the patent yield (number of patents and quality of patents produced) over the R&D expense is too low or unexpectedly high. In our case, this information content also lies in patents being identifiable in terms of technological class, and providing information on the climate mitigation or adaptation value of a given innovation. As such, we estimate the following equation:

We use the 15% following Hall et al., 2005, which is widely adopted by the innovation literature. However, results are stable when we depreciate patent stocks at different rates.

$$R\&D\_Stock_{i,t} = RD\_expense_{i,t} + 0.85R\&D\_Stock_{i,t-1}$$

$$Patent\_Stock_{i,t} = \#\_of\_patents\_issued_{i,t} + 0.85Patent\_Stock_{i,t-1}$$

Constructing the stock of citations is less straightforward, since unlike patent grants or R& D expense, citations are received over time (Hall et al., 2005). Following Gu, 2005, for a given firm we measure citation impact of their overall patents in a given year as the sum of the adjusted number of citations received on firm's patents issued in the last previous five years:

$$Citations_{i,t} = \sum_{j=1}^{5} \sum_{n_{t-j}=1}^{N_{t-j}} C_{in_{t-j}}$$

where $C_{in_{t-j}}$ is the adjusted number of citations received by a patent n at time $t-j$ and is owned by firm i. We adjust the number of citations by dividing it by the mean number of citations received in year t by all patents of the same IPC subclass granted in year $t-j$. This process helps deal with the truncation bias and technological bias related to citations, which are more severe in citation counts compared to patent counts (Lerner and Seru, 2022). Finally, we sum the adjusted number of citations received by N patents assigned to the firm from year t to year $t-j$ ($j = 5$).

In our regressions, we use both the current and one year-forward Tobin's Q in our empirical estimations. When using one-year forward Tobin's Q, we control for the current Tobin's Q.

3 Data and Descriptive Statistics

3.1 Patent Data

We retrieve the data on patents and citations issued by the United States Patent and Trademark Office (USPTO) from Patentsview. The bulk download files, which are retrieved from the USPTO website, include information on patent's grant and application year, its forward and backward citations, as well as on IPC and Cooperative Patent Classification (CPC) codes. CPC is derived from European Patent Office's own classifications, and as such is a more granular subdivision of IPC, with the exception that unlike IPC, it also contains the Y02 class to identify climate patents (Mailänder, 2016). We use KPSS data which is made public by Kogan et al.

(2017) to match patents to firms using PERMNO (permanent security identification number assigned by CRSP to each security). This dataset is updated to include data until 2022. The matched sample includes 4328 unique patenting firms between 1995 and 2020. In our study, we only include firm-year observations where a firm has either issued a patent or has received a citation for one of its recently issued patents. This sample of firms issuing patents represents 26 % of firms in the Compustat CRSP merged universe and 50 % of the total market capitalization of the US market.[2] Matching between the assignees of patents and public firms is done based on company names, which may be not standardized or include the subsidiaries of the listed parent company. However, Kogan et al. (2017) take rigorous steps to deal with the issues related to non-standardization of names and changes in ownership of the firms.

Figure 1 graphs the three year moving average of the number of patents in each category of innovation with the base year value indexed at 100. Between 1995 and 2005, the pace of increase in climate technologies is similar to that of the general increase in all technological fields. However, both Carbon Intensive and Non-Carbon Intensive Climate patents see a rapid increase after 2008, with Climate CI multiplied by ten compared to 1995. Moreover, while in 1995, only 38% of patents issued within all carbon intensive IPC codes received a climate tag, in 2020, this number climbs to 53%. In other words, in the recent years, the production of patents in Climate CI surpasses the number of patents issued in Non Climate CI (Pure CI).

Nevertheless, as shown in Table 1, climate innovation still remains niche, with climate patents representing around 7% of total patents in the sample. Similarly, patents with a carbon intensive IPC code also is a relatively small category within climate innovation, accounting for almost 7% of all climate patents. Table 1 also reports the average number of forward citations, and adjusted forward citations of the patents that belong to different innovation categories. Forward citations are adjusted by the average number of citations received in the citation year and technology class,

[2]The matched sample includes only around half of the patent population, due to the fact that patents can be assigned to unlisted firms, firms not listed in the US stock market, to individuals, universities, and non-profit research organisations.

as explained in Section 2. We see that adaptation patents are more cited on average, however, this discrepancy narrows when we look at adjusted number of citations. We adjust the number of citations by total number of citations received in the specific IPC technology class in a given citation year as explained in Section 2.

Table 2 reports the summary statistics of our variables of interest at the firm-year level. Patent stocks are scaled by R&D stock, while R&D stock is scaled by total assets of the company. As such, they represent the research efficiency and intensiveness of the company, respectively. Scaling also helps account for size of the firm, and ensures that our results are not driven by a size effect, since larger firms are more likely to issue more patents.

While the mean value for the stock of patents in Non-CI Climate is 1.12, it is only 0.008 for the third quartile. This is because even within innovating firms, which make up our study sample, there are only a small number of climate innovators.

Table 3 reports the industry distribution of the number of patents in different innovation categories in terms of 2 digit Standard Industry Classification (SIC) codes. Overall, we observe that innovative sectors (those with most patents overall) are also active in climate and carbon intensive innovation. However, for some industries, climate innovation represents a larger share of the total patents issued. In terms of most patents produced in Climate Non CI, firms in Electronics and Other Electric Equipment and Transportation Equipment are first and second respectively. Furthermore, we also confirm that firms in industries related to fossil fuel (SIC 13 and 29) produce a lot of climate patents. Transportation firms produce more than half of Climate CI patents in the sample, followed by Nonclassifiable Establishments that mostly include conglomerates such as General Electric or Siemens.

Figure 3 graphs the time series evolution of the industry composition of climate innovation along the sectors from Table 3. Overall, the industry composition of climate patents has not changed much between 1995 and 2020. However, in the last five years patent production has been more concentrated in the top industries, namely in Transportation Equipment for Climate CI and Electric Equipment for Climate Non CI.

3.2 Financial Variables

We obtain accounting data and year-end stock price data on North American firms listed on US major stock exchanges (NYSE, NYSE Arca, AMEX, and NASDAQ) from Compustat-CRSP merged through Wharton Research Data Services (WRDS) from 1995 to 2020. In case of dual-listings, namely when there are two PERMNOs assigned to one Permnant Company Number (PERMCO), we keep the observation (PERMNO) with the higher market capitalization. We calculate Tobin's Q as the the sum of total tangible assets minus book value of equity plus market capitalization at the end of the fiscal year divided by total tangible assets. We remove observations with a non-positive market capitalization or total assets. Total tangible assets is equal to the sum of current assets, property, plant and equipment, investment and advances, and other assets. We include known risk factors from Fama and French (2020). Market Beta is estimated annually using daily returns. Size is equal to the log of market capitalization at the fiscal year end. Book to Market is the book value of equity divided by market capitalization. Operating profitability is the sale minus cost of goods sold and general and interest expense divided by book value of equity. Investment is the change in total asset compared to year t-1, divided by total assets at year t-1. Leverage is the long-term debt divided by equity. Tangibility is equal to Property, Plant and Equipment divided by total assets. ΔEPS is the change in earning per share compared to year t-1, normalized by share price. ΔSale is the sale growth normalized by market capitalization.

In our regression analysis, we standardize all independent variables to have a mean of zero and a standard deviation of 1.

4 Results

4.1 Climate versus non Climate Innovation

We begin by regressing the market valuation of a company on its patent stocks in climate and non-climate technologies. This allows us to see whether stock markets value climate innovation, overall. In every table, we regress both the current and one-year-forward log of Tobin's Q on the stock of patents in year t and account for time fixed effects.

Table 4 reports the results of the first exercise. In Columns 1-3, we use current year's Tobin's Q, and in Columns 4-6, 1 year forward Tobin's Q as the dependent variable, while controlling for current Tobin's Q. In Columns 1 and 4, we regress our variables without including the firm-level controls and industry-fixed effects. In Columns 2 and 5, we add industry fixed effects. Industries are defined based on 2-digit SIC codes. Finally, we add control variables in Columns 3 and 6 (from Table 2).

Across all specifications, the coefficient on climate innovation is not statistically not different from zero. This lack of impact may be due to many climate technologies still being at the early development stage. For example, IEA, 2023 reports that many climate technologies that allow to reach net-zero are yet to be commercialized. If the financial benefits of many of these climate patents were to accrue in the long term, then they are less likely to be appreciated by equity investors. A similar result appears for non-climate innovation. This suggests that innovation, in general, may be considered too risky or uncertain for investors. Another reason may stem from a mispricing of innovation, proxied by patents (Hirshleifer et al., 2013).

