Pricing of green regulatory and technological risks *

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Abstract

I use text analysis of U.S. firms' press releases to build monthly measures of their exposure to environmental policies and to green technologies. I estimate the associated regulatory risk premium and technological opportunity premium. The time series of these premia reveal two findings. First, they exhibit a significant negative correlation. Second, their sign and magnitude depend on the political orientation of the government. Under Democrat administrations, green policy risk commands a positive premium, which switches sign under Republican presidents. Firms the most exposed to this risk have expected returns 1.5% higher under Democrats than under Republicans. Similarly, green innovation is associated with a negative risk premium under Democrat mandates, which becomes positive under Republicans. The most innovative firms have expected returns 3.5% lower under Democrats than under Republicans. I introduce a tractable consumption-based asset pricing model, which features both policy and innovation risks as well as their interactions. The model captures well my empirical findings and explains the impact of governments and policy makers on transition risk premia.

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1 Introduction

The issue of climate change and the transition to a low-carbon economy are among the most critical challenges facing governments and policy makers in the 21th century. In pursuit of climate neutrality goals, governments typically employ strategies involving either regulatory mandates for firms or the provision of subsidies intended to promote innovation and adoption of green technologies. These environmental policies impose risk on firms that are more carbon-intensive, as they are likely more affected by restrictions and taxes. I refer to this risk as *regulatory risk*. Additionally, as green subsidies stimulate innovation, firms that are least innovative may fall behind and become increasingly susceptible to the arrival of new, greener competitors. This risk is termed *technological risk*.

I provide a granular analysis of regulatory and technological risks and of their interactions, empirically and theoretically. This analysis is based on new and timely measures of firm-level exposure to these risks. An empirical analysis of the associated risk premia reveals interesting interactions and links with the political party in place. I present a consumption-based asset pricing model which features both regulatory and technological risks, and can explain these empirical findings. The model provides insights on the interactions between regulatory and technological risks, and on their asset pricing implications. These insights may guide governments and policy makers in their pursuit of climate-neutrality goals.

Monthly time series of firms' exposure to regulatory and technological risks are built using textual analysis methods on a large set of firms' press releases. I assume that a firm's increased mention of environmental policies within its press releases correlates with heightened regulatory risk exposure. Similarly, I consider the volume frequency of mentions pertaining to green technologies in press releases as a proxy of genuine research and development activity or adoption of green technologies. An analysis of the resulting exposure measures supports these assumptions, which I also back using a comparison with measures built from carbon emissions data and from patents data.

I rely on a machine learning approach to identify the press releases that mention environmental policies or green technologies. This approach is semi-supervised. It starts from small sets of press releases that are unambiguously about policies or technologies, identified using a dictionary approach. These sets are used by the algorithm to learn the patterns of the press releases in them and identify new press releases with the same patterns. The resulting measures of firm-level exposure to policy and technological risks show interesting trends depending on the political party in place. Both measures increase, on average across firms, over the first presidency of Barack Obama, as several regulations and subsidies to green innovation were implemented. They decrease during his second mandate, which coincides with the Democrats losing control over Congress. Firms' average exposure to regulatory risk remains relatively flat after that. Their exposure to technological risk also remains flat during the presidency of Donald Trump, but increases following the election of Joe Biden.

I apply Fama MacBeth regressions to the constructed measures of firm-level exposure to policy and technological risks, and estimate the associated risk premia jointly. The regulatory risk premium is on average positive whereas the technological risk premium is negative, in line with Sautner et al. (2023a) and Leippold and Yu (2023). The analysis of the dynamics of these risk premia uncovers two results. First, the two risk premia are strongly negatively correlated, with a correlation coefficient of -53%, statistically significant. This negative correlation underlines the importance of studying the two risks together. Second, the sign of the premia is strongly dependent on the political party in place. The technological premium tends to be negative under Barack Obama's presidencies, and positive during Donald Trump's mandate. Under Democrat administrations, firms that innovate more thus earn less expected returns, in line with investors valuing companies' efforts to mitigate climate change, Boermans et al. (2024). The regulatory premium, in contrast, tends to be positive with a Democrat president whereas it oscillates around zero then turns negative during Donald Trump's office. Under Democrat administrations, more carbon-intensive firms thus earn higher expected returns, in line with the theory of Pastor, Stambaugh, and Taylor (2022). Regressions confirm that these switches in the sign of risk premia depending on the administration in place are statistically significant. They also show that the level of support of the Congress for the president additionally plays a role in the magnitude of the premia.

To rationalize these findings, I propose a consumption-based asset pricing model which features environmental policies and green innovations. Economic growth is driven by two long-run components, one led by brown activities and the other by green activities. I refer to them as green and brown growth. Environmental policies are modeled by a Poisson process. Brown growth increases the intensity of this Poisson process, hence the probability of a new green policy. Whenever the process hits, brown growth decreases. Green innovations are modeled by another Poisson process. Policies increase the intensity of this Poisson process and hence the probability of an innovation. Innovations increase green growth and the probability of a new policy.

This model leads to an equity premium that can be decomposed into two components, one lined to green policies and the other to green innovations. The regulatory and the technological premia are thus not independent, they are functions of both probabilities of green policy and innovation. An increase in the probability of new policy leads to both an increase in the regulatory risk premium and a decrease in the technological risk premium.

In contrast, an increase in the probability of innovation leads to a decrease in the regulatory risk premium and to an increase in the technological risk premium. These effects enable the model to explain my empirical findings well. As Republicans tend to apply less regulations than Democrats, Republican regimes are characterized by a smaller intensity of regulation jumps. Under Democrats, the higher intensity pulls the technological premium down and the regulatory premium up, explaining their negative correlation and their changes in sign.

There results allow to reconcile the mixed evidence on the sign of the unconditional transition premium.[1] I show that the sign of the premium strongly depends on the political party in place. This finding is important as it highlights the critical role of governments' and policy makers' actions and their impact on firms' cost of capital. The resulting effect on the cost of capital directly translates into firms' incentives to become, or not, more sustainable. The determination of governments to advance the environmental transition is thus pivotal for financial markets to establish the appropriate incentives.

Finally, the uncovered interaction between regulatory and technological risk premia shows that firms' exposure to these two risks should not be studied in isolation of each other. As changes in the political party in place lead to switches in the sign of risk premia, higher risk exposure to one of them translates into higher return volatility. In comparison, higher exposure to both risks can reduce and stabilize the cost of capital.

The rest of this paper is organized as follows. Section 2 reviews the related literature. Section 3 introduces some selected empirical facts on transition risks. Section 4 presents the empirical analysis. It describes the methodology to build the firm-level measures of exposure to climate risks and analyzes the resulting exposure measures, as well their associated risk premia. Section 5 introduces and solves the model and shows that its predictions for the equity risk premia match the data well.

[1] Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) find a positive premium. Some find on the contrary a negative premium: In et al. (2017), Garvey et al. (2018), Duan et al. (2023), Pastor et al. (2022), and Pedersen et al. (2021). Finally, other obtain mixed evidence: Görgen et al. (2020), Aswani et al. (2024), and Lindsey et al. (2021).

2 Literature Review

This paper contributes to several branches in the literature. The first one is the literature that uses textual analysis to build firm-level measures of exposure to climate risks. Sautner et al. (2023a) use a dictionary approach based on the algorithm of King et al. (2017) to quantify how much earning calls talk about climate risk for each company. They distinguish three components of that risk: physical, regulatory, and opportunity risks. Li et al. (2024) similarly use dictionaries to build measures based on earning calls transcripts to measure physical and transition climate risks, identifying firms which respond proactively. Leippold and Yu (2023) propose a measure of green innovation based on the use of ClimateBERT on earnings conference calls after having trained it on the abstracts of green patents reformulated by GPT-3. They also categorize firms as inventors and adopters. Kölbel et al. (2022) use BERT to classify sentences from a firm's 10-K report and generate a firm-specific measure of both transition and physical risks.

Compared to this literature, this paper is the first to use a large collection of firms' press releases to build climate change risks' exposure. As spontaneous and real-time communications from firms aimed at communicating new information, press releases are an ideal support to evaluate a firm's climate risk exposure at a high frequency. The machine learning technique I use, has been shown by Gourier and Mathurin (2024) to perform better than dictionary approaches, and remains more transparent and interpretable than large language models.

A related literature uses textual analysis to build aggregate indices of climate risks: Engle et al. (2020), Ardia et al. (2022), Faccini et al. (2023), and Gourier and Mathurin (2024). My measures, in contrast, are at the firm level.

This project also belongs to the empirical literature that attempts to assess whether the different components of climate transition risk are integrated into equity prices. The most studied dimension is regulatory risk, but technological risk has also become the subject of recent studies. Most papers find a significant positive, but small, regulatory premium and a significant negative technological premium: Matsumura et al. (2014); Chava (2014); Hong et al. (2019); Engle et al. (2020); Choi et al. (2020); Barnett et al. (2020); Bolton and Kacperczyk (2021); Hsu et al. (2022); Bolton and Kacperczyk (2023); Sautner et al. (2023a); Leippold and Yu (2023), and Li et al. (2024). The intuition behind these results is that a firm whose activity is more threatened by possible future regulations delivers, in expectation, higher returns than a firm that would not be affected by these regulations. Similarly, a firm that invests more in green technologies, and is thus more innovative, delivers, in expectation, smaller returns than a less innovative firm.

The results in this paper are in line with these unconditional risk premium. In addition, I study the dynamics of conditional risk premia over time as well as their interaction.

Finally, the theoretical part of this article builds on a literature that uses consumption-based asset pricing models to represent climate risk. This literature was reviewed by Giglio et al. (2021). Bansal et al. (2016a) and Bansal et al. (2016b) consider that a climate disaster has an immediate and a long-run negative effects on consumption growth. The carbon intensity of the economy is either exogenous or the result of the government's chosen abatement policy. In Giglio et al. (2021)'s paper, the climate rare event has an immediate negative impact on consumption but a positive one on the long-run component of economic growth. It also increases the probability of another disaster. Lontzek et al. (2023) also represent a disastrous climate event that has an instantaneous negative effect on consumption growth. They integrate temperature thresholds and investors with divergent beliefs about climate change. Policy responses, implicitly included in the consequences of the climate disaster, affect brown firms more than green firms.

This paper is the first, to the best of my knowledge, to decompose climate transition risk into a regulatory risk and a technological risk using two types of rare events, one for green regulations and one for green innovations. It allows the simultaneous study of both regulatory premium and technological premium as well as their co-dependency.

3 Transition risks: Selected stylized facts

In this section, I define and provide selected stylized facts on the two transition risks that are the focus of this paper: regulatory and techonological risk. These facts guide important choices made in the design of the model.

3.1 Definitions

In its Policy Instruments for the Environment (PINE) database, the OECD employs five principal categories to organize governmental environmental interventions.[2] The "Taxes and fees" classification is the largest in terms of the number of policies, with 63.1% of the total number of policies in the database. Environmentally related taxes and fees increase the cost

[2]The OECD started building the PINE database in the 1990s, initially with a limited policy scope. Today, the database includes information on taxes and fees, subsidies, tradable permits and offsets, deposit-refund schemes and voluntary approaches relevant to 22 environmental domains. The information in the PINE database is collected via a network of country experts (including government agencies, research institutes and international organizations). Country experts update and validate the data once per year.

of polluting products or activities to discourage their consumption and production. The tax bases covered include energy products such as vehicle fuels and measured pollution emissions. I refer to the risk that these policies represent for firms as *regulatory risk*.

The classification "Environmentally beneficial subsidies and payments" constitutes the second most extensive category in terms of the number of policies: 27.9% of the total number of policies in the database. These subsidies can take many forms, such as VAT exemptions on electric cars, feed-in tariffs on renewable energy generation, tax credits for environmentally relevant investments, accelerated depreciation schemes for low-carbon assets or payments for nature conservation projects. These subsidies represent a risk to firms with limited involvement in the invention or adoption of green technologies, and an opportunity for innovative firms. I refer to this risk as *technological risk*.

The OECD identify 22 relevant environmental domains. These two types of policies are particularly prominent in domains such as "Climate change mitigation", "Energy efficiency", "Fossil fuels", "Renewable Energy", or "Air pollution", which are inherently connected to the issue of climate change rather than the degradation of natural ecosystems and biodiversity or the emergence of health-related concerns.

3.2 Policy and innovation efforts

The impact of environmental policies can be measured using a tool created in 2014 by the OECD, the Environmental Policy Stringency (EPS) index. This index is composed of three sub-indices. The first one, "Market based instruments", is built using policies that put a price on pollution. The second one, "Non-Market Based instruments", entails policies that mandate emission limits and standards. The last one "Technology Support policies", is built using policies that support innovation in clean technologies and their adoption. This classification is consistent with the two main instruments of environmental policies discussed in Section 3.1.

In an OECD working paper, Kruse et al. (2022) show that the share of patents in climate change mitigation technologies out of overall patents, follows similar trends over time as the Technology Support sub-index of the EPS index. They were both low and stable from 1990 to 2000, then increased rapidly until 2010. The level of technology support policies has declined between 2011 and 2015 and a similar trend is observed for patents in climate change mitigation technologies. Both stabilized from 2015 to 2020 to a relatively high level compared to 2000.

Using the three sub-indices of the EPS index, Benatti et al. (2024) show that environmental policy tightening, in particular the stringency of technology support policies and non-market based policies, leads to higher innovation activity in technologies mitigating climate change.

Both studies indicate that governments' interventions, in particular in the form of green technology support, stimulate innovation activities.

3.3 Green innovations

In a recent report, the Energy Institute gives the breakdown of the renewable energy mix into the relative contribution of each renewable technology since 2000. It shows that although hydropower is by far the largest modern renewable source with more than 4,000 TWh (terawatt hours) generated per year in the world since 2016, wind and solar power have seen the highest growth in recent years. Almost inexistent in 2000, solar energy has been produced above 1,000 TWh per year since 2021. Also inexistent in the energy mix in 2000, wind energy has reached 1,000 TWh per year since 2016 and is above 2,000 TWh per year since 2022. Other renewables, including bioenergy, represent less than 1,000 TWh per year even in 2023.

In recent years, a radical change has been initiated in the automobile industry. The share of new cars that are electric or hybrid is significantly increasing, approximately 20% in 2023. However, most of the changes have not yet been made. Non-electric cars still represent the vast majority of the car stock (around 97%). The share of cars currently in use that are electric has increased exponentially since 2015, especially in China.

4 Empirical Analysis

4.1 Data sources

4.1.1 Press releases

Firm-level measures of exposure to climate risks are built using textual analysis of US press releases, obtained from Dow Jones Factiva. I use the primary sources published by Dow Jones. The firm issuing each press release is identified from the ISIN field of the database. This field is filed by Factiva for releases classified as "Company News" from 2004. The information is available only for 35% of the press releases from 2004 to 2007, then for 75% from 2008 onwards. Therefore, I use documents from 2008, and estimate risk premia from 2010.

Press releases are a key instrument of firms' public relations. They use them to make announcements about significant events, such as earnings results, product launches, mergers, or executive changes. They are created for immediate public dissemination and aimed at journalists, investors, and the general public. They represent new information and are a voluntary communication from the company. As a result, they are an ideal channel to announce decisions made as part of firms' strategy to tackle climate change risk and green innovation. Unlike other firms' disclosures, the content of press releases is timely and thus allows measuring climate risk more precisely over time. In contrast, regulatory filings are highly scripted and may lack informativeness and timeliness (e.g., Brown and Wu Tucker (2011)).

Table 1 displays general statistics about the press release database per year. There are on average around 500,000 press releases per year. Following the Financial Crisis, from 2009 to the end of 2013, companies issued more press releases, around 800,000 on average per year. The low number of press releases in 2023 can be explained by the fact that the dataset ends in June 2023. Every year, around 10,000 US firms publish press releases. The five last columns of the table give the monthly average number of press releases per firm at different percentiles. It shows that every year, more than 25% of firms have only one press release. The median number of press releases in a month for a firm is approximately 3. A significant number of companies emit press releases more often: around 25% of firms post more than 6 press releases per month on average and the firms that rely the most on press releases for their communications release more than 15 of them monthly.

4.1.2 Other datasets

Firm-level measures of exposure to environmental regulatory risk further rely on the use of patents obtained from the United States Patent and Trademark Office (USPTO).

Validation tests for my measures of exposure to regulatory risk are done using carbon emissions data. Specifically, I use carbon intensities from S&P Global Trucost.

Firm-level accounting data necessary as control variables in the estimation of the risk premia are downloaded from the merged database of CRSP and Compustat.

4.2 Construction of firm-level risk exposure measures

4.2.1 Algorithm

To identify to what extent a press release talks about climate regulation or technological risk, I adapt the algorithm of King et al. (2017). This algorithm was first used by Sautner et al. (2023a) for climate risk measurement, to build dictionaries related to physical, regulatory and opportunity climate risks. Exposure measures are computed from these dictionaries, by counting the number of occurrences of each term in earning conference calls. Gourier and Mathurin (2024) modify this algorithm to identify articles that mention greenwashing in the archive of the Wall Street Journal. The output of the algorithm is binary: articles that receive a 1 are classified as greenwashing-related. An aggregate index is built from the fraction of greenwashing-related articles to climate change-related articles. They show that their method outperforms the dictionary approach of Sautner et al. (2023a).

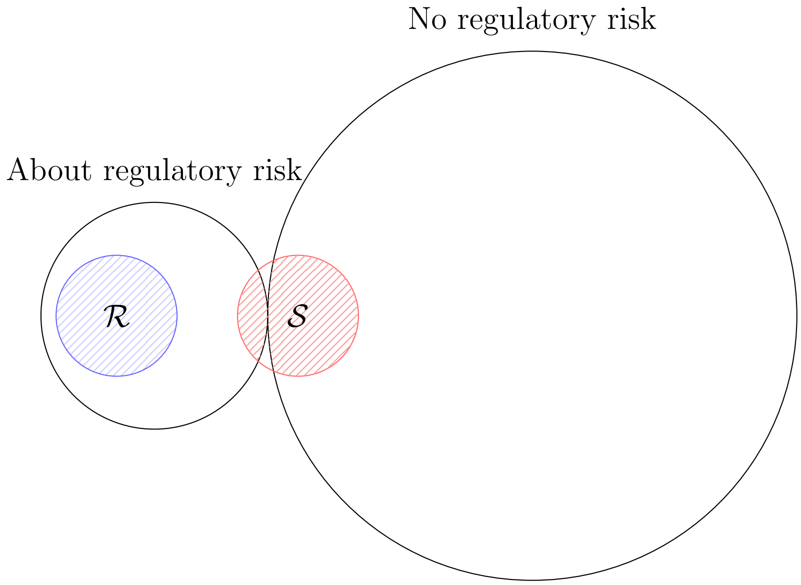
I slightly modify the methodology of Gourier and Mathurin (2024) to produce a continuous score (instead of a 0 or 1), which represents the average probability of a press release to mention a given type of risk. I detail below the algorithm.

This algorithm is a semi-supervised learning method. It is based on the training of three classifiers (Naive Bayes, Random Forest and Support Vector) on a labeled dataset. As press releases are unlabelled, the first step consists to create a labelled dataset. It is composed of two parts: the reference set $\mathcal{R}$, which contains documents that are highly likely to be about regulatory or technological risk, and the search set $\mathcal{S}$, composed of documents that are likely not to contain the topic. Press releases in $\mathcal{R}$ are chosen using a dictionary approach. This dictionary is created so that it unambiguously identifies press releases that mention regulatory or technological risk. As these press releases are a tiny part of all the press releases in the database, picking press releases randomly in the database, but are not in $\mathcal{R}$, yields a set of articles that are most likely not related to regulatory or technological risk, and can thus be used to form $\mathcal{S}$. Figure 1 illustrates the creation of the two sets $\mathcal{R}$ and $\mathcal{S}$. I fix the size of each set to 2,000 press releases. Once these sets are formed, the classifiers are trained to learn the patterns that most characterize press releases in $\mathcal{R}$.[3] Each classifier then provides a probability that a press release discusses the risk considered. The final score for a document is the average of the three probabilities.

Large Language Models (LLM), like ClimateBERT or GPT, can be of a great help to identify topics which cannot be isolated using unigrams or bigrams specific to the thematic,

[3]Compared with dictionary approaches used in the literature, here, building a dictionary is only an intermediary step.

Figure 1: Decomposition of the database of press releases



like greenwashing. However, Gourier and Mathurin (2024) show that climate risks can be well identified with the semi-supervised approach described above. Inspection of the press releases with a high score confirms that they are, as expected, related to climate regulations or green technologies. Furthermore, it is more simple, transparent and interpretable than LLMs, and it is easily reproducible.

4.2.2 Dictionary for climate regulatory risk exposure

I choose to include only bigrams in the dictionaries, and not unigrams. This is a common practice in the literature as bigrams are more specific than unigrams. Almost all unigrams can be found with a different meaning in another context. For example, "climate" can be used to refer to "business climate" or to "professional climate". Additionally, the topics of green regulations and green technologies contain two ideas: the idea of regulation or technologies and the specific context of climate change.

I start by preprocessing the content of the texts, applying standard treatments: replacing capital letters with small letters, removing punctuation, excluding texts which are either too long (more than 2000 words) or too short (less than 200 words)...etc. More importantly, I remove common stopwords. Indeed the condition for bigrams extracted to be more specific than unigrams is for them not to contain stopwords that are uninformative.

In order to build the dictionary for climate regulatory risk exposure, I establish a list of 48 green policies' names and I isolate press releases mentioning one of them. I obtain a dataset of almost 30.000 press releases over the whole period. I choose the list of policy names such that they include the major US environmental actions, like the "Clean Air Act" or the "Inflation Reduction Act", the international agreements, like the "Paris Agreement" or the "Kyoto Protocol", and the major policies from other regions of the world, like the "European Green Deal", susceptible to have an impact on US firms. Several policies' names are actually never mentioned in the press releases. The five most frequently mentioned on the whole period are in decreasing order: the "Clean Power Plan", the "Clean Air Act", the "Sustainable Development Goals", the "Renewable Fuel Standard" and the "Paris Agreement".

I extract the bigrams that meet three conditions: first, they are present in the press releases that mention a green policy; second, they contain one unigram that is directly evoking a policy instrument like "regulation" or "subsidy"; third, they have a much higher document frequency (10 times higher) in the set of press releases mentioning a green policy that in a set containing press releases talking about regulations in general. I obtain a final list of almost 5,000 bigrams characteristic of environmental policies. The top most frequent bigrams in press releases from this dictionary are given in Table 2.

4.2.3 Dictionary for climate innovation risk exposure

The approach to build the dictionary for green innovation benefits for the existence of the USPTO patents database. I make the hypothesis that if a firm is investing in developing or adopting green technologies, it is likely to mention the given technology in its press releases. Although not all innovation activities are patented, the database of patents is likely to contain all major green technologies. Another advantage of this database is that green patents are tagged by the "Y02" code given by the Cooperative Patent Classification (CPC) and the International Patent Classification.[4]

The CPC classification divides the category "Y02" for green patents into eight subclasses: A (Adaptation), B (Buildings), C (Carbon capture), D (Digital), E (Energy), P (Production), T (Transportation) and W (Waste). This paper focuses on the green technologies aimed at climate change mitigation, i.e., which have an effect on carbon emissions. Therefore I remove patents that present adaptation technologies (category A) from this analysis. I only consider the abstracts of patents. As the body of patents usually contains the technical details of the developed technology, they are of less relevance.

[4]The CPC is a patent classification system, which has been jointly developed by the European Patent Office and the United States Patent and Trademark Office (USPTO). The CPC is substantially based on the previous European classification system, which itself was a more specific and detailed version of the International Patent Classification (IPC) system.

I extract the bigrams that meet three conditions: first, they are present in the abstracts of green patents; second, they have a much higher document frequency (10 times higher) in green patents than in other patents; third, they do not have a document frequency superior to 25% in the corpus of IPCC reports used in Engle et al. (2020). I obtain a final list of almost 18,000 bigrams characteristic of green technologies. The top most frequent bigrams in press releases from this dictionary are given in Table 3.

Figure 1 shows two word clouds. Each of them represents the final dictionary of the green innovation topic but the frequencies corresponding to the size of the words in the graphs are either based on green patents (Panel A) or press releases (panel B). The difference between the two figures can be explained by the fact that the green patents' content is fairly technical compared to the one of press releases which is business oriented. Technical words that might be common in patents will never appear in business communications, but their presence is not problematic for the construction of the measures. The most important is that the dictionary extracted from green patents contains the expressions that will be used to describe green technologies. Expressions like "fuel cell", "lithium ion", "fuel ethanol" or "wind turbine", although technical, are known from investors because they are used by companies when they talk about their investments in green technologies.