4.2 Climate Innovation in Carbon Intensive Technologies

Having found no relationship between climate patent stock and Tobin's Q, we next turn our attention to a specific type of climate innovation - those related to efficiency improvements in carbon intensive polluting technologies. Table 5 reports the results of regression of Tobin's Q on four different categories of innovation, as described in Section 2.1.

The main finding across the six columns is that Climate CI is positively linked with market valuation. Holding other types of innovation and R&D intensity of a firm fixed, one standard deviation increase in patent stock in Climate CI divided by R & D is associated with almost 1 % increase in Tobin's Q. This effect survives even after accounting for firm-level controls and industry fixed effects. The coefficients stay positive and significant in Columns 4-6, even after accounting for the current year's Tobin's Q, suggesting that the relationship persists in the year following the patent's issue.

In contrast to the positive and significant coefficient on Climate CI, Non Climate CI patents are not significantly related to market value. Among carbon-intensive technologies (*e.g.* combustion apparatus and internal combustion engines) only innovations with a climate mitigation potential, that is with a possible contribution to climate mitigation goals due to efficiency improvements, enjoy a positive market performance. Since both groups are relatively similar - both in terms of the number of patents within each group and technological classes they belong to, except for having a climate mitigation tag, these findings provide some evidence that a potential to contribute to climate change mitigation through innovation is valued by the markets.

Simply looking at the relationship between stock market valuation and green patents and comparing it to the coefficient on non-green patents (grouping the rest of the patent universe) may fail to account for time horizon, technological class, and other patent characteristic differences. Lerner and Seru, 2022 discuss how patent statistics depend highly on technological classes, and failing to account for this may lead to biases in regression estimates.

Furthermore, as discussed in the previous subsection, the economic benefits of many inventions may be far into the future and highly uncertain. At the time of issue, the information on the economic potential of a patent may not be available for stock market participants, making estimates with a one-year time horizon unreliable. There is extensive literature on the misvaluation of hard-to-process information by stock markets, specifically regarding firm-level innovation (Cohen et al., 2013, Hirshleifer et al., 2013, Fitzgerald et al., 2021) and climate change uncertainty (Ilhan et al., 2023, Giglio et al., 2021).

Reducing potential carbon emissions through efficiency improvements in fossil fuel technologies may, indeed, be an important mitigation effort. Lanzi et al., 2011 mention the importance, at least in the short run, of these efficiency improvements in reducing greenhouse gas emissions and achieving climate goals. Our results suggest that equity investors value these efforts to mitigate climate change impact within the brown technological space. von Schickfus, 2021 argue that efficiency improvements in fossil fuel technologies may only be a short-term solution to mitigating climate change. However, investors may adopt a short-term outlook to deal with the transition risk, and only value innovation efforts that can help firms deal with climate and pollution regulations in the short-term.

Similar to the non-significant coefficient on overall climate innovation in Table 4, we cannot establish a positive link between Climate Non-CI and Tobin's Q. Since patents in this category make up the bulk of climate innovation - around 93 % of climate patents are Non Carbon Intensive (see Table 3), this result is not surprising.

These findings are consistent with other studies that look into the relationship between stock market valuation and green innovation based on a similar sample of firms (see Andriosopoulos et al., 2022, Leippold and Yu, 2023). It also supports the notion that climate risk is not fully priced yet (Krueger et al., 2020). Since the benefits of climate technologies may be materialized in more than 20 years, the average valuation of the climate innovation during our sample study period is not different than zero. Interesting theoretical literature (summarised in Heal, 2017) discusses how the present valuation of actions taken to mitigate climate is very sensitive to the rate at which future cash flows are discounted. Given the high market premium equity investors demand from their investments, investments in innovating in climate technologies such as alternative energy production are likely to be severely discounted.

We also show that the R&D stock of a firm is correlated with higher Tobin's Q. This is in line with previous works on firm innovation and stock valuation (Hall et al., 2005). However, we do not report a positive relationship between valuation and the overall innovative output of a firm, neither in terms of patents or citations.

To summarise, only one type of innovation - innovation in Climate Carbon Intensive, based on our explotary analysis, is positively correlated with market value. This may stem from markets seeing overall innovation as too risky (*i.e.* non-significant coefficient on Non Climate Non CI) or its economic contribution in terms of transition too far into the future (*i.e* non-significant coefficient on Climate Non-Carbon Intensive). On the other hand, Climate Carbon Intensive may be valued as a short-term solution to transition risk.

4.3 Comparing Adaptation versus Mitigation patents

Y02 class identifies patents that contribute to climate mitigation in different areas such as buildings, production, and alternative energy, but also patents that can help with climate adaptation mainly in medicine and agriculture. Therefore, we further distinguish these climate technologies along the adaptation and mitigation dimension. This distinction may be relevant since from an investor perspective, adaptation and mitigation technologies may account for two different types of climate risk: physical and transition risk (Giglio et al., 2021). Recently emerging literature on transition versus physical risk has not reached conclusive evidence on which of these risks are priced to what extent by financial markets.

There are also considerable differences between these two types of patents. Hötte and Jee, 2022 report that, unlike patents in mitigation technologies, adaptation patents have not shown significant growth in the last two decades. This may be due to less political pressure on the issue of climate adaptation compared to mitigation until the very recent period (Hallegatte et al., 2011). However, increased weather events in recent years may have also changed the focus towards adaptation.

In short, even though overall climate innovation may not be valued, a given category of innovation (adaptation vs mitigation) within the non carbon-intensive climate innovation may command a positive premium.

Nevertheless, around 25 % of adaptation patents in our sample also help with climate mitigation. We create a separate category to group patents that are labeled both as mitigation and adaptation. According to Hötte and Jee, 2022, many of these "dual purpose" patents are developed to deal with regulatory pollution controls, and the adaptation impact is a byproduct of that process. For example, technologies that control air pollution also are considered health-related adaptation technologies.

Figure 4 graphs the industry composition of adaptation and mitigation patents in our sample. While the industry composition for mitigation patents resembles closely that of Climate Non-CI, since they make the bulk of the patents in this category, Climate Adaptation innovation is concentrated in Chemicals and Allied Products, which include Pharmaceutical drugs, Instruments, and Related Products, which include medical instruments. This figure, again, highlights differences between the two patent categories and confirms our prior about their industry composition based on the patent technological classes they belong to.

Table 6 shows that among the three sub-categories of Climate Non-CI patents, only the double-purpose patents in adaptation and mitigation are valued positively to a small extent. After accounting for industry fixed effects and firm-level controls, the coefficient on the stock of knowledge in patents with a dual purpose is significant and positive at 1% significance level. Even though our exploratory study does not find an evidence of a positive relationship between Tobin's Q and adaptation or mitigation patents separately, markets may value innovation that contribute to both. Investors could be taking a multiplicative perspective toward climate technologies.

Finally, in Table 7, we add back the carbon intensive categories to the regression. As discussed in Section 2.1, we do not differentiate Climate CI on adaptation and mitigation. The results of this regression confirms the previous tables. Climate CI is positively correlated with market valuation. Moreover, patents that contribute to both adaptation and mitigation are also related to higher market valuation, albeit to a lesser extent [3] .

4.4 Short-term solutions to climate change transition

One possible hypothesis to explain the economic mechanism behind our results is that investors may value more immediate and short-term solutions to climate change transition. Improving efficiency of fossil-fuel based technologies can offer a short-term solution to reducing carbon emissions (von Schickfus, 2021). Due to regulatory pressure, investors may prefer such short-term response to emission reduction compared to more radical and risky inventions.

[3] In the Appendix (Table A3), we cluster standard errors by time and industry, and our results remain unchanged.

In order to see whether climate patent categories associated with higher market valuation, are indeed more quickly applicable compared to other inventions, we look at the length between patent issuance and citation. Figure 5a plots the proportion of citations received in t years after patent application in four innovation categories from Table 5. Each column of the figure represents the total number of citations received by all patents in a given category t years after patent's application, divided by all citations received by that category of patents during their entire lifetime. The graph shows that a greater proportion of Climate CI citations are received in the early years of patent application, compared to other types of innovations. This suggests that these innovations may offer more short-term applications compared to other innovation categories. In Figure 5b, we look at adaptation and mitigation categories, and the same pattern for dual purpose Adaptation and Mitigation patents appears. Since most of these patents were developed to deal with pollution controls in automobiles they may have also provided a more applicable use-case for firms (Hötte and Jee, 2022).

It could then be argued that the positive relationship we observe between Climate CI patents and market valuation (and to a lesser extent between Climate Adaptation & Mitigation) is only due to the more applicable nature of those innovations and unrelated to climate transition. In Table 8, we regress market valuation on firm-level short-term innovation proxy constructed on citations. Namely, in each firm year, we use the proportion of citations received in the first 1, 3 and 5 years by patents issued to the firm in that year as the independent variable. We do not find a positive relationship between this proxy and market valuation, suggesting that our results in Table 7 are specific to climate innovation. Furthermore, adding this citation variable to the baseline regressions do not alter our results significantly, as seen in Table A4.