4.2.4 Topic analysis of green technologies

The Cooperative Patent Classification of green patents relies on 6 sub-classes: Energy, Production, Transportation, Buildings, Adaptation and Environment. These categories are oriented towards specific sectors of activities or perimeters of application. In order to understand the key innovations in green technologies that are mentioned in press releases, I apply a topic analysis to those containing expressions from the green innovation dictionary. I use the Keyword Assisted Topic Model of Eshima et al. (2023), which is an extension of the standard Latent Dirichlet Allocation (LDA) method. This semi-supervised topic model allows the researcher to predefine several topics through a list of keywords. These topics are passed as priors, and help resolve two well-known issues of the LDA: the creation of multiple topics with similar content and the combination of different themes into a single topic.[5]

Table 4 shows the four topics that result from the topic analysis. Each topic is composed of a set of ten bigrams which are the most characteristic of this topic. The name of the

[5] One limitation of this method is that it does not take into account n-grams. It sees a text as a list of unigrams, which makes the output of the algorithm less relevant. To get around this constraint, I artificially transform each bigram of the dictionary into a single unigram and remove other words from the press releases' texts. For example, I replace "fuel" and "cell" found next to each other in a press release with "fuel_cell" which will now be interpreted by the algorithm as a unigram.

topic is chosen based on the interpretation of the list of keywords. "Wind energy" is the most present topic with a proportion of 22.3%. It is characterized by keywords like "wind power", "wind farm" or "wind turbine". In fourth position, with a weight of 5.8%, comes the topic of "Solar Energy" with clear keywords like "photovoltaic power", "solar farm" and "photovoltaic module". These two topics echo the observation in Section 3.3: wind and solar are the two renewable energies which have witnessed the greatest development in the recent decades. The two last topics, with similar weights around 15% are both related to the Transportation sector and electric or hybrid vehicles. One refers to the new types of batteries, in particular lithium-ion; the other to fuel cells and the production of electricity based on hydrogen. These two topics evoke the observation in Section 3.3: a major change has been initiated in the area of electric and hybrid cars.

4.2.5 Definition of firms' risk exposures

I build a firm's monthly exposure to policy or technological risk by averaging the probabilities of its press releases to mention these topics during a given month.

Specifically, the score of press release j of firm i in month t for the green technology topic is given by

$$TechScore_{i,t,j} = \frac{Pb^T_{RF} + Pb^T_{MNB} + Pb^T_{SVC}}{3},$$

where Pb^T_{RF} is the probability that the press release is about green technologies, estimated by the Random Forest classifier. Pb^T_{MNB} and Pb^T_{SVC} are the corresponding probabilities estimated by the Multinomial Naive Bayes (MNB) and the Support Vector (SVC) classifiers.

All press releases thus have a score between 0 and 1. With a score of 1, a press release almost surely mentions a green technology. The lower the score, the less likely it is that the press release is about a green technology.

Similarly, the score of press release j of firm i in month t for the green policy topic is given by

$$RegScore_{i,t,j} = \frac{Pb^R_{RF} + Pb^R_{MNB} + Pb^R_{SVC}}{3},$$

where Pb^R_{RF}, Pb^R_{MNB} and Pb^R_{SVC} are the probabilities that the press release refers to environmental regulations, estimated by the three classifiers. Exposure measures for firm i are then obtained by averaging scores obtained in a given month:

$$TechExposure_{i,t,j} = \frac{1}{P_{i,t}}.\sum_{p=1}^{P_{i,t}} TechScore_{i,t,j} \quad ; \quad RegExposure_{i,t,j} = \frac{1}{P_{i,t}}.\sum_{p=1}^{P_{i,t}} RegScore_{i,t,j},$$

where $P_{i,t}$ is the number of press releases of firm i in month t.

The exposure measures *RegExposure* and *TechExposure* thus capture the fraction of press releases issued by a company during a given month, related to green technologies or regulations. In this fraction, each press releases that is ambiguous about whether it mentions green technologies of regulations gets a weight that is smaller than 1.

4.3 Interpretation of firms' exposure measures

The two exposure measures are built in a similar way, but capture different exposures to risks.

On the one hand, I consider that the higher the regulatory exposure (*RegExposure*) of a firm, the more this firm is exposed to regulatory risk. The logic behind this assumption is that the more firms mention regulations in press releases, the more likely it is in order to reassure investors that these (or future) regulations do not pose too much of a threat to them.

Averaging the exposure measure of firms within each sector reveals that the Utilities and the Coal sectors are the two sectors with the largest average *RegExposure* measure, as shown in Table 7. Among the top-15 industries, there is also the Automobiles and Trucks, and the Aircraft industries. In contrast, the top bottom contains industries such as Healthcare, Pharmaceutical Products, Medical Equipment, Real Estate and Banking. This ranking is in line with my interpretation of the *RegExposure* measure.

To further validate the assumption that the *RegExposure* captures well the regulatory risk exposure of firms, I compare the regulatory exposure of firms to their carbon emissions, which is a standard measure of regulatory risk firms are exposed to. In Table 9, I regress the *RegExposure* values, multiplied by 100, on the firm' carbon intensity of Scope 1 emissions expressed in mega tons per million dollars. I control for year and industry fixed effects. All variables are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. Standard errors are clustered by industry. The coefficient for carbon intensity is positive and significant at the 1% level. It confirms that the *RegExposure* captures a similar information than carbon intensities.

On the other hand, I assume that the higher the technology exposure measure of a firm, the more innovative it is, and hence, the lower its exposure to technological risk. Note that the measure captures in the same way firms that position themselves as innovators and firms that are adopters of the new technologies. Indeed, the measure is based on a vocabulary extracted from green patents, mentioning green technologies, not references to the topic of innovation. The distinction is beyond the scope of this paper, which considers that both invention and adoption of green technologies contribute to making a firm less exposed to technological risk.

Among the sectors with the highest average *TechExposure* measure, I find sectors that are already in the top 15 more exposed sectors in terms of regulatory risk, including Utilities, Automobiles and Trucks, Coal, Petroleum and Natural Gas, and Aircraft, see Table 8. This result is in line with the results of Cohen et al. (2024), who find, based on studying firms' patents, that the most innovative firms are also the most polluting. My classification by *TechExposure* is close to theirs by patents: their top industries are Manufacturing, Energy, Services, and Transportation & Public Utilities.

A legitimate concern would be that both measures actually capture the same information. Figure 3 shows that there is no particular relation between the *RegExposure* and the *TechExposure* of a given firm. Indeed, this scatter plot shows a cloud of points, where each point indicates the average value over time of the *RegExposure* and *TechExposure* for a given firm.

4.4 Time series of firms' exposure measures

Figure 2, Panel A, displays the quarterly average of the measure of the *RegExposure* measure across firms over time. The average measure increases sharply from 2009 until 2013. This period coincides with the first mandate of Barack Obama, who enjoys control over both chambers (the Senate and the House) until 2010. In 2010, Democrats lose seats in both chambers, and lose their majority in the House, but still control the Senate. Barack Obama thus benefits from quite some freedom in the way he leads. Several climate-related regulations and initiatives were implemented to address climate change, reduce greenhouse gas emissions, and promote renewable energy. This included the Endangerment Finding under the Clean Air Act in 2009, which laid the groundwork for the EPA to regulate GHG emissions. It also included regulations such as the Cross-State Air Pollution Rule in 2011 and the Mercury and Air Toxics Standards in 2012, which required power plants to reduce specific emissions. On the international scene, the Obama administration helped to establish the Copenhagen Accord in 2009, which aimed to mobilize climate finance and set voluntary emission reduction targets. From 2013, the trend in the average *RegExposure* measure reverts, to decline almost linearly until 2018, except a short peak in the end of 2015 that correspond to the decision of the Paris Agreement. Whereas Obama is still in power in 2013, for his second mandate, he enjoys much less freedom, as the Democrats lose control of Congress in 2014. Republicans thus control the Congress (both the Senate and the House), limiting Obama's actions. In 2017, Donald Trump becomes President, with the support of Congress. His administration focused on deregulation, support for fossil fuel industries, and withdrawal from international climate agreements such as the Paris agreement. Firms' exposure to regulation stagnates, on average, until the end of the time period.

Table 5 shows that the yearly average value of the *RegExposure* measure is stable over time, slightly decreasing during the second half of the period. This decrease in the average measure over time is present for the different percentiles. It is therefore not driven by "brown" or "green" firms and is a general trend. The standard deviation of the measure is also stable over the sample. It confirms the interpretation of the previous paragraph.

Figure 2, Panel B, shows that firms' *TechExposure* measure is high until 2014, then drops until 2017 and increases again. The high initial level may be due to the subsidies to innovation given by the Obama administration, such as the American Recovery and Reinvestment Act, in 2009 (also known as the "stimulus bill,"), which allocated approximately \$90 billion for clean energy investments, including renewable energy, energy efficiency, and green jobs.

Table 6 presents similar summary statistics for the *TechExposure* measure. The mean value stands at 0.18. The average value of the measure shows a decrease from 2014 to 2019, consistent with Figure 2 (Panel B). The phenomenon is driven by firms in the highest percentiles: the firms the more involved in green technologies slow down their engagements during the middle part of the period. It is confirmed by the stable values in the other percentiles and the decreased standard deviation between 2014 and 2019.

4.5 Risk premia estimation

When a company has released a communication regarding some specific climate topics, it is likely not to immediately mention the same news again in the subsequent releases. However, the information would still be present in investors' mind. That is why I exponentially smooth monthly observations of the exposure measures using a half-life of three months. I replace each exposure measure $x_{i,t}$ with its exponentially weighted moving average $y_{i,t}$:

$$y_{i,t} = \frac{\sum_{z=0}^{t} x_{i,t-z}(1-\alpha)^z}{\sum_{z=0}^{t}(1-\alpha)^z},$$

where the decay α is related to half-life τ as $\alpha = 1 - \exp(-\ln(2)/\tau)$.

To test whether the *RegExposure* and *TechExposure* are related to excess returns in the cross-section of stocks, I use the two-stage approach by Fama and MacBeth (1973). I follow closely the estimation method of Sautner et al. (2023b). That is, in the first stage, I estimate stock betas with respect to a six-factor model, which combines the four- and five-factor models by Carhart (1997) and Fama and French (2015).

Factor betas are estimated at the end of each month with a rolling-window procedure using daily excess returns and factor realizations over the past 12 months. In the second stage, at the end of each month, I estimate cross-sectional regressions of excess stock returns on the estimated factor model betas and a number of stock characteristics that are known return predictors or possibly correlated with the exposure measures.

These stock characteristics include (i) firm fundamentals: Log(Market Cap), Log(Assets), Debt/Assets, Cash/Assets, PP&E/ Assets, EBIT/Assets Capex/Assets, and R&D/Assets; (ii) market variables: Momentum12 and Volatility, and (iii) oil exposure measure: OilBeta, computed jointly with the six-factor model noted earlier. I also include as controls industry dummies based on the Fama-French 49 classifications. All variables are normalized to a zero mean and 1% standard deviation, and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. Standard errors are adjusted using the Newey-West correction for 12 lags. I estimate the regulatory and technological risk premia jointly.

4.6 Dynamics of risk premia

Figure 4 displays the dynamics of the estimated regulatory and technological risk premia from November 2009 to June 2023. The time series capture the trend of the risk premia extracted from a decomposition of the raw estimate into additive seasonal, trend, and residual components using the STL decomposition of Cleveland et al. (1990), with a period of 12 months. The green vertical lines mark three US presidential elections: Barack Obama for a second mandate in November 2012, Donald Trump in November 2016, and Joe Biden in November 2020. Additionally, the figure features some colored zones: blue (red) zones indicate a period in which the United States have a Democrat (Republican) president in power. The details about which party dominates in the Senate and in the House of Representatives are given at the top of the graph following the same color code. Red letters stand for the Chamber being dominated by Republicans while blue letters mean Democrat control.

The average of the regulatory risk premium on the sample period is positive but small, and the average of the technological risk premium is negative but also small. The estimation shows that the sign of the premia is not always the same. The regulatory premium is positive only for 69% of the months and the technological premium 57% of the months.

The analysis of the time series of these risk premia underlines two interesting results. First, there is a strong comovement between the two risk premia. Figure 5 plots the correlation between innovations in regulatory risk premium at time t and innovations in the technological premium at time $t+h$, with an increasing number of lags h. The correlation is at -53% at lag 0 then decreases linearly with the number of lags for the following 6 months. The correlation is significant for the first three months.

Second, the sign of the premia is strongly dependent on the political party in place. The technological premium is mostly negative during Barack Obama's mandates and mostly positive during Donald Trump's mandate. The regulatory premium, on the other hand, tends to be positive during Obama's presidencies, and oscillates around 0 at the beginning of Trump's office before turning negative. The trends in the risk premia are of opposite sign 72% of the months.

Table 10 regresses separately each risk premium on a constant and a dummy variable equal to 1 when there is a Democrat party at power in the United States. The coefficients of the constant confirm that the average negative sign of regulatory premium and the average positive sign of the technological premium with a Republican president. They are both significant, the first at the 4% level and the second at the 1% level. The coefficients on the dummy indicate that the regulatory risk premium is on average 1.4% higher and the technological premium on average 4.1% lower during the presidency of a Republican candidate. They are both significant at the 1% level.

Table 11 regresses separately each risk premium on a constant and a dummy variables equal to 1 respectively if the Democrat president has full support (DD), partial support (DR) or no support (RR) from the Congress. Full support means that both the Senate and the House of Representatives have the same political orientation than the president. Partial support means that only one of the two chambers is Democrat and the absence of support correspond to the case in which both the Senate and the House of representatives are Republican. The coefficients on the constant are unchanged. The coefficients of the three dummies in the first column looking at the regulatory premium indicate that the more support the president receives from the Congress, the higher the premium, from 0.05% without support, to 1.3% with partial support and almost 2% with full support. Regarding the second column on the technological premium, the coefficients are similar at -3.6% for full and partial support and stronger at -5.5% in the absence of support. Although the signs of the coefficients are consistent with the previous table, the technological premium is not as sensitive to the composition of the Congress as the regulatory premium. The only period with no support from the Congress in the period studied is for the years 2015 and 2016. The high magnitude of the coefficient could be explained by the anticipation of Clinton being elected rather than Trump.

5 A Model with Climate Transition Risks

In this section, I build an asset pricing model which features two different long-run processes to distinguish brown and green growths. The transition to a low carbon economy is considered as the path leading from a situation where growth is due only to brown activities to an economy in which growth is instead ensured by green activities. To allow this transition process to happen, two mechanisms are necessary, one to decrease brown economic growth and the other one to make green production possible. They are ensured by the use of two jump processes, one to represent the occurrence of a new environmental regulation and the other one to model the emergence of a green breakthrough innovation. In the model, green regulations are assumed to have two main instruments: the implementation of standards and requirements to limit carbon emissions of "brown" activities and the stimulation of research to develop new clean methods of production and consumption. As for green innovations, they generate green growth and facilitate the application of stricter environmental policies.

5.1 The Model Economy

This model aims at modelling the process of transition to a low-carbon economy. It focuses on the transition risks, decomposed into regulatory risk and technological risk.

I assume that aggregate consumption follows:

$$\begin{cases} \Delta c_{t+1} = \mu_C + x_t^B + x_t^G \\ x_{t+1}^B = \mu_B + \rho_B x_t^B - J_t^R \\ x_{t+1}^G = \mu_G + \rho_G x_t^G + J_{t+1}^I, \end{cases} \tag{1}$$

where c_t is the log of aggregate consumption. The processes x_t^B and x_t^G capture persistent changes in the growth rate of consumption. In this model, growth can be driven either by brown (x^B) production activities or green (x^G) ones. The distinction is key to represent the "transition" process, which consists in replacing carbon emitting production by clean production. As in Giglio et al. (2021), I remove any risk sources not related to climate risk, in particular Gaussian shocks. They could be added without changing the qualitative implications of the model.

The economy is subject to two types of jump processes. J^R represents a new environmental policy and has a negative effect on brown growth. Indeed, one of the two main instruments of climate policies is the definition of rules and constraints to limit carbon emissions, which affect "brown" firms whose activities use fossil energies. It takes value $\xi^R \in (0,1)$ with probability λ_t^R in each period, and value 0 otherwise. J^I represents a breakthrough innovation in green technologies which leads to an increase of "clean" economic growth, assuming its adoption. It takes value $\xi^I \in (0,1)$ with probability λ_t^I in each period, and value 0 otherwise. The use of jumps to feature innovations is common in financial mathematics (see for example, Ludkovski and Sircar (2015)).

The probability of green regulation, λ_t^R, increases with the growth rate of brown activities, as in Giglio et al. (2021). Since x_t^B enters positively through $\nu > 0$, the probability of a new environmental regulation increases over time when the economy grows at a faster rate. It is a stylized and concise way to represent physical climate change without modeling explicitly emissions or temperature:

$$\lambda_{t+1}^R = \mu_R + \rho_R \lambda_t^R + \nu x_t^B + \alpha J_{t+1}^I. \tag{2}$$

The intensity of the regulation jump process is also positively related to innovation jumps, through the parameter α. Indeed the point of developing green technologies is to facilitate the replacement of current manufacturing methods which are the source of carbon emissions and climate change by "clean" ones. The availability of green technologies makes it easier for governments to implement more stringent policies and accelerate the transition process without impacting aggregate growth.

The probability of a breakthrough green innovation is driven by regulations J^R which stimulate directly innovation efforts with subsidies for example, but also indirectly as regulations constraining "brown" firms are likely to encourage them to invest in green innovation:

$$\lambda_{t+1}^I = \mu_I + \rho_I \lambda_t^I + \epsilon J_{t+1}^R, \tag{3}$$

Finally, I assume that the log dividend growth of an asset is given by:

$$\Delta d_{t+1} = \mu_D + \Phi k^B x_t^B + \Phi k^G x_t^G. \tag{4}$$

k^B indicates if the asset is more or less exposed to variations in brown economic growth x_t^B, and hence to regulatory risk, than the market portfolio which has an exposure of $k^B = 1$. Consequently, brown stocks have $k^B > 1$, and green stocks $k^B < 1$. Similarly, k^G indicates if the asset is more or less exposed to variations in green economic growth x_t^G, and hence to technological risk, than the market portfolio which has an exposure of $k^G = 1$. Consequently, $k^G > 1$ means that the firm invests in green research and development or the adoption of green technologies more than the average firm and is therefore less exposed to technological risk. Similar reasoning applies for $k^G < 1$. Mean log dividend growth is represented by μ_D and Φ denotes the leverage parameter to account for the excess volatility of dividend growth over consumption growth.

The representative agent's preferences on the consumption stream are of the Epstein and Zin (1989) form, allowing for the separation of risk aversion and the intertemporal elasticity of substitution (IES). Thus, the agent maximizes his life time utility, which is defined recursively as:

$$V_t = \left[(1-\delta)C_t^{\frac{1-\gamma}{\theta}} + \delta\left(E_t[V_{t+1}^{1-\gamma}]\right)^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}}, \tag{5}$$

where C_t is consumption at time t, $0 < \delta < 1$ reflects the agent's time preference, γ is the coefficient of risk aversion, $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, and ψ is the intertemporal elasticity of substitution.

5.2 Sample paths

To illustrate the richness of the patterns generated by the model, Figure 2 displays a sample path of the economy in which a regulation occurs after 20 periods followed by an innovation 5 periods later. I assume for simplicity that the economy starts from an economy with 2% of brown economic growth and an absence of green growth.

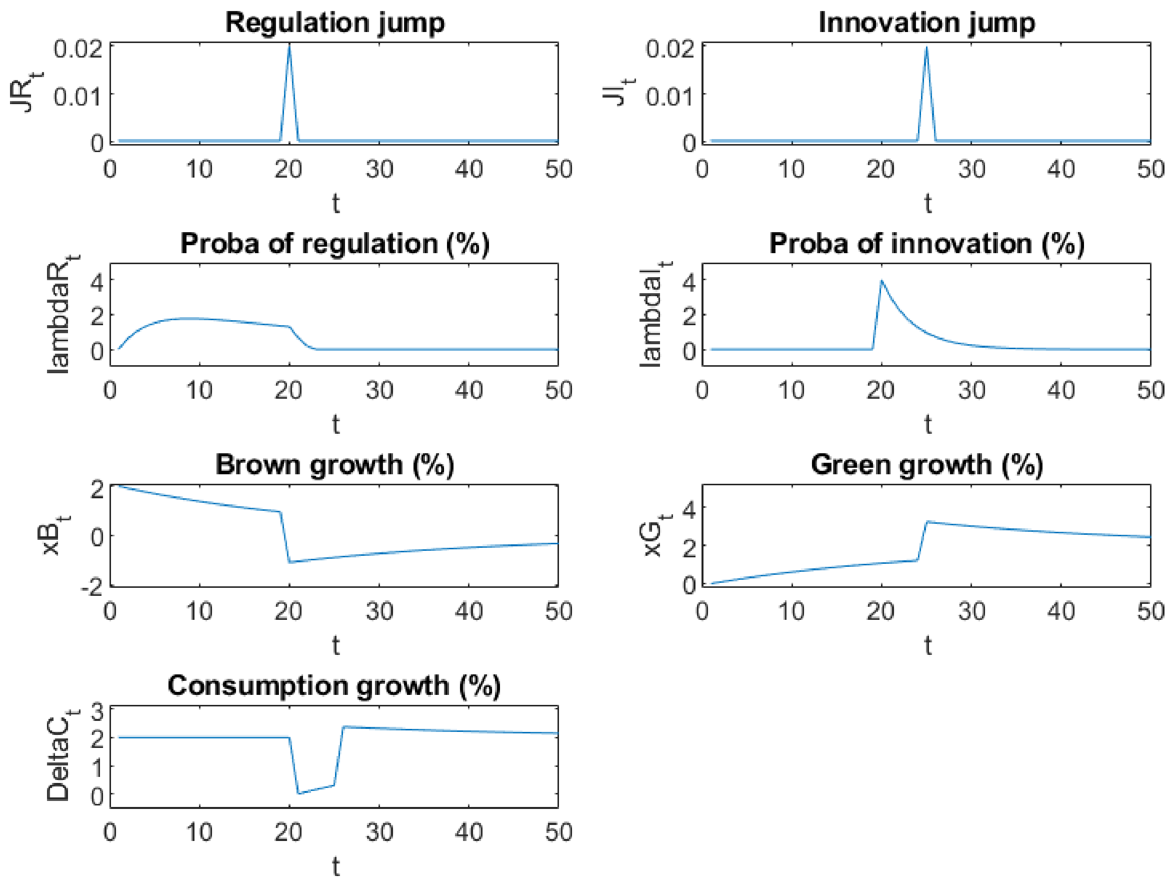


Figure 2: Sample path: regulation and innovation shocks

In the beginning of the sample period, the probability of regulation λ_t^R increases because of the positive brown growth, following (2). It summarizes in a reduced mechanism the fact that brown growth x_t^B generates by definition carbon emissions increasing global temperature, incentivizing governments and policy makers to regulate more. A regulation jump J_t^R, i.e., the decision and implementation of a stringent environmental policy, is more likely to happen. Such regulation has two effects on the economy: first, it has a negative impact on brown growth x_t^B, following (1); second, it increases the probability of innovation λ_t^I, following (3). An innovation jump J_t^I is more likely to occur. When it does, it increases green growth x_t^G following (1). Aggregate consumption growth Δc_t, as the sum of brown and green growth, shows a decrease at the time of the regulation jump and an increase when the innovation jumps occurs.

The transition process to a low-carbon economy includes a period of low consumption growth. The longer the time between the regulation jump and the innovation jump, the more severe this episode of low consumption. This result highlights the importance of green innovation for an efficient transition, and the importance for governments and policy makers to foster innovation.