Nevertheless, as highlighted in the beginning, our study remains exploratory and the test only offers a preliminary and descriptive evidence in support of this hypothesis.

5 Conclusion

Technological solutions to climate change make a vital part of an effective transition strategy. However, evidence on the valuation of the overall climate innovation by equity investors remains mixed. In this paper, we take a granular approach and look at the relationship between Tobin's Q and different types of climate innovation, specifically regarding whether or not they relate to carbon intensive technologies such as internal combustion engines. We also further distinguish non-carbon intensive climate patents based on whether or not they contribute to climate adaptation or mitigation.

First, we do not report a significant relationship between market valuation and overall climate patents. However, when we distinguish climate patents between carbon intensive and non-carbon intensive categories, we find that only Climate Carbon Intensive innovation is positively related to Tobin's Q. A similar group of patents without a climate tag (Non Climate Carbon Intensive) is not linked with higher market valuation. This may suggest that investors value firms' efforts in providing short-term technological solutions to deal with climate change transition. Finally, when we further divide Climate Non-CI along mitigation and adaptation, we report a statistically significant positive coefficient only on dual-purpose patents that contribute to both.

Future research may benefit from understanding the characteristics of innovation that drive market value. For example, future research can analyze textual data such as company reports and news to unveil whether Climate CI innovators deserve more short term applications and revenue generation for the firms that non carbon intensive climate technologies. It may also focus on the qualitative characteristics of patents across different categories to further understand what correlates with market value.

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6 Figures

Figure 1: The number of patents issued over the the sample period

This figure graphs the three year moving average in the number of USPTO patents issued to the firms in in the sample in each innovation category. The sample period is between 1995 and 2020. The base year (1995) value is indexed at 100.

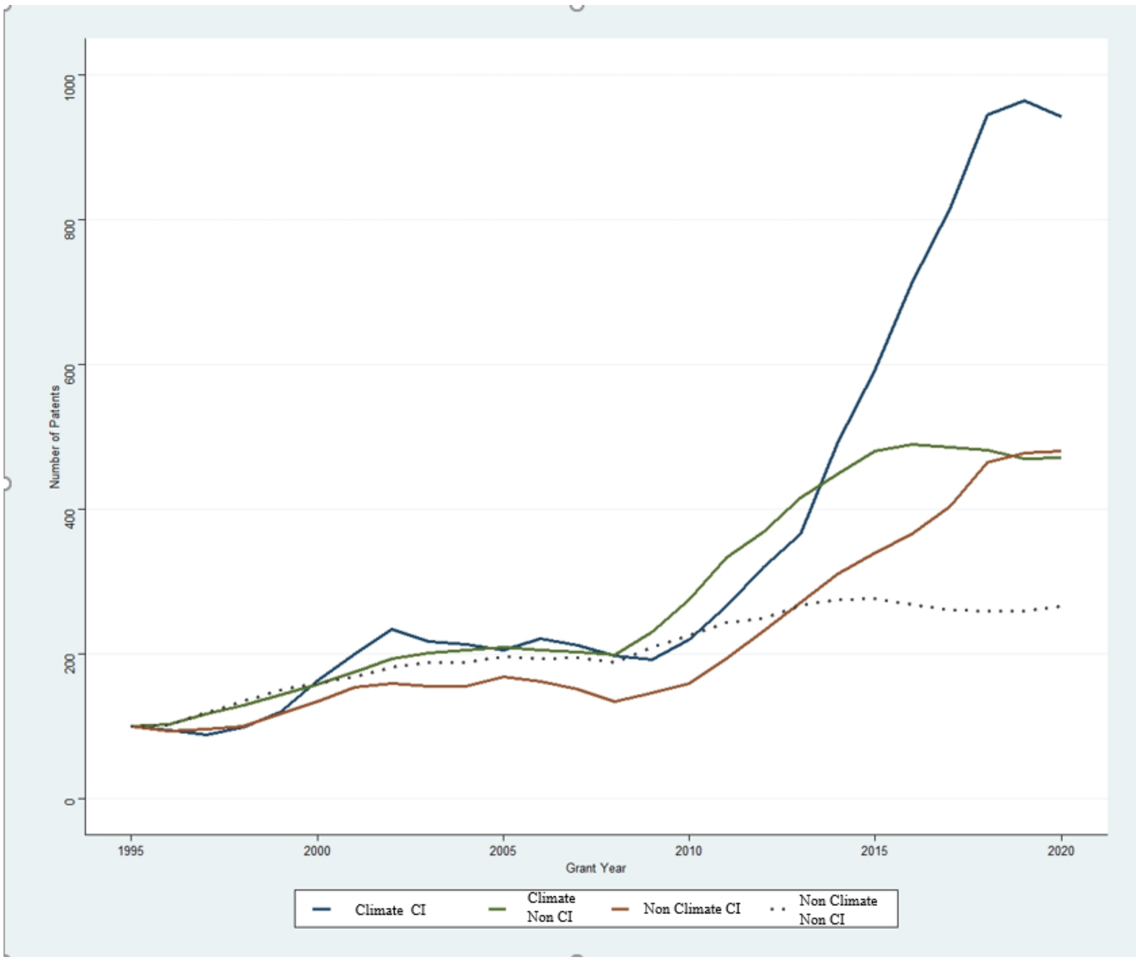


Figure 2: Example of an IPC hierarchy

Example of a portion of the IPC hierarchy starting in level 1, section B. Source: Gomez and Moens, 2014

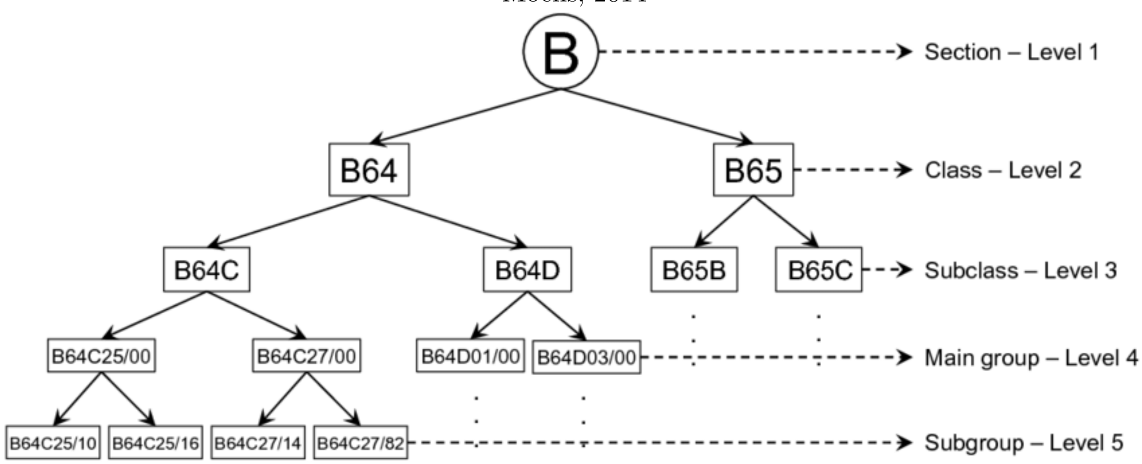
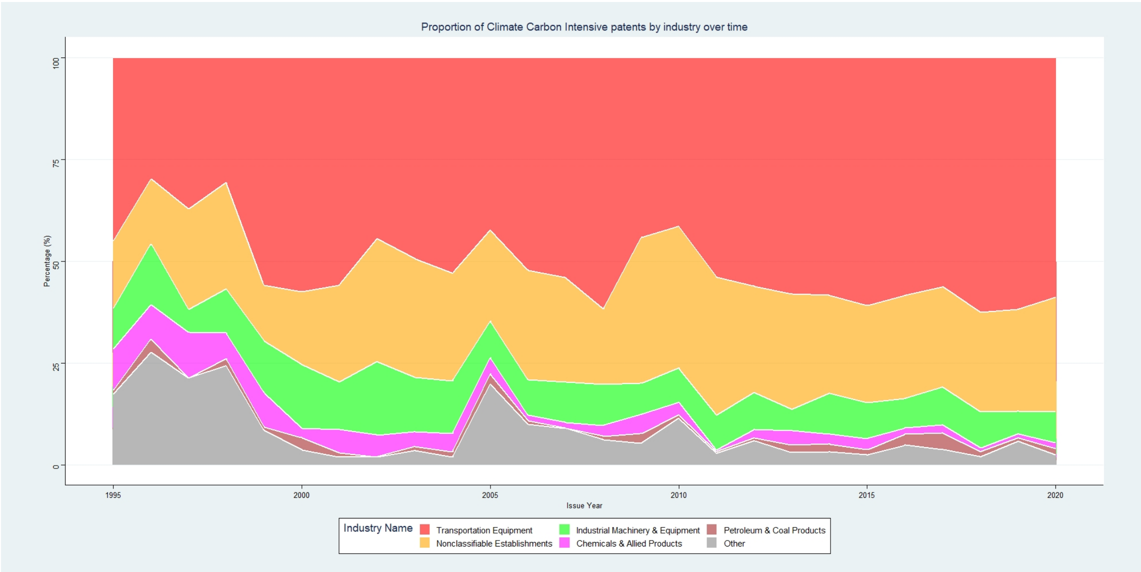
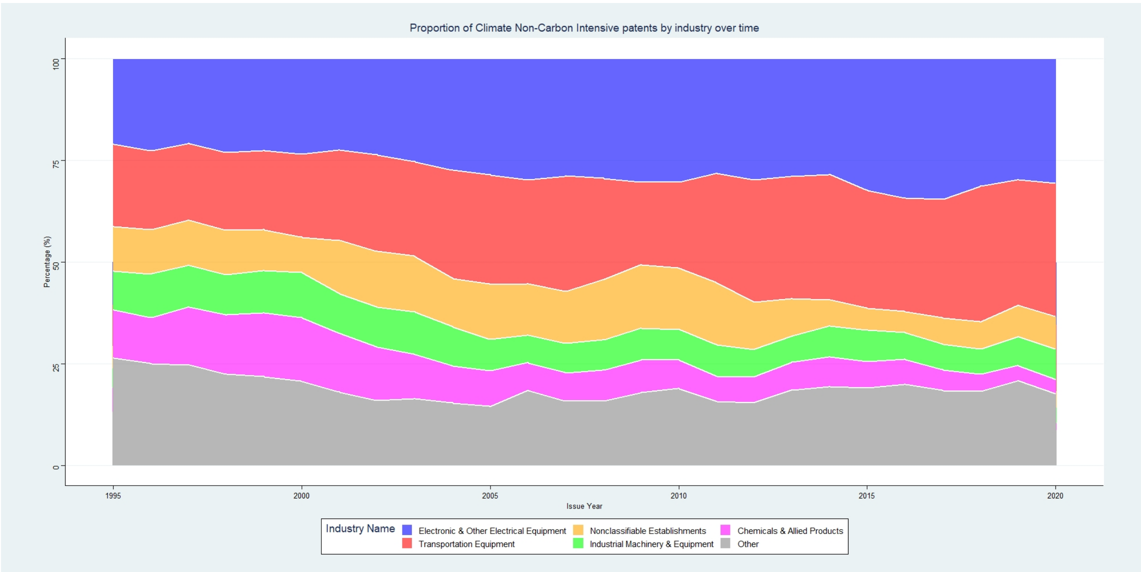