5.3 Equilibrium

The specified model is in discrete time and contains jumps within a long-run risk setup. In their paper, Drechsler and Yaron (2011) provide the general solution for this type of framework. Consistent with their notation, I define the state vector of the economy Y_t by:

$$Y_{t+1} = \mu + F\,Y_t + \upsilon\,J_{t+1} \tag{6}$$

where

$$Y_{t+1} = \begin{pmatrix} \Delta c_{t+1} \\ x^B_{t+1} \\ x^G_{t+1} \\ \lambda^R_{t+1} \\ \lambda^I_{t+1} \\ \Delta d_{t+1} \end{pmatrix}, \qquad \mu = \begin{pmatrix} \mu_C \\ \mu_B \\ \mu_G \\ \mu_R \\ \mu_I \\ \mu_D \end{pmatrix} \quad \text{and} \quad F = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & \rho_B & 0 & 0 & 0 & 0 \\ 0 & 0 & \rho_G & 0 & 0 & 0 \\ 0 & \nu & 0 & \rho_R & 0 & 0 \\ 0 & 0 & 0 & 0 & \rho_I & 0 \\ 0 & \Phi\,k^R & \Phi.k^I & 0 & 0 & 0 \end{pmatrix}$$

J_{t+1} is the vector of jump shocks, which are compound-Poisson jumps:

$$J_{t+1} = \begin{pmatrix} J^R_{t+1} \\ J^I_{t+1} \end{pmatrix} \quad \text{and} \quad \upsilon = \begin{pmatrix} \upsilon^R & \upsilon^I \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ -1 & 0 \\ 0 & 1 \\ 0 & \alpha \\ \epsilon & 0 \\ 0 & 0 \end{pmatrix}$$

5.3.1 Pricing kernel

The solution proceeds via the representative agent's Euler condition:

$$E_t[\exp(m_{t+1} + r_{j,t+1})] = 1. \tag{7}$$

Let me first solve for the return on the wealth claim, $r_{c,t+1}$. Denote the log of the wealth-to-consumption ratio at time t by v_t.

I use Campbell and Shiller (1988) log-linearization to linearize $r_{c,t+1}$ around the unconditional mean of v_t:

$$r_{c,t+1} = k_0 + k_1\, v_{t+1} - v_t + \Delta d_{t+1}. \tag{8}$$

The log-linearization constants κ_0 and κ_1 are given by $\kappa_1 = \frac{\exp(E(v))}{1+\exp(E(v))}$ and $\kappa_0 = \ln\big(1 + \exp(E(v))\big) - \kappa_1 E(v)$. I then conjecture that the solution for the log wealth-consumption ratio is affine in the state vector:

$$v_t = A_0 + A'\, Y_t, \tag{9}$$

where A is a vector of pricing coefficients. The requirement that the Euler equation holds for any realization of Y_t implies that A_0 and A jointly satisfy a system of equations that determine their values. The system is augmented with the equations that define κ_0 and κ_1 and solved jointly. I substitute $r_{c,t+1}$ into m_{t+1} to obtain an expression for the log pricing kernel at time $t+1$:

$$\begin{aligned} m_{t+1} &= \theta\, \ln\delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta - 1)\, r_{c,t+1} \\ &= \theta \ln\delta + (\theta - 1)\kappa_0 + (\theta - 1)(\kappa_1 - 1)A_0 - (\theta - 1)A'Y_t - \Lambda' Y_{t+1}, \end{aligned} \tag{10}$$

where $\Lambda = (\gamma e_c + (1-\theta)\kappa_1 A)$ and e_c is $(1, 0, 0, 0, 0)'$ (the selector vector for Δc).

5.3.2 Market return

A share in the market is modeled as a claim to a dividend with growth process given by Δd_{t+1}. To solve for the price of a market share, I proceed along the same lines as for the consumption claim.

I denote $v_{m,t+1}$ the log price dividend ratio of the market and I log-linearize the return on the market, $r_{m,t+1}$, around the unconditional mean of $v_{m,t+1}$:

$$r_{m,t+1} = \kappa_{0,m} + \kappa_{1,m}\, v_{m,t+1} - v_{m,t} + \Delta d_{t+1}. \tag{11}$$

I conjecture that $v_{m,t}$ is affine in the state variables:

$$v_{m,t} = A_{0,m} + A'_m\, Y_t, \tag{12}$$

where A_m is the vector of pricing coefficients for the market. Substituting into the Euler equation also leads to a system of equations that must hold for all values of Y_t. The equations for A_m are in terms of the solution of A. The system is augmented with the equations that define $\kappa_{0,m}$ and $\kappa_{1,m}$ and solved jointly.

By substituting the expression for $v_{m,t}$ into the linearized return, I obtain an expression for $r_{m,t+1}$ in terms of Y_t and its innovations:

$$r_{m,t+1} = r_0 + (B_r' F - A_m')Y_t + B_r' J_{t+1}, \tag{13}$$

where r_0 is a constant, $B_r = (\kappa_{1,m} A_m + e_d)$, and e_d is $(0, 0, 0, 0, 1)'$ (the selector vector for Δd).

5.4 Calibration

I define a baseline calibration, summarized in Table 12, before illustrating graphically the mechanisms presented in the previous paragraph. The calibration is not intended to be quantitatively exact as many parameters cannot be estimated accurately. Indeed, as the transition process to a low-carbon economy is an unprecedented event, the historical data required for the estimation do not exist.

As often as possible, I rely on the parameters' value used in the literature on long-run consumption risks (see Bansal and Yaron (2004) and Bansal et al. (2012)). For example, for the agent's preferences, I set the coefficient of risk aversion γ is equal to 5, Ψ the intertemporal elasticity of substitution (IES) to 1.5 and δ the parameter of time preference to 0.98. The persistence for both green and brown growths, ρ_B and ρ_G, are set to 0.96 and the leverage ϕ to 2.6.

I set the persistence in the probabilities of green policy and innovation both equal to 0.85. The main reason for this choice is the observation of a high persistence when fitting an AR(1) process on the time-series of the empirically estimated risk premia.

The jumps' sizes, are both set equal to 2%. This value is chosen in reference to the average consumption growth rate of about 2% per year in the United States. A regulation jump basically temporarily brings economic growth from its trend to zero. An innovation jump brings it back to its trend.

The impact of the brown growth on the probability of a green regulation is set to $\nu = 0.1$ as in Giglio et al. (2023). ϵ is chosen equal to 2, and α equal to 1. This choice implies that a green regulation increases the probability of green innovation by 4% and a green innovation increases the probability of a green regulation by 2%.

Finally, I fix the long-run values of the state variables, which also determine the drift terms μ in the dynamics of the model's variables. I assume that once the transition process to a low-carbon economy is achieved, the trend in economic growth is still 2%, $\overline{\Delta c} = 0.02$, but entirely driven by green activities, with $\overline{x}^G = 0.02$ and $\overline{x}^B = 0.00$. This choice is consistent with the definition of the transition as the switch from economic growth based on fossil energy to growth based on clean energies and technologies. By setting the long-term economic growth to 2%, I assume that we can reach the same level of economic growth as before the transition while producing in a clean way. This assumption is debatable, but is it not the point of this project to take a stand on this complicated question. I set the long-run values for the jumps' intensities both at zero, meaning that the probability of green regulation and green innovation fall to zero once the transition is over, as there is no need for green regulations anymore.

5.5 Equity Risk Premia

I derive the following expression for the conditional equity premium:

$$\ln E_t(R_{m,t+1}) - r_{f,t} = \alpha^R \, \lambda_t^R + \alpha^I \, \lambda_t^I, \tag{14}$$

where

$$\alpha^R = \Big(\psi^R(-\Lambda) - 1\Big)\Big(1 - \psi^R(B_r)\Big), \tag{15}$$

$$\alpha^I = \Big(\psi^I(-\Lambda) - 1\Big)\Big(1 - \psi^I(B_r)\Big), \tag{16}$$

and ψ^k is the moment-generating function of the jump size ξ_t^k.

The equity premium is the sum of two premia: the first one directly attributable to green regulation events and the second to green innovation events. These are covariances between state prices and market returns during rare events, multiplied by probabilities that the rare events occur. They represent the contributions from the jump processes, as there are no Gaussian shocks in the model. So, they reflect the covariance of the jump component in the pricing kernel with the jump component in the return. Variations in jump contributions are driven by the intensities of jump shocks λ_t^R and λ_t^I.

Both premia are positive because marginal utilities and valuations move in opposite directions during rare events: during regulation jumps, marginal utility is high, but valuations are low while during innovation jumps the opposite is true. Thus, both regulations and innovations have a direct positive impact on the equity premium. The possibility of an innovation raises risk premia, because it is also a source of risk.

5.6 Regulatory and technological opportunity premia

The coefficients α^R and α^I both depend on k^B and k^G, the exposure of a given firm to green policy and technological risks, through the matrix B_r:

$$\ln E_t(R_{m,t+1}) - r_{f,t} = \alpha^R(k^B, k^G)\lambda_t^R + \alpha^I(k^B, k^G)\lambda_t^I. \tag{17}$$

I define the technological premium as the difference of risk premium between two firms with the same exposure to policy risk k^B but different exposure to technological risk k^G:

$$\begin{aligned} TechPremium_t =& \left[\alpha^R(k^B, k^G_{high}) - \alpha^R(k^B, k^G_{low})\right]\lambda_t^R + \left[\alpha^I(k^B, k^G_{high}) - \alpha^I(k^B, k^G_{low})\right]\lambda_t^I \\ =& \underbrace{\Delta\alpha^R_G}_{<0}\lambda_t^R + \underbrace{\Delta\alpha^I_G}_{>0}\lambda_t^I. \end{aligned} \tag{18}$$

Similarly, the policy risk premium is the difference of risk premium for two firms with the same exposure to technological risk k^G but different exposure to policy risk k^B:

$$\begin{aligned} RegPremium_t =& \left[\alpha^R(k^B_{high}, k^G) - \alpha^R(k^B_{low}, k^G)\right]\lambda_t^R + \left[\alpha^I(k^B_{high}, k^G) - \alpha^I(k^B_{low}, k^G)\right]\lambda_t^I \\ =& \underbrace{\Delta\alpha^R_B}_{>0}\lambda_t^R + \underbrace{\Delta\alpha^I_B}_{<0}\lambda_t^I. \end{aligned} \tag{19}$$

Figure 6 shows how α^I and α^R vary with the exposure parameters k^B and k^G. α^I decreases with k^B and increases with k^G. Indeed, by increasing k^B, a firm increases its brown activities, relatively decreasing the proportion of its activities that are green, hence it reduces its exposure to the uncertainty around green innovation. By increasing k^G, a firm, on the other hand, increases its exposure to this technological risk. Similarly, α^R increases with k^B and decreases with k^G. By increasing k^B, a firm increases the proportion of its activities which is subject to policy risk, while by increasing k^G, it increases its green activities, proportionally decreasing the brown activities and hence the exposure to this risk. These results imply that $\Delta\alpha^R_G$ and $\Delta\alpha^I_B$ are negative and $\Delta\alpha^I_G$ and $\Delta\alpha^R_B$ positive.

This structure of the risk premia explains the two empirical findings described in Section 4.6. They are that (i) the policy and the technological premia tend to co-move, and to move in opposite directions, and (ii) they can change sign. As $\Delta\alpha_B^R$ and $\Delta\alpha_G^R$ are of opposite sign, the *TechPremium* and the *RegPremium* move in opposite directions when λ_t^R varies. More precisely, $\Delta\alpha_G^R$ is negative and $\Delta\alpha_B^R$ is positive. So, *RegPremium* increases and *TechPremium* decreases when λ_t^R increases. In the same way, since $\Delta\alpha_B^I$ and $\Delta\alpha_G^I$ are of opposite sign, the *TechPremium* and the *RegPremium* move in opposite directions when λ_t^I varies: *RegPremium* increases and *TechPremium* decreases when λ_t^I increases. In other words, the regulation premium increases and the technological premium decreases when there is an increased probability of a new green policy. On the contrary, an increased probability of green innovation has the effect of increasing the technological premium and decreasing the regulation premium.

The changing signs of the two premia is explained by a similar set of arguments. For the green regulation risk premium, it is explained by variations in λ_t^R and λ_t^I because $\Delta\alpha_G^R$ and $\Delta\alpha_G^I$ are of opposite sign. The same applies to the green technological risk because $\Delta\alpha_B^R$ and $\Delta\alpha_B^I$ are of opposite sign. When λ_t^R is small, the second term in λ_t^I in each risk premium dominates, hence the *TechPremium* is positive and the *RegPremium* negative. As Republicans tend to apply less regulations than Democrats, λ_t^R is usually smaller when they are in office. Then, when λ_t^R increases for a fixed value of λ_t^I, at some point the *TechPremium* becomes negative and the *RegPremium* becomes positive. Large values of λ_t^R correspond to when Democrats are in office, and have control over the Senate and House. These predictions are summarized in Figure 7 obtained in the baseline calibration of the model.

The model is therefore well able to reproduce the stylized facts observed.

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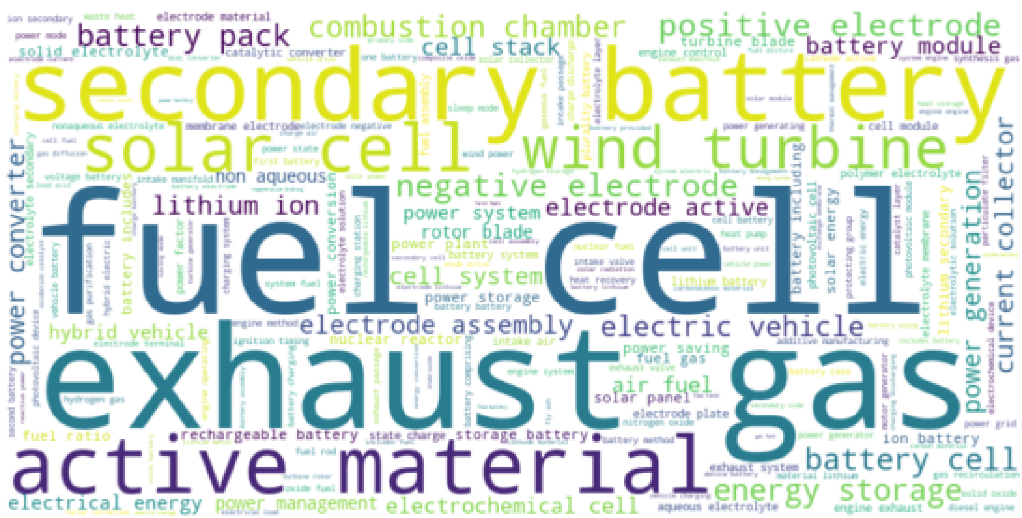
Figure 1: Word clouds of green innovation dictionary

This figure shows the word clouds associated with the green innovation dictionary. In Panel A, the size of the words correspond to their frequency in green patents. In Panel B, the size corresponds to the frequency in press releases.

Panel A: Green patents



Panel B: Press Releases

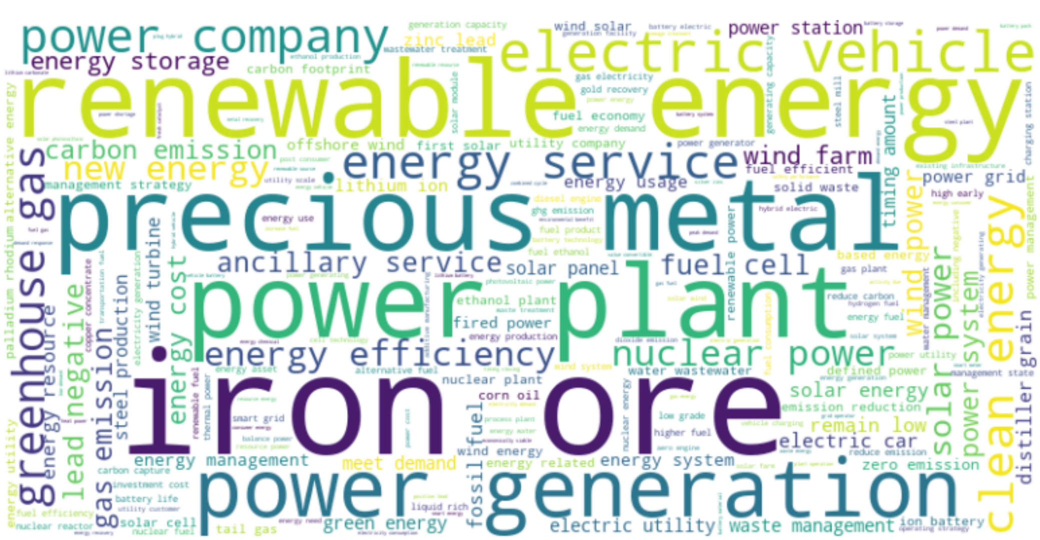
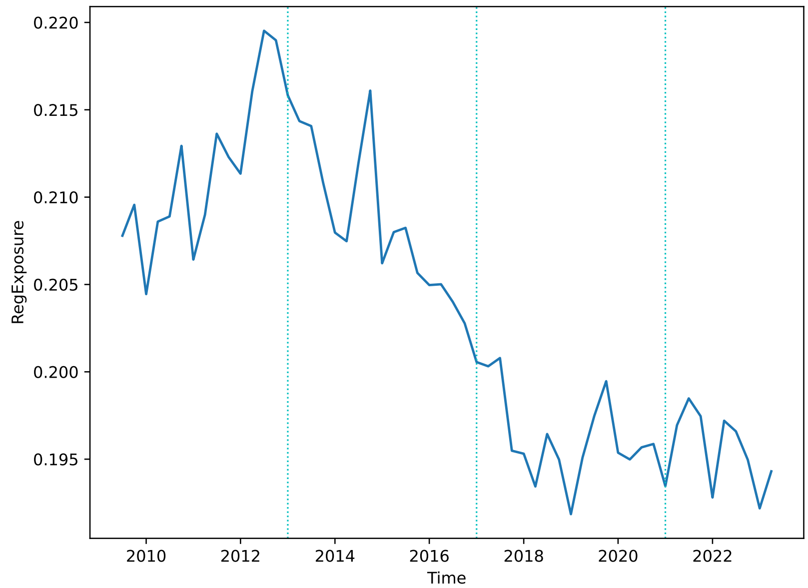


Figure 2: Time-Series Variation of Exposure Measures

This figure depicts the mean value per quarter of *RegExposure* and *TechExposure* measures across firms over time. The vertical lines correspond to the election of a new U.S. president.

Panel A: *RegExposure*



Panel B: *TechExposure*

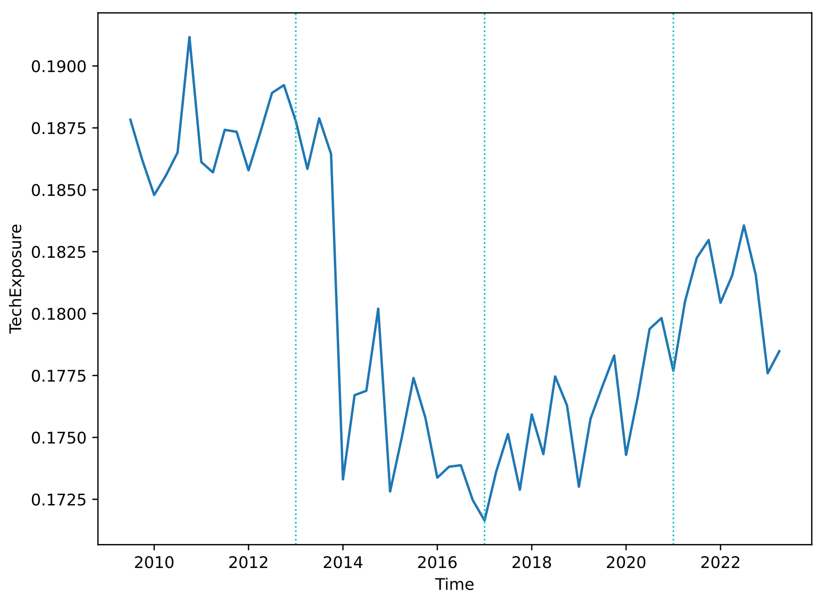


Figure 3: Correlation between *RegExposure* and *TechExposure*

This figure depicts the relationship for a given firm between its *RegExposure* and its *TechExposure*. This scatter plot shows a cloud of points, where each point indicates the average value over time of the *RegExposure* and *TechExposure* for a given firm.

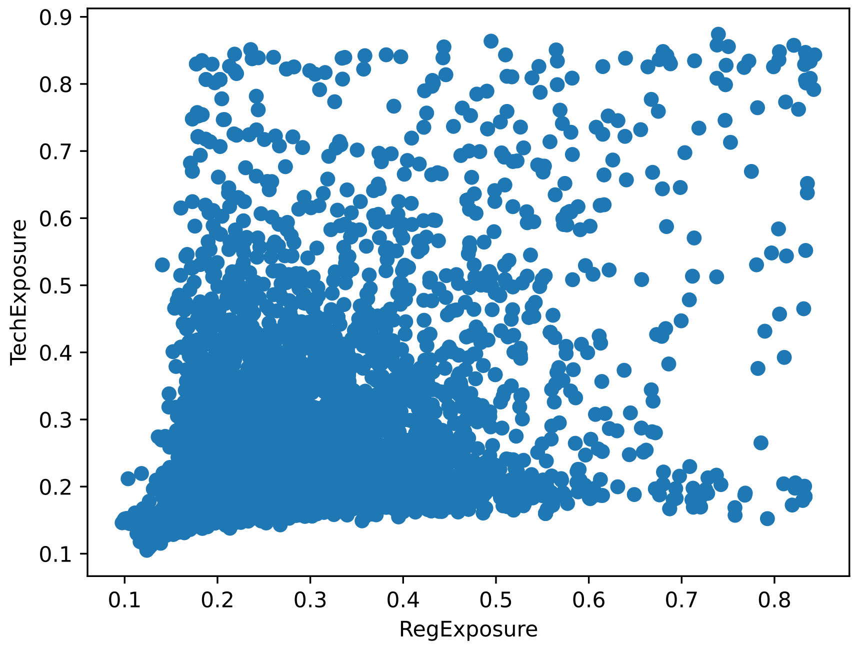


Figure 4: Dynamics of climate regulatory and technological risk premia

This figure shows the evolution of the trends in the regulatory and technological risk premia from November 2009 to June 2023. Blue (red) zones represent periods where a Democrat (Republican) president was in power in the US. Green vertical lines indicate U.S. presidential elections while black ones represent midterm elections of the Congress. The details about which party dominates in the Senate and in the House of Representatives are given at the top of the graph. Red letters mean that Republicans control the chamber while blue letters mean a control of Democrats.

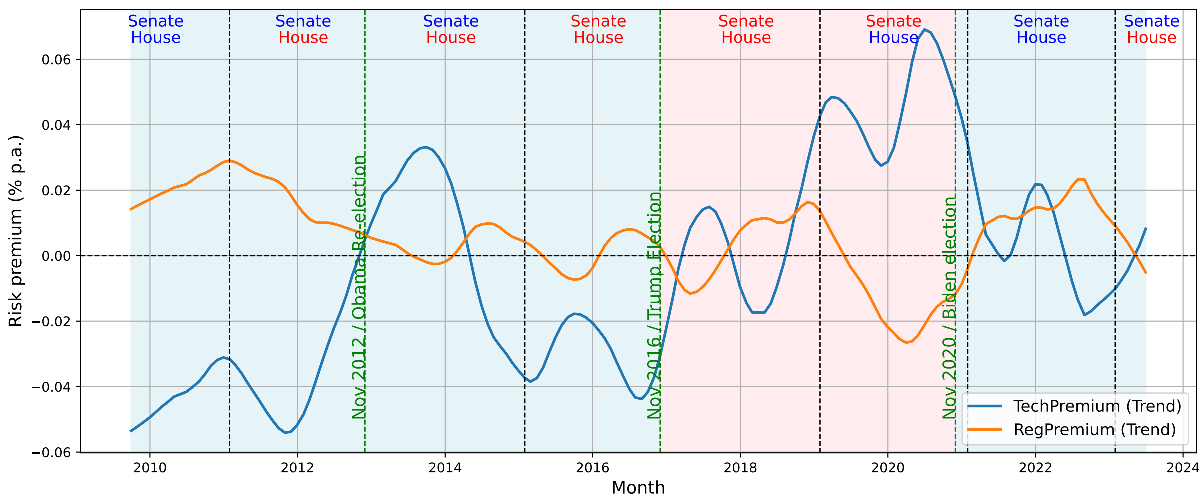


Figure 5: Cross-correlation between regulatory and technological risk premia

This figure shows the evolution of the cross-correlation between the trends of the regulatory and technological risk premia depending on the number of lags. The correlation is computed between the regulatory risk premium at time t and the innovation risk premium at time t+lags.