Figure 3: The evolution of the Industry Composition of Climate Patents

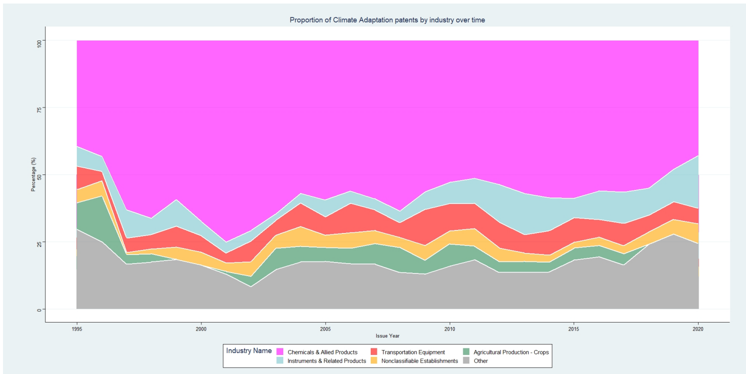


(a) Climate Carbon Intensive

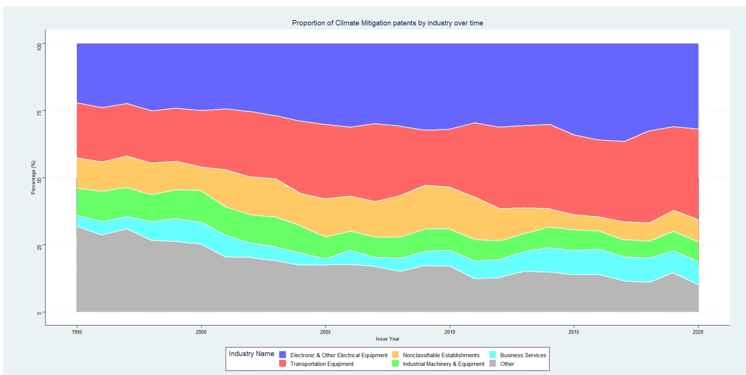


(b) Climate Non Carbon Intensive

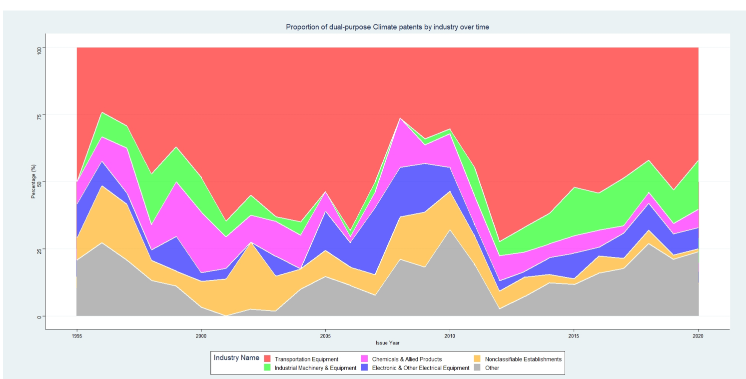
Figure 4: The evolution of the Industry Composition of Climate Patents - Mitigation versus Adaptation