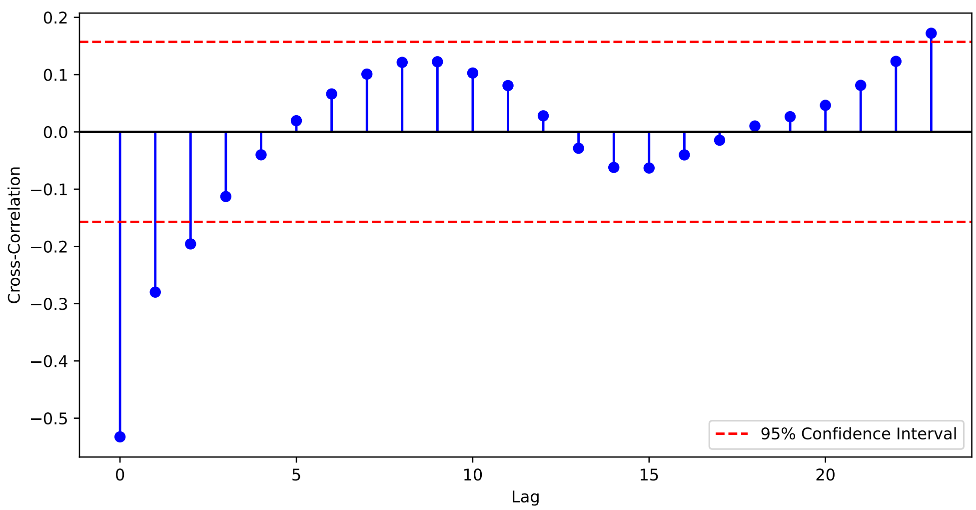


Figure 6: Variation in equity premium components with change in exposure

This figure shows how the coefficient α^R and α^I, loadings respectively of λ_t^R and λ_t^I in the equity premium, vary with k_G and k_B, the exposure to green regulations and green technologies.

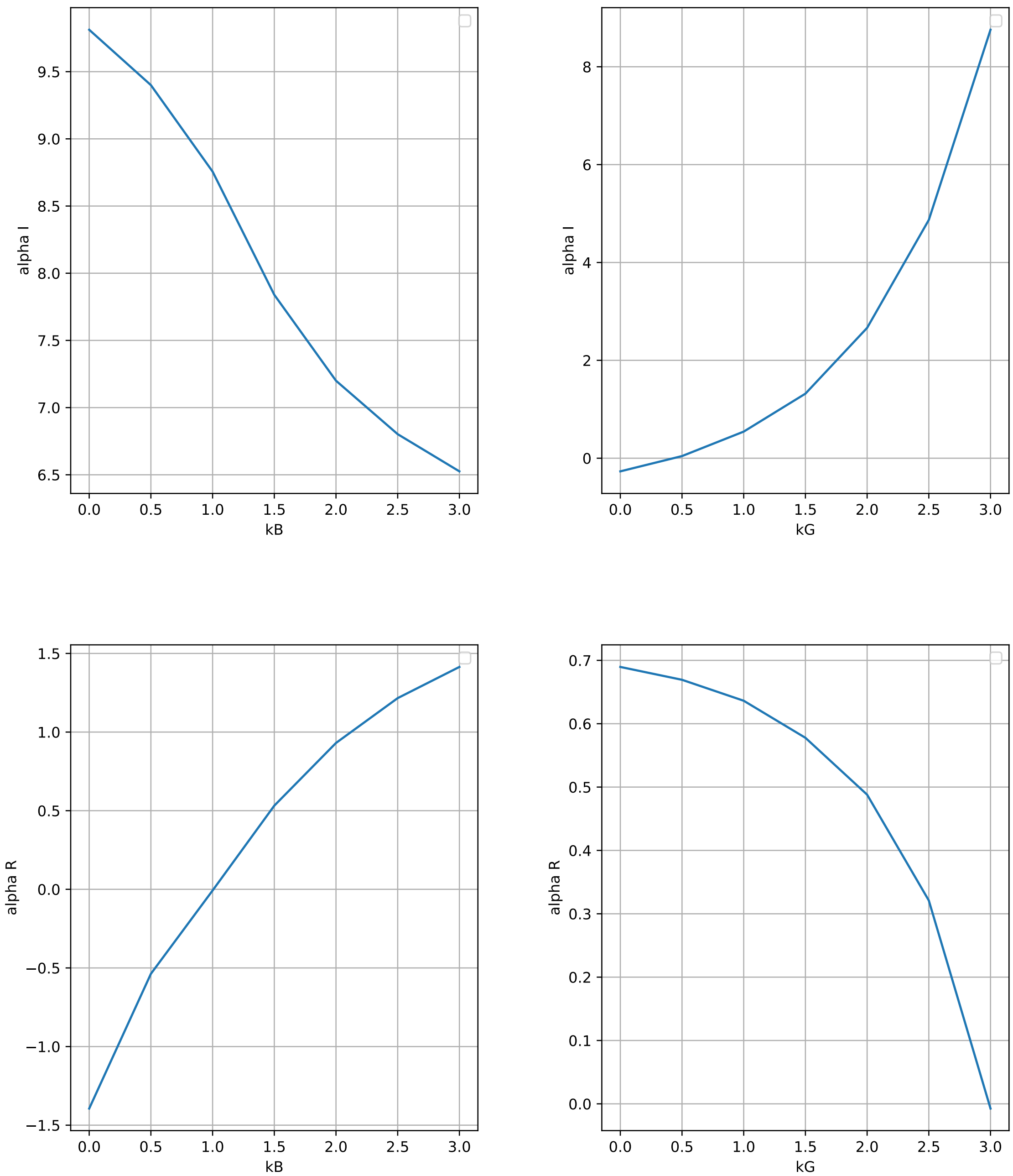


Figure 7: Variation in regulatory and technological risk premia with state variables

This figure shows how the regulatory risk premium and the technological risk premium, *RegPremium* (here noted RP R) and *TechPremium* (here noted RP I), vary with changes in the state variables, λ_t^R and λ_t^I, the probabilities of green regulations and green innovations.

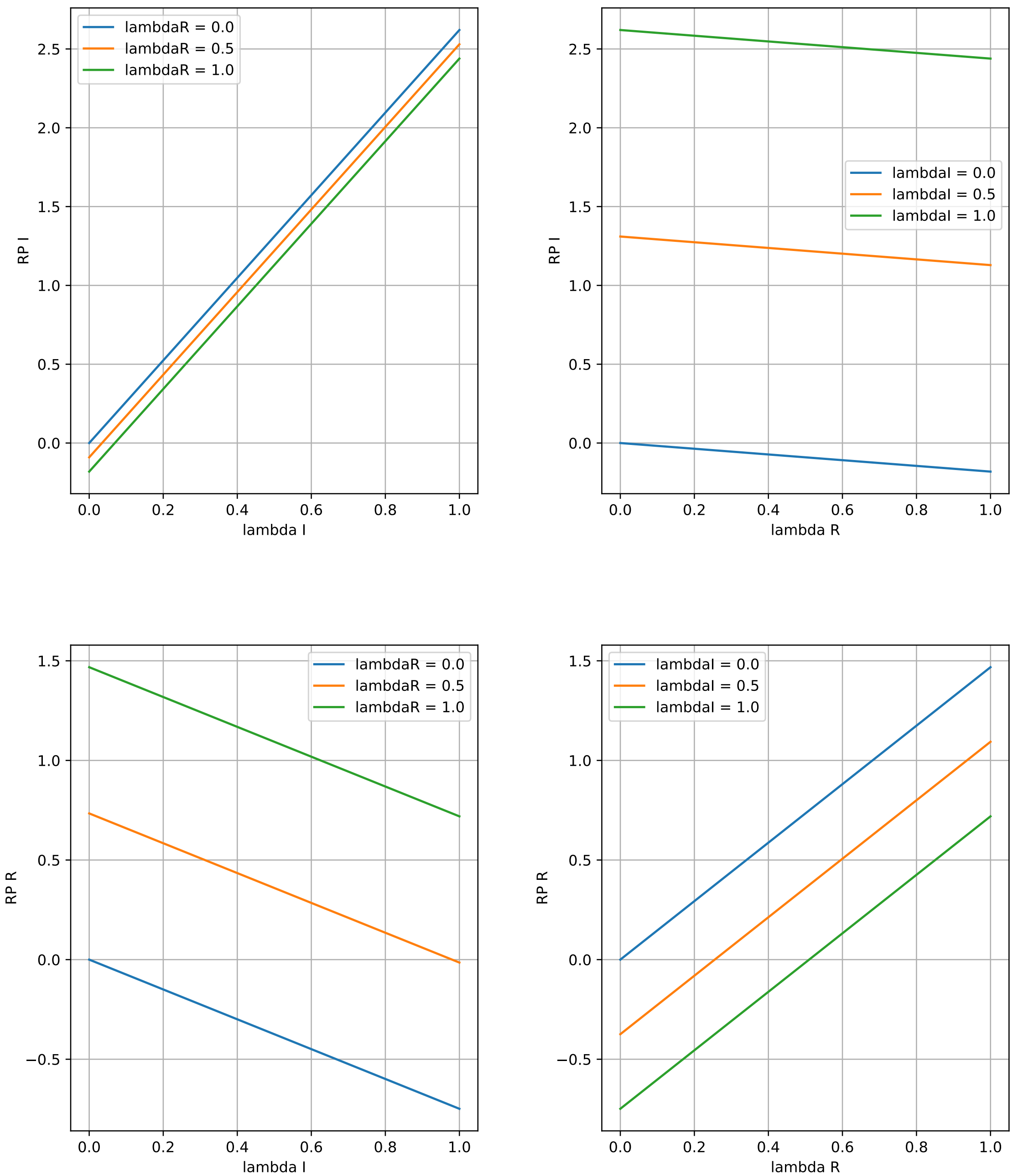


Table 1: Summary Statistics: Press release database

This table presents summary statistics for the dataset of press releases by year. It gives in the first column the number of press releases each year, and in the second column the number of firms with at least one press release that year. The five last columns represent the monthly average number of press releases per firm at the 5th, 25th, 50th, 75th and 95th percentiles.

Year	Nb of PR	Nb of firms	p5	p25	Median	p75	p95
2008	521,575	10,676	1.0	1.0	2.8	5.8	19.0
2009	722,765	11,486	1.0	1.0	2.25	5.7	22.2
2010	821,936	11,420	1.0	1.0	2.4	6.6	25.3
2011	828,677	11,381	1.0	1.1	2.4	6.7	25.5
2012	822,295	11,144	1.0	1.1	2.5	7.0	25.1
2013	760,268	10,422	1.0	1.2	2.8	8.0	23.7
2014	665,396	10,008	1.0	1.4	3.1	7.6	19.9
2015	553,519	10,342	1.0	1.0	2.8	6.1	16.9
2016	512,487	10,130	1.0	1.2	2.8	6.3	15.5
2017	513,924	9,744	1.0	1.3	2.8	6.2	15.9
2018	474,670	9,520	1.0	1.2	2.7	5.5	15.3
2019	467,287	9,315	1.0	1.2	2.6	5.7	16.0
2020	459,939	9,294	1.0	1.2	2.7	5.6	15.4
2021	502,983	10,915	1.0	1.0	2.6	5.5	14.5
2022	443,923	12,175	1.0	1.0	1.8	4.4	11.6
2023	239,679	9,376	1.0	1.0	2.5	5.6	15.1

Table 2: Top-100 Bigrams in the dictionary for Green Regulations

This table reports the top-100 bigrams from the dictionary about green regulations identified to build the reference set for the training of the algorithm. The score provided by the algorithm is then used to compute the measure of exposition to the risk of environmental policies.

Bigram	Frequency	Bigram	Frequency	Bigram	Frequency
general disclosure	13403	eastern air	2775	standard food	1972
clean air	13321	emolument policy	2759	law aimed	1948
increase agreement	13268	act support	2606	approval environmental	1938
development goal	12031	fuel use	2588	pollutant emission	1932
climate action	6651	transition sustainable	2553	rule committee	1921
code year	6132	pas law	2512	tougher rule	1921
paris agreement	5415	policy president	2486	initiative gri	1897
inflation reduction	5178	financial amendment	2409	sustainable supply	1889
reduction act	5114	climate bill	2387	company air	1853
reporting guide	5023	fuel low	2322	emission total	1842
fuel inventory	4988	presentation report	2252	need policy	1837
esg reporting	4823	sustainability accounting	2244	emission tonne	1829
labour standard	4368	tougher regulation	2231	use agreement	1823
ordinance sfo	4274	principle code	2222	expenditure sustainability	1816
fuel standard	4074	policy investment	2192	code dealing	1809
climate change	3970	saving emission	2188	nation sustainable	1788
air pollutant	3932	society environment	2173	conservation environmental	1775
fuel retailer	3816	emission operation	2163	fulfil obligation	1772
global reporting	3636	climate target	2147	emission group	1772
air act	3607	emission cut	2123	the law	1769
gas australia	3559	national environmental	2120	based environmental	1764
target initiative	3555	emission across	2112	volatility fuel	1758
higher electricity	3511	bond framework	2109	policy study	1755
reporting initiative	3225	climate talk	2084	capital environmental	1750
joint amendment	3196	measurement requirement	2073	policy analysis	1741
labour law	3157	australian gas	2046	nox emission	1735
offset fall	3154	code practice	2044	consideration esg	1733
produce electricity	3130	view policy	2016	largest renewable	1727
emission scope	2924	act stock	2013	action climate	1726
heavy fuel	2860	sustainability bond	1996	policy promote	1711
environmental initiative	2800	privacy ordinance	1992	data fuel	1700
adjustment fuel	2784	tackle climate	1982	climate neutral	1673
report appendix	2778	policy act	1980	target working	1652

Table 3: Top-100 Bigrams in the dictionary for Green Innovations

This table reports the top-100 bigrams from the dictionary about green innovations identified to build the reference set for the training of the algorithm. The score provided by the algorithm is then used to compute the measure of exposition to green technologies.