(a) Climate Adaptation

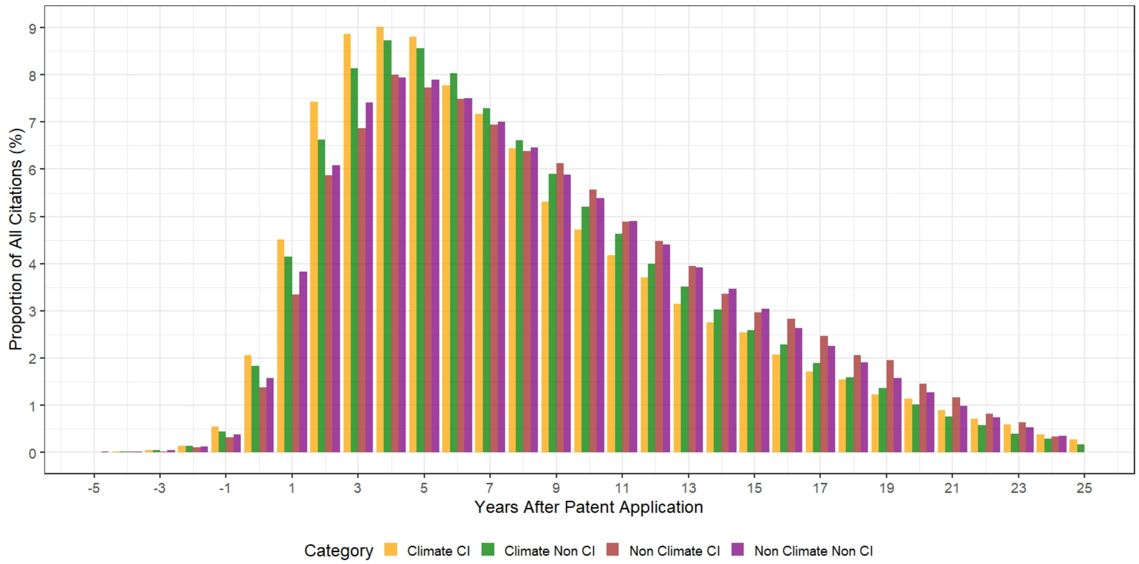


(b) Climate Mitigation

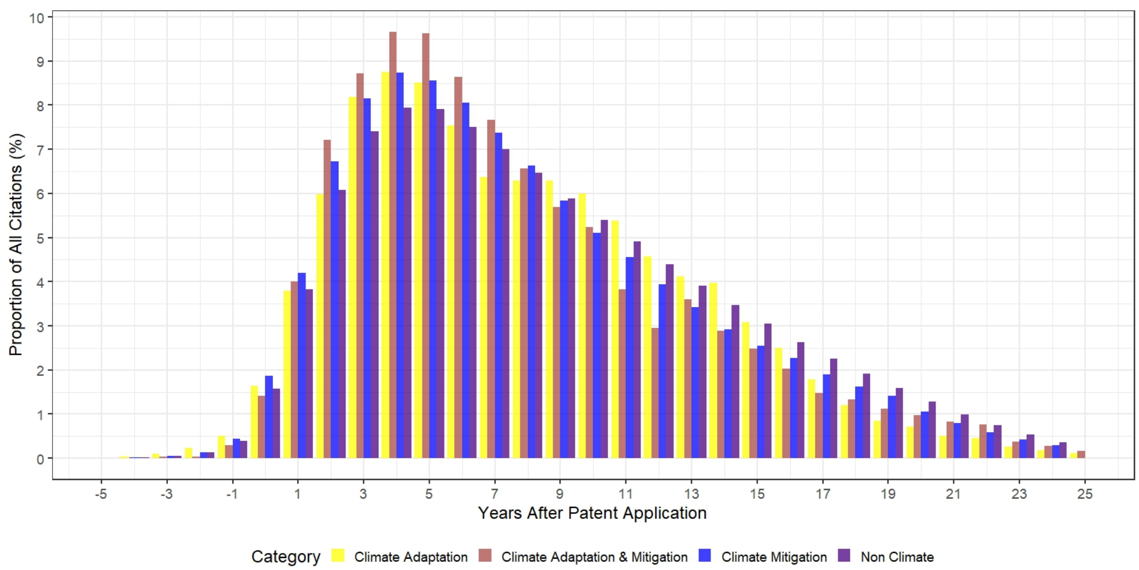


(c) Climate Adaptation & Mitigation

Figure 5: Proportion of citations received in each year after the patent application per innovation category



(a) Climate CI and Climate Non CI



(b) Climate Adaptation and Mitigation

7 Tables

Table 1: Number of Patents and average forward citations per innovation category

Category	N	Citations	Citations adjusted
	Climate versus Non Climate		
Climate	102848	2.87	1.08
Non-Climate	1587105	3.20	1.04
	Adding Carbon Intensive dimension		
Climate CI	7204	2.21	1.12
Climate Non CI	95644	2.92	1.08
Non Climate CI	9630	2.16	1.08
Non Climate Non CI	1577475	3.20	1.04
	Climate Adaptation and Mitigation		
Climate Adaptation	4630	4.68	1.30
Climate Adaptation & Mitigation	1444	2.69	1.21
Climate Mitigation	96774	2.78	1.07
Non Climate	1587105	3.20	1.04
	Combining all categories		
Climate Adaptation & Mitigation CI	62	2.03	1.00
Climate Adaptation CI	10	1.21	0.70
Climate Adaptation Non CI	4620	4.68	1.30
Climate Mitigation & Adaptation Non CI	1382	2.72	1.21
Climate Mitigation CI	7132	2.21	1.12
Climate Mitigation Non CI	89642	2.83	1.07
Non Climate CI	9630	2.16	1.08
Non Climate Non CI	1577475	3.20	1.04

Table 2: Summary Statistics

This table reports the summary statistics for the variables used in our estimations. The sample period is 1995-2020. Panel Stock in Climate Non-CI, Climate CI, Pure CI, and Other refer to the stock of patents (depreciated at 15%) a company holds in the respective innovation category divided by R&D Stock. R&D Stock is the capitalized R&D expense depreciated at 15% scaled by Total Assets. Citations are the adjusted number of citations a company has received over its patents issued in the last five years. Tobin's Q is the sum of total tangible assets minus book value of equity plus market capitalization at the end of the fiscal year divided by total tangible assets. Market Beta is estimated annually using daily returns. Size is equal to the log of market capitalization at the fiscal year-end. Book to Market is the book value of equity divided by market capitalization. Operating profit is the sale minus the cost of goods sold and general and interest expense divided by the book value of equity. Investment is the change in total assets compared to year t-1, divided by total assets at year t-1. Leverage is the long-term debt divided by equity. Tangibility is equal to Property, Plant, and Equipment divided by total assets. ΔEPS is the change in earnings per share compared to year t-1, normalized by the share price. ΔSale is the sale growth normalized by market capitalization.

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Patent Stock							
Climate Non-CI	41862	1.132	47.882	0	0	0.008	4020.718
Climate CI	41862	0.01	0.739	0	0	0	111.111
Non Climate CI	41862	0.052	1.563	0	0	0	80.39
Non Climate Non CI	41862	14.89	313.634	0	0.07	0.533	22858.645
Other Innovation Measures							
R&D Stock	41862	0.465	1.1	0	0.064	0.474	54.807
Citations	41862	80.273	413.757	0	0.271	21.066	13109.811
Financial Variables							
Tobin's Q	41862	2.779	3.738	0.003	1.261	3.215	305.714
Beta	41862	0.976	0.626	-6.872	0.545	1.34	6.756
Size	41862	6.258	2.377	-0.54	4.49	7.862	14.492
BTM	41862	0.549	0.557	0	0.231	0.698	18.15
Operating Profit	41851	-0.67	111.414	-22614	-0.062	0.288	1417.333
Investment	41628	0.169	0.99	-0.987	-0.055	0.186	82.264
Leverage	41862	1.162	68.617	-505.783	0.003	0.661	13380
Tangibility	41862	0.187	0.164	0	0.066	0.26	0.993
ΔEPS	41778	0.007	5.729	-463.672	-0.028	0.036	998.272
$\Delta Sale$	41772	0.035	1.203	-38.718	-0.019	0.101	203.081

Table 3: Total Number of Patents per Innovation Category - Industry Breakdown

SIC	Industry Name	C. CI	C. Non-CI	Non-C. CI	Non-C. Non-CI
1	Agriculture Crops	3	338	3	4724
10	Metal Mining	7	130	21	233
13	Oil & Gas Extraction	21	992	52	27075
14	Nonmetallic Minerals (except fuels)	0	15	0	257
15	General Building Contractors	0	1	0	31
16	Heavy Construction, Except Building	18	72	71	163
20	Food & Kindred Products	0	195	7	4377
21	Tobacco Products	4	44	29	1733
22	Textile Mill Products	1	21	0	437
23	Apparel & Other Textile Products	0	1	2	391
24	Lumber & Wood Products	11	74	11	656
25	Furniture & Fixtures	0	97	0	3864
26	Paper & Allied Products	3	839	32	21844
27	Printing & Publishing	0	12	0	1005
28	Chemical & Allied Products	224	8791	254	133031
29	Petroleum & Coal Products	138	2290	131	12998
30	Rubber & Plastics Products	2	197	10	8498
31	Leather & Leather Products	0	0	0	169
32	Stone, Clay, Glass, & Concrete	5	218	4	1412
33	Primary Metal Industries	13	218	51	2338
34	Fabricated Metal Products	58	522	74	7749
35	Industrial & Commercial Machinery	767	9118	1029	251575
36	Electronic & Other Electric Equipment	93	34483	492	540087
37	Transportation Equipment	4803	32001	3489	121810
38	Instruments & Related Products	36	3066	244	125961
39	Miscellaneous Manufacturing	0	110	6	4939
40	Railroad Transportation	1	4	1	79
42	Trucking & Warehousing	0	14	1	666
44	Water Transportation	0	0	0	18
45	Transportation By Air	1	57	1	262
47	Transportation Services	0	2	0	88
48	Communications	33	1580	61	54242

Continued on next page

Table 3: Total Number of Patents per Innovation Category - Industry Breakdown

SIC	Industry Name	C. CI	C. Non-CI	Non-C. CI	Non-C. Non-CI
49	Electric, Gas & Sanitary Services	99	748	59	1687
50	Wholesale Durable Goods	1	182	5	2978
51	Wholesale Nondurable Goods	0	24	1	389
52	Building & GaR & Dning Supplies	0	0	0	52
53	General Merchandise Stores	0	15	0	947
54	Food Stores	0	0	0	23
55	Automotive Dealers & Service Stations	3	84	1	379
56	Apparel & Accessory Stores	0	0	0	45
57	Furniture & Furnishings Stores	0	6	0	204
58	Eating & Drinking Places	0	4	1	77
59	Miscellaneous Retail	2	400	0	14197
60	Depository Institutions	0	48	0	6607
61	Non-depository Credit Institutions	0	31	0	3554
62	Security & Commodity Brokers	0	10	0	1984
63	Insurance Carriers	1	79	6	1986
64	Insurance Agents, Brokers, & Service	0	3	0	24
65	Real Estate	1	2	2	67
67	Holding & Other Investment Offices	51	807	158	10188
70	Hotels & Other Lodging	0	1	0	68
72	Personal Services	0	4	0	37
73	Business Services	14	8240	77	299705
75	Auto Repair, Services, & Parking	0	0	0	40
76	Miscellaneous Repair Services	0	1	0	21
78	Motion Pictures	0	4	0	349
79	Amusement & Recreation Services	0	9	2	2419
80	Health Services	0	29	0	1822
82	Educational Services	0	6	0	53
87	Engineering, & Management Services	1	176	19	4159
99	Nonclassifiable Establishments	2215	11624	3352	96276
Total		8630	118040	9759	1783058

Table 4: Market Valuation of Climate Innovation

The table reports the results of the linear OLS regression of current and one-year forward Tobin's Q on firm's patent stock in climate and non-climate technologies between 1995 and 2020 with time fixed effects . Industry dummies are based on 2 digit SIC codes. Control variables include the market beta, size, operating profitability, investment, tangibility, leverage, EPS and Sale growth. The variables are defined in Table 2. Columns 4-6 also includes contemporaneous Tobin's Q as a control. All the independent variables are normalized to have a mean of 0 and standard deviation of 1. Heterogeneity-consistent standard errors are reported in parentheses.