Bigram	Frequency	Bigram	Frequency	Bigram	Frequency
iron ore	280937	solar panel	37881	renewable power	21939
renewable energy	215737	steel production	37678	ethanol plant	21636
precious metal	198216	meet demand	36512	palladium rhodium	21562
power plant	194621	power station	35406	tail gas	21487
power generation	140099	timing amount	34200	first solar	21135
electric vehicle	136854	wind turbine	33510	fuel economy	20793
energy service	105898	energy management	33481	energy utility	20702
power company	104593	energy system	32072	generation capacity	20262
clean energy	99618	zinc lead	30962	steel mill	20216
greenhouse gas	88337	energy usage	30814	nuclear reactor	19157
nuclear power	77308	lithium ion	29556	energy production	19113
energy efficiency	77193	power grid	29120	energy fuel	19068
new energy	76782	fired power	28425	carbon capture	19026
solar power	67710	zero emission	28209	management state	19016
ancillary service	61768	offshore wind	27831	electricity generation	18927
fuel cell	60410	utility company	27391	low grade	18695
lead negative	59707	nuclear plant	27027	wastewater treatment	18543
gas emission	58616	based energy	26424	fuel ethanol	18541
wind power	58610	defined power	26414	higher fuel	18450
power system	53389	carbon footprint	26394	nuclear energy	18402
energy cost	52862	water wastewater	26323	thermal power	18400
carbon emission	51428	management strategy	25974	investment cost	18278
energy storage	50211	wind energy	25912	generating capacity	18071
wind farm	49449	ion battery	25022	smart grid	17916
solar energy	47034	energy related	24907	gas plant	17897
distiller grain	46096	wind solar	24877	battery life	17591
energy resource	44571	emission reduction	24732	diesel engine	17448
remain low	42410	solar cell	24316	ghg emission	17105
fossil fuel	41641	fuel efficient	24096	gas electricity	17030
electric car	40062	solid waste	23901	solar module	16844
electric utility	39113	power management	23616	charging station	16623
green energy	38514	alternative energy	23229	alternative fuel	16378
waste management	38375	corn oil	23149	renewable fuel	16285

Table 4: Topic Analysis of Green Technologies

This table indicates the 10 bigrams identified as the most representative of each topic identified by the keyATM method. The topic are ordered in decreasing order of importance in the content of press releases.

Topic	%	Most characteristic words
Wind	22.3%	wind power, wind farm, wind turbine, wind energy, combined cycle, photovoltaic power, coal power, power company, generation electricity, green energy
Battery	16.2%	battery material, lithium ion, battery grade, lithium battery, spherical graphite, battery anode, lead acid, battery production, battery recycling, ion battery
Fuel cell	15.4%	fuel cell, hydrogen energy, hydrogen fueling, distributed generation, hydrogen powered, hydrogen refueling, renewable hydrogen, solid oxide, including renewable, variety fuel
Solar	5.8%	photovoltaic power, solar farm, photovoltaic module, utility scale, solar photovoltaic, silicon solar, energy solar, combiner box cell module, new solar

Table 5: Summary Statistics: *RegExposure* measure

This table presents summary statistics for the *RegExposure* measure in the whole dataset, then by year.

Variable	N	Mean	std	p5	Median	p95
Panel A: *RegExposure* measure, overall dataset						
RegExposure	1145040	0.20	0.08	0.14	0.17	0.37
Panel B: *RegExposure* measure, by year						
2008	55557	0.19	0.06	0.15	0.17	0.31
2009	80249	0.20	0.07	0.15	0.17	0.37
2010	80568	0.20	0.08	0.15	0.17	0.38
2011	82374	0.21	0.08	0.15	0.17	0.38
2012	78915	0.21	0.08	0.15	0.18	0.39
2013	76089	0.21	0.08	0.15	0.18	0.38
2014	75857	0.21	0.07	0.15	0.18	0.37
2015	75800	0.20	0.08	0.14	0.17	0.38
2016	74092	0.20	0.08	0.14	0.17	0.38
2017	72783	0.19	0.07	0.14	0.17	0.36
2018	71313	0.19	0.07	0.14	0.16	0.35
2019	68431	0.19	0.07	0.13	0.16	0.35
2020	67801	0.19	0.08	0.13	0.16	0.35
2021	74272	0.19	0.08	0.13	0.16	0.36
2022	75412	0.19	0.08	0.13	0.16	0.36
2023	35527	0.19	0.08	0.13	0.16	0.35

Table 6: Summary Statistics: *TechExposure* measure

This table presents summary statistics for the *TechExposure* measure in the whole dataset, then by year.

Variable	N	Mean	std	p5	p50	p95
Panel A: *TechExposure* measure, overall dataset						
TechExposure	1145040	0.18	0.07	0.13	0.16	0.28
Panel B: *TechExposure* measure, by year						
2008	55557	0.18	0.07	0.13	0.16	0.28
2009	80249	0.18	0.07	0.13	0.16	0.29
2010	80568	0.18	0.06	0.13	0.16	0.29
2011	82374	0.18	0.07	0.13	0.16	0.29
2012	78915	0.18	0.07	0.13	0.16	0.29
2013	76089	0.18	0.06	0.13	0.16	0.29
2014	75857	0.17	0.05	0.13	0.16	0.25
2015	75800	0.17	0.06	0.13	0.16	0.24
2016	74092	0.17	0.05	0.13	0.15	0.24
2017	72783	0.17	0.06	0.13	0.15	0.24
2018	71313	0.17	0.06	0.13	0.16	0.26
2019	68431	0.17	0.06	0.12	0.16	0.26
2020	67801	0.17	0.07	0.12	0.16	0.27
2021	74272	0.18	0.08	0.12	0.15	0.30
2022	75412	0.18	0.08	0.12	0.15	0.31
2023	35527	0.17	0.08	0.12	0.15	0.29

Table 7: Industry Distribution: *RegExposure* measure

This table presents summary statistics for the *RegExposure* measure across firms for the top-15 and bottom-15 industries. The measure has been averaged across firms within the same industry based on the Fama-French 49 industry classifications.

Variable	N	Mean	std	p5	p50	p95
Panel A: *RegExposure* measure, top-15 industries						
Utilities	19258	0.26	0.11	0.14	0.22	0.49
Coal	2308	0.23	0.09	0.14	0.20	0.40
Precious Metals	2291	0.23	0.09	0.14	0.19	0.41
Petroleum and Natural Gas	30751	0.22	0.09	0.14	0.19	0.41
Non-Metallic and Industrial Metal Mining	3621	0.22	0.09	0.13	0.19	0.40
Tobacco Products	1110	0.22	0.07	0.14	0.20	0.36
Beer & Liquor	2572	0.21	0.07	0.14	0.20	0.35
Chemicals	13304	0.21	0.09	0.13	0.18	0.40
Defense	1506	0.21	0.06	0.13	0.20	0.32
Steel Works Etc	7047	0.21	0.07	0.13	0.18	0.36
Transportation	16688	0.21	0.06	0.14	0.18	0.34
Electrical Equipment	9627	0.20	0.09	0.13	0.17	0.39
Automobiles and Trucks	10136	0.20	0.07	0.14	0.18	0.33
Aircraft	3988	0.20	0.06	0.14	0.18	0.32
Communication	18668	0.20	0.06	0.14	0.18	0.32
Panel B: *RegExposure* measure, bottom-15 industries						
Construction Materials	9812	0.18	0.06	0.13	0.16	0.31
Computers	8664	0.18	0.04	0.14	0.17	0.25
Wholesale	18709	0.18	0.05	0.13	0.16	0.27
Business Services	31289	0.18	0.05	0.13	0.16	0.27
Insurance	19417	0.18	0.04	0.14	0.17	0.26
Computer Software	61355	0.18	0.04	0.14	0.17	0.26
Recreation	3144	0.18	0.04	0.13	0.16	0.26
Rubber and Plastic Products	2560	0.18	0.05	0.13	0.16	0.27
Textiles	1168	0.18	0.06	0.13	0.16	0.27
Real Estate	5949	0.18	0.04	0.13	0.16	0.26
Measuring and Control Equipment	10923	0.18	0.04	0.13	0.16	0.25
Healthcare	11371	0.17	0.04	0.13	0.16	0.24
Pharmaceutical Products	81934	0.17	0.03	0.13	0.16	0.24
Banking	81519	0.17	0.04	0.13	0.16	0.25
Medical Equipment	23723	0.17	0.03	0.13	0.16	0.23

Table 8: Industry Distribution: *TechExposure* measure

This table presents summary statistics for the *TechExposure* measure across firms for the top-15 and bottom-15 industries. The measure has been averaged across firms within the same industry based on the Fama-French 49 industry classifications.

Variable	N	Mean	std	p5	p50	p95
Panel A: *TechExposure* measure, top-15 industries						
Utilities	19258	0.27	0.14	0.13	0.21	0.33
Electrical Equipment	9627	0.27	0.18	0.12	0.18	0.32
Automobiles and Trucks	10136	0.23	0.13	0.13	0.18	0.25
Coal	2308	0.22	0.10	0.13	0.19	0.26
Non-Metallic and Industrial Metal Mining	3621	0.19	0.08	0.12	0.17	0.22
Fabricated Products	1001	0.19	0.09	0.12	0.16	0.20
Steel Works Etc	7047	0.19	0.07	0.12	0.17	0.21
Chemicals	13304	0.19	0.08	0.12	0.16	0.19
Petroleum and Natural Gas	30751	0.19	0.06	0.13	0.17	0.21
Construction	8655	0.19	0.09	0.12	0.16	0.19
Electronic Equipment	34915	0.18	0.08	0.13	0.16	0.18
Machinery	17527	0.18	0.08	0.12	0.16	0.19
Aircraft	3988	0.18	0.05	0.13	0.17	0.20
Precious Metals	2291	0.18	0.04	0.13	0.17	0.19
Tobacco Products	1110	0.17	0.02	0.13	0.17	0.19

Panel B: *TechExposure* measure, bottom-15 industries						
Restaurants, Hotels, Motels	10888	0.16	0.02	0.13	0.16	0.18
Agriculture	1790	0.16	0.04	0.12	0.16	0.18
Apparel	6086	0.16	0.03	0.13	0.16	0.18
Printing and Publishing	2889	0.16	0.02	0.13	0.16	0.18
Entertainment	8520	0.16	0.03	0.13	0.16	0.17
Computer Software	61355	0.16	0.03	0.13	0.16	0.17
Wholesale	18709	0.16	0.04	0.12	0.15	0.17
Insurance	19417	0.16	0.03	0.12	0.16	0.17
Banking	81519	0.16	0.03	0.12	0.15	0.17
Recreation	3144	0.16	0.03	0.12	0.15	0.17
Real Estate	5949	0.16	0.03	0.12	0.15	0.17
Healthcare	11371	0.16	0.02	0.12	0.15	0.17
Textiles	1168	0.16	0.03	0.12	0.15	0.17
Pharmaceutical Products	81934	0.16	0.03	0.12	0.15	0.16
Medical Equipment	23723	0.15	0.02	0.12	0.15	0.16

Table 9: Validation of *RegExposure*

This table examines the relationship between between the regulatory exposure and carbon intensities. *RegExposure* is multiplied by 100. All variables are winsorized at the 1st and 99th percentiles to reduce the impact of outliers. Standard errors are clustered by industry