	Dependent variable:					
	Tobin's Q			Lead Tobin's Q		
	(1)	(2)	(3)	(4)	(5)	(6)
Climate	-0.001	0.00003	0.005	-0.0001	0.00004	0.0001
	(0.009)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)
Non Climate	-0.003	-0.004	-0.007	0.0003	-0.0002	-0.0003
	(0.013)	(0.011)	(0.010)	(0.005)	(0.005)	(0.005)
Citations	0.00002	0.00003^{+}	-0.0002^{***}	0.00001^{*}	0.00001^{*}	0.00000
	(0.00002)	(0.00002)	(0.00003)	(0.00000)	(0.00001)	(0.00000)
R&D	0.117^{***}	0.054^{***}	0.146^{***}	0.034^{***}	0.022^{*}	0.023^{*}
	(0.018)	(0.013)	(0.021)	(0.009)	(0.009)	(0.010)
Controls	No	No	Yes	No	No	Yes
Industry FE?	No	Yes	Yes	No	Yes	Yes
Observations	41,862	41,862	41,567	37,987	37,987	37,733
R^2	0.014	0.114	0.298	0.630	0.634	0.636
Adjusted R^2	0.014	0.112	0.296	0.630	0.633	0.635

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 5: Market Valuation of CI and Non-CI Climate Innovation

The table reports the results of the linear OLS regression of current and one-year forward Tobin's Q on firm's patent stock in carbon intensive and non-carbon intensive climate technologies with time fixed effects between 1995 and 2020. Industry dummies are based on 2 digit SIC codes. Control variables include the market beta, size, operating profitability, investment, tangibility, leverage, EPS and Sale growth. The variables are defined in Table 2. Columns 4-6 also includes contemporaneous Tobin's Q as a control. All independent variables are normalized to have a mean of 0 and standard deviation of 1. Heterogeneity-consistent standard errors are reported in parentheses.

	Dependent variable:					
	Tobin's Q			Lead Tobin's Q		
	(1)	(2)	(3)	(4)	(5)	(6)
Climate CI	0.009***	0.010***	0.014***	0.004***	0.005***	0.004***
	(0.002)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.0002)
Climate Non CI	−0.0004	0.001	0.007	0.0002	0.0002	0.0004
	(0.010)	(0.008)	(0.008)	(0.004)	(0.004)	(0.003)
Non Climate CI	0.007	0.005	0.009	0.002	0.002	0.002
	(0.007)	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)
Non Climate Non CI	−0.005	−0.005	−0.010	−0.0004	−0.001	−0.001
	(0.015)	(0.013)	(0.012)	(0.006)	(0.006)	(0.005)
Citations	0.007	0.014+	−0.067***	0.004*	0.006*	0.001
	(0.008)	(0.008)	(0.013)	(0.002)	(0.002)	(0.002)
R&D	0.117***	0.054***	0.146***	0.034***	0.022*	0.023*
	(0.018)	(0.013)	(0.021)	(0.009)	(0.009)	(0.010)
Current Q				0.783***	0.762***	0.755***
				(0.006)	(0.006)	(0.007)
Controls	No	No	Yes	No	No	Yes
Industry FE?	No	Yes	Yes	No	Yes	Yes
Observations	41,862	41,862	41,567	37,987	37,987	37,733
R^2	0.015	0.114	0.298	0.630	0.634	0.636
Adjusted R^2	0.014	0.112	0.297	0.630	0.633	0.635

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 6: Market Valuation and Climate Adaptation and Mitigation Innovation

The table reports the results of the linear OLS regression of current and one-year forward Tobin's Q on firm's patent stock in climate adaptation and mitigation technologies with time fixed effects between 1995 and 2020 . .Industry dummies are based on 2 digit SIC codes. Control variables include the market beta, size, operating profitability, investment, tangibility, leverage, EPS and Sale growth. The variables are defined in Table 2. Columns 4-6 also includes contemporaneous Tobin's Q as a control. All the dependent variables are normalized to have a mean of 0 and standard deviation of 1. Heterogeneity-consistent standard errors are reported in parentheses.

	Dependent variable:					
	Tobin's Q			Lead Tobin's Q		
	(1)	(2)	(3)	(4)	(5)	(6)
Climate Adaptation	0.001	0.00002	−0.001	−0.0003	−0.001	−0.001
	(0.007)	(0.006)	(0.005)	(0.003)	(0.003)	(0.002)
Climate Mitigation	−0.002	−0.00001	0.007^{+}	0.00004	0.0004	0.001
	(0.006)	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)
Climate Adaptation & Mitigation	0.005^{+}	0.005^{**}	0.007^{***}	0.001^{+}	0.002^{**}	0.001^{*}
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Non Climate	−0.003	−0.004	−0.006	0.0003	−0.00001	−0.0001
	(0.014)	(0.012)	(0.010)	(0.005)	(0.005)	(0.005)
Citations	0.007	0.014^{+}	-0.067^{***}	0.004^{*}	0.006^{*}	0.001
	(0.008)	(0.008)	(0.013)	(0.002)	(0.002)	(0.002)
R&D	0.117^{***}	0.054^{***}	0.146^{***}	0.034^{***}	0.022^{*}	0.023^{*}
	(0.018)	(0.013)	(0.021)	(0.009)	(0.009)	(0.010)
Controls	No	No	Yes	No	No	Yes
Industry FE?	No	Yes	Yes	No	Yes	Yes
Observations	41,862	41,862	41,567	37,987	37,987	37,733
R^2	0.014	0.114	0.298	0.630	0.634	0.636
Adjusted R^2	0.014	0.112	0.296	0.629	0.633	0.635

Note: + p¡0.1; * p¡0.05; ** p¡0.01; *** p¡0.001

Table 7: Market Valuation and Climate Adaptation and Mitigation Innovation

The table reports the results of the time-fixed-effect linear OLS regression of current and one-year forward Tobin's Q on firm's patent stock in carbon intensive and non-carbon intensive climate adaptation and mitigation technologies between 1995 and 2020 . Industry dummies are based on 2 digit SIC codes. Control variables include the market beta, size, operating profitability, investment, tangibility, leverage, EPS and Sale growth. The variables are defined in Table 2. Columns 4-6 also includes contemporaneous Tobin's Q as a control. All the independent variables are normalized to have a mean of 0 and standard deviation of 1. Heterogeneity-consistent standard errors are reported in parentheses.

	Dependent variable:					
	Tobin's Q			Lead Tobin's Q		
	(1)	(2)	(3)	(4)	(5)	(6)
Climate CI	0.009***	0.010***	0.014***	0.004***	0.005***	0.004***
	(0.002)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.0002)
Climate Adaptation Non CI	0.002	0.001	0.001	0.00005	−0.0004	−0.001
	(0.008)	(0.007)	(0.006)	(0.003)	(0.003)	(0.003)
Climate Mitigation Non CI	−0.002	0.0002	0.007	0.0002	0.0005	0.001
	(0.006)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
Climate Adaptation & Mitigation Non CI	0.005+	0.005**	0.007***	0.001+	0.002**	0.001*
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Non Climate CI	0.007	0.005	0.009	0.002	0.002	0.002
	(0.007)	(0.007)	(0.008)	(0.002)	(0.002)	(0.003)
Non Climate Non CI	−0.005	−0.005	−0.009	−0.0004	−0.0005	−0.001
	(0.016)	(0.013)	(0.012)	(0.006)	(0.006)	(0.005)
Citations	0.007	0.014+	−0.067***	0.004*	0.006*	0.001
	(0.008)	(0.008)	(0.013)	(0.002)	(0.002)	(0.002)
R&D	0.117***	0.054***	0.146***	0.034***	0.022*	0.023*
	(0.018)	(0.013)	(0.021)	(0.009)	(0.009)	(0.010)
Controls	No	No	Yes	No	No	Yes
Industry FE?	No	Yes	Yes	No	Yes	Yes
Observations	41,862	41,862	41,567	37,987	37,987	37,733
R^2	0.015	0.114	0.298	0.630	0.634	0.636
Adjusted R^2	0.014	0.112	0.297	0.630	0.633	0.635

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 8: Market Valuation and Short-term innovation proxy

The table reports the results of the time-fixed-effect linear OLS regression of current and one-year forward Tobin's Q on the proportion of citations of the patents issued in year t that were cited in the first three years of the patent application. Industry dummies are based on 2 digit SIC codes. Control variables include the market beta, size, operating profitability, investment, tangibility, leverage, EPS and sales growth, and contemporaneous Tobin's Q for columns 4-6. The variables are defined in Table 2. All the independent variables are normalized to have a mean of 0 and standard deviation of 1. Heterogeneity-consistent standard errors are reported in parentheses.

	Dependent variable:		
	Tobin's Q		
	(1)	(2)	(3)
% cites in 1 year	-0.005		
	(0.005)		
% cites in 3 years		-0.024^{***}	
		(0.006)	
% cites in 5 years			-0.028^{***}
			(0.007)
Controls	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes
Observations	27,644	27,644	27,644
R^2	0.285	0.286	0.286
Adjusted R^2	0.283	0.283	0.284
Note:	* p<0.10; ** p<0.05; *** p<0.01		

Appendix

Figure A1: Example of a carbon intensive climate patent

US005377631A

United States Patent [19]

Schechter

[11] **Patent Number:** **5,377,631**

[45] **Date of Patent:** **Jan. 3, 1995**

[54] **SKIP-CYCLE STRATEGIES FOR FOUR CYCLE ENGINE**

[75] Inventor: **Michael M. Schechter**, Farmington Hills, Mich.

[73] Assignee: **Ford Motor Company**, Dearborn, Mich.

[21] Appl. No.: **124,172**

[22] Filed: **Sep. 20, 1993**

[51] **Int. Cl.**⁶ **F02B 77/00**

[52] **U.S. Cl.** .... **123/198 F**

[58] **Field of Search** .... 123/21, 198 F, 481, 123/90.12

[56] **References Cited**

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Primary Examiner—Noah P. Kamen
Attorney, Agent, or Firm—Jerome R. Drouillard; Roger L. May

[57] **ABSTRACT**

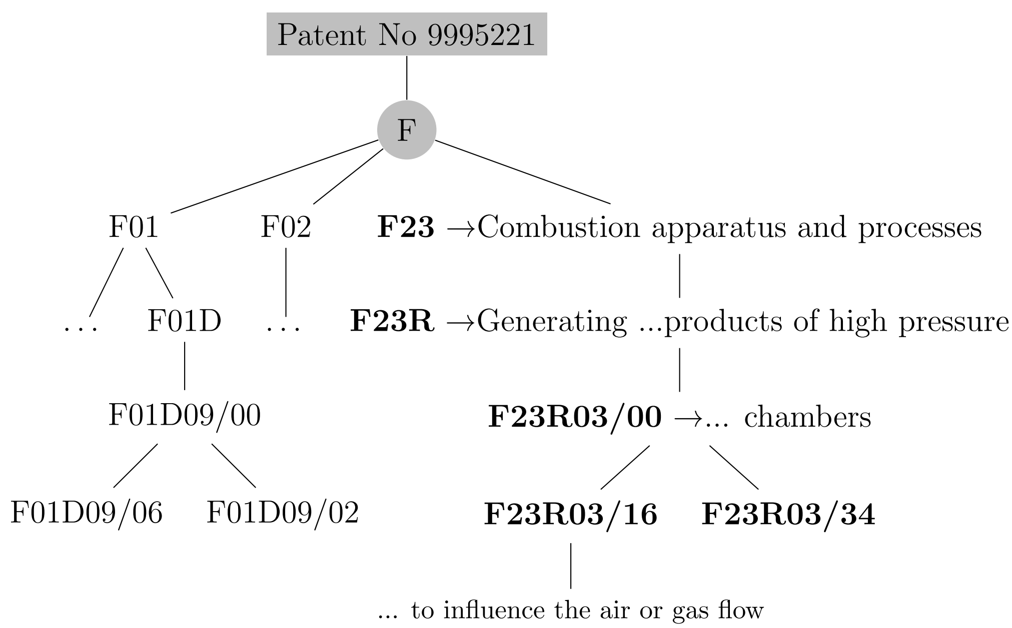
Strategies for operating a four cycle engine in skip-cycle manner include providing the engine with a valve control so that each intake and exhaust valve for each cylinder can be individually activated or deactivated essentially instantaneously to provide a skip-cycle pattern that varies as a function of the load. Individual of the valves permits changing the purpose of the stroke off each piston of each deactivated cylinder from compression to exhaust or intake to expansion, as the case may be, to assure firing of all of the engine cylinders within as short a period as one skip cycle to prevent cylinder cooldown, which promotes emissions. Unthrottled operation also is provided by closing the intake and exhaust valves in a particular sequence during skip cycle operation, and controlling the intake valve closure timing during load periods between skip cycle periods to continue unthrottled operation for all load levels. Further individual activation or deactivation of the fuel injectors and spark plugs enhances the skip cycle, unthrottled operation.

7 Claims, 3 Drawing Sheets

Details of IPC hierarchy

IPC is structured in a hierarchical manner, starting with main sections that refer to broad categories such as mechanical engineering or electricity, and becoming more granular, as technological class, subclass and groups are added. Figure 2 provides an example of such a hierarchy, expressing the five levels of an IPC code. It also expresses the fact that a given patent may receive more than one IPC code, if it contributes to different areas of technology. To give another specific example related to our sample, the below scheme in Figure A2 graphs an example patent with the ID code 9995221 that appears in our data. The patent, titled as *Staged fuel and air injection in combustion systems of gas turbines*, is assigned to General Electric in 2018. It has received 7 different IPC subgroup codes, which belong to 3 different IPC classes. Definitions of every IPC code can be found on the following website address by World Intellectual Property Organization, which provides detailed information on IPC.

Figure A2: An example patent with a carbon intensive IPC



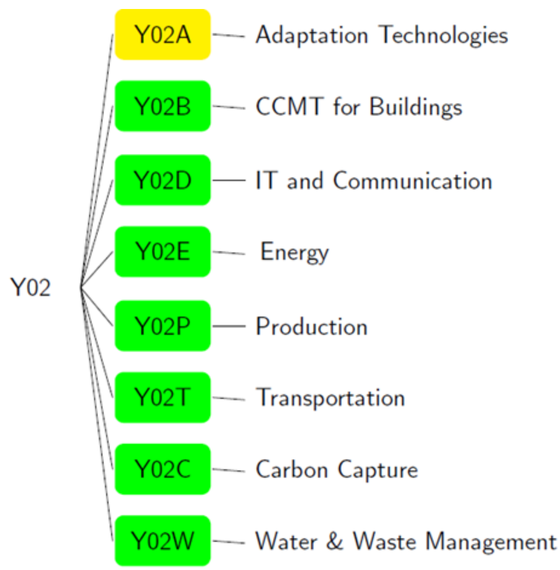
In Figure A2, to illustrate, we highlight class F23, which is identified as a carbon intensive class of technology in our study. F23 is broadly defined as Combustion apparatus; combustion processes. Getting more granular, we see that in class F23, the patent belongs to subclass F23R, which refer to generating combustion products of high pressure or high velocity and to group F23R 3/00, which describes technologies in continuous combustion chambers using liquid or gaseous fuel. Finally, both subgroups F23R03/16 and F23R03/34 add more description to the group. However, note that we never need this much granularity, since IPC codes we use in identifying carbon intensive patents are only at class or subclass level (see Table A2).

Furthermore, our classification is binary in both climate and carbon intensive dimensions. Namely, having one carbon intensive IPC code is sufficient to classify that patent as carbon intensive. Similarly, having one Y02 subclass from Table A1 is enough to classify a patent as climate. Note that patents may also receive several Y02 codes as well, showing climate contribution in different areas. Finally, if a given patent has both at least one climate tag, and at least one CI tag, then it belong to the intersection of these two categories (Climate CI).

Benefits of Y02 scheme

In the face of growing global attention on climate change, EPO launched a dedicated classification scheme for Climate Change mitigation technologies (CCMT) in 2010, which with further developments also started to include technologies helping with climate change adaptation(Angelucci et al., 2018). The goal of the classification is to help a wide range of stakeholders identify climate technologies.

Figure A3: Subclasses of Y02



EPO worked with a specialist team of patent examiners in collaboration with researchers, analysts and NGOs to develop the new climate identification system in three steps:

1. Identify a relevant entry for Y02 (e.g. CO2 capture technology)

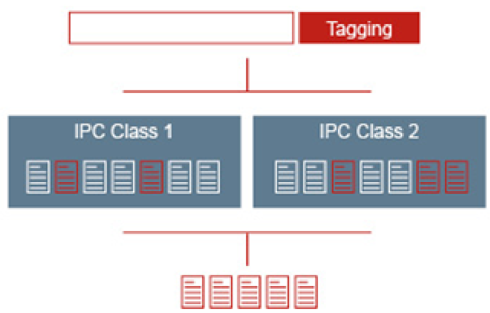
2. Look for existing classification entries (e.g. ECLA, IPC codes) and search strategies (e.g. terms in abstracts, patent claim texts)

3. Use search and classification tools to develop search algorithms which are now

used to find and update all documents relating to CCMTs (periodically updated)

The three steps procedure leads to the Y02 classification system, which are attached to patent documents as kind of a tag (see A4). This tagging allows for the identification of climate patents without the existing CPC or IPC classifications being affected.

Figure A4: Y02 as a tag
Source: EPO, 2021



An example of how Y02 leads to less noise and more complete results is given in EPO, 2021 with the carbon capture technology. To identify patents related to their Carbon Capture of CO2, we may rely on the following IPC code: B01D 53/00: Separation of gases or vapors; Recovering vapors of volatile solvents from gases; /62 . . . carbon dioxides . However, the authors show that this would give a noisy and incomplete result compared to the relevant Y02 code (Y02C 20/40). Another example is Y02E 10/70 which tracks patents related to wind turbines, but a relevant IPC class (F05B2240/95) would give 650 documents not related wind turbines.

Figure A5: Noise and completeness
Source: EPO, 2021

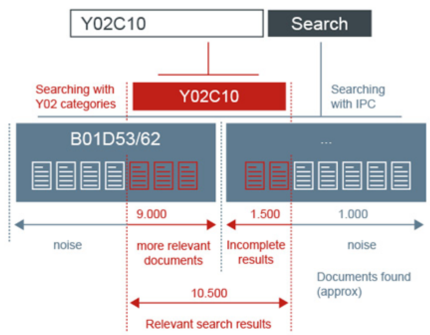


Table A1: Y02 CPC subsections used in identifying Climate Innovation

CPC	Definition
Y02A	Technologies for Adaptation to Climate Change
Y02B	Climate Change Mitigation Technologies (CCMAT) related to buildings, e.g. housing, house appliances or related end-user applications
Y02C	Capture, storage, sequestration or disposal of Greenhouse Gases [GHG]
Y02D	CCMAT in Information and Communication Technologies i.e ICT aiming at the reduction of their own energy use
Y02E	Reduction of Greenhouse Gas [GHG] emissions, related to energy generation, transmission or distribution
Y02P	CCMAT in the production or processing of goods
Y02T	CCMAT related to transportation
Y02W	CCMAT related to wastewater treatment or waste management

Source: https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html

Table A2: IPC sections and subsections used in identifying Carbon Intensive Technologies

IPC	Definition
C10J	Production of producer gas, water-gas, synthesis gas from solid carbonaceous material, or mixtures containing these gases carburetting air or other gases
F01K	Steam engine plants; steam accumulators; engine plants not otherwise provided for; engines using special working fluids or cycles
F02B	Internal-combustion piston engines; combustion engines in general
F02C	Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants
F02G	Hot gas or combustion-product positive-displacement engine plants use of waste heat of combustion engines; not otherwise provided for
F22	Steam generation
F23	Combustion apparatus; combustion processes
F27	Furnaces; kilns; ovens; retorts

Source: Dechezlepretre, Mucklay, and Neelakantan, 2020

Table A3: Market Valuation of All Climate Patent Categories - IndustryxTime effects

The table reports the results of the time-fixed-effect linear OLS regression of current and one-year forward Tobin's Q on firm's patent stock in carbon intensive and non-carbon intensive climate adaptation and mitigation technologies between 1995 and 2020 . Industry dummies are based on 2 digit SIC codes. We include industry and time fixed effects and their interaction in every column. Control variables include the market beta, size, operating profitability, investment, tangibility, leverage, EPS and Sale growth, and contemporaneous Tobin's Q for columns 4-6. The variables are defined in Table 2. All the independent variables are normalized to have a mean of 0 and standard deviation of 1. Heterogeneity-consistent standard errors are reported in parentheses. Standard errors are clustered by year and industry.

	Dependent variable:			
	Tobin's Q		Lead Tobin's Q	
	(1)	(2)	(3)	(4)
Climate CI	0.0109 ***	0.0143 ***	0.0172***	0.0066 ***
	(0.0015)	(0.0012)	(0.0018)	(0.0004)
Climate Adaptation Non CI	0.0013	0.0010	0.0004	-0.0007
	(0.0057)	(0.0058)	(0.0096)	(0.0035)
Climate Mitigation Non CI	−0.0003	0.0068	−0.0004	0.0011
	(0.0045)	(0.0043)	(0.0075)	(0.0027)
Climate Adaptation & Mitigation Non CI	0.0066***	0.0094***	0.0097 ***	0.0033 **
	(0.0008)	(0.0006)	(0.0022)	(0.0012)
Non Climate CI	0.0056	0.0094	0.0091	0.0034
	(0.0059)	(0.0070)	(0.0100)	(0.0035)
Non Climate Non CI	-0.0049	-0.0085	-0.0048	-0.0006
	(0.0115)	(0.0117)	(0.0194)	(0.0071))
Citations	0.0138	−0.0653***	0.004*	0.0017
	(0.0085)	(0.0104)	(0.0123)	(0.0046)
R&D	0.0580**	0.1468***	0.0774***	0.0329***
	(0.0162)	(0.0376)	(0.0122)	(0.0179)
Controls	No	Yes	No	Yes
Observations	41,862	41,567	38,766	37,929
R^2	0.18212	0.35023	0.18725	0.66514
Within R^2	0.00466	0.20953	0.00628	0.59069

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table A4: Market Valuation of All Climate Patent Categories - Controlling for proportion of citations received in the short term

The table reports the results of the time-fixed-effect linear OLS regression of current and one-year forward Tobin's Q on firm's patent stock in carbon intensive and non-carbon intensive climate adaptation and mitigation technologies between 1995 and 2020 . Industry dummies are based on 2 digit SIC codes. Control variables include the market beta, size, operating profitability, investment, tangibility, leverage, EPS and Sale growth, and contemporaneous Tobin's Q for columns 4-6. The variables are defined in Table 2. All the independent variables are normalized to have a mean of 0 and standard deviation of 1. Heterogeneity-consistent standard errors are reported in parentheses.

	Dependent variable:					
	log(q)			log(plm::lead(q))		
	(1)	(2)	(3)	(4)	(5)	(6)
Climate CI	0.009***	0.010***	0.014***	0.004***	0.004***	0.004***
	(0.002)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.0003)
Climate Adaptation CI	0.002	0.001	0.001	0.0001	−0.0004	−0.001
	(0.008)	(0.007)	(0.006)	(0.003)	(0.003)	(0.003)
Climate Mitigation CI	−0.001	0.001	0.007	0.0002	0.001	0.001
	(0.006)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
Climate Adaptation and Mitigation Non CI	0.006**	0.006***	0.007***	0.001*	0.002***	0.001**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Non Climate CI	0.008	0.006	0.009	0.002	0.002	0.002
	(0.008)	(0.008)	(0.008)	(0.002)	(0.003)	(0.003)
Non Climate Non CI	−0.006	−0.007	−0.009	−0.0004	−0.001	−0.001
	(0.016)	(0.013)	(0.012)	(0.006)	(0.006)	(0.005)
Citations	−0.003	0.005	−0.067***	0.003*	0.003*	0.001
	(0.008)	(0.007)	(0.013)	(0.002)	(0.002)	(0.002)
R&D	0.117***	0.056***	0.149***	0.034***	0.023**	0.020**
	(0.017)	(0.013)	(0.021)	(0.009)	(0.009)	(0.010)
% of citations in 3 years	−0.018***	−0.005	−0.005	0.009***	−0.001	−0.001
	(0.006)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)
Controls	No	No	Yes	No	No	Yes
Industry FE?	No	Yes	Yes	No	Yes	Yes
Observations	41,862	41,862	41,567	37,987	37,987	37,733
R^2	0.029	0.125	0.299	0.630	0.635	0.637
Adjusted R^2	0.028	0.123	0.298	0.630	0.634	0.636

Note: * p<0.10; ** p<0.05; *** p<0.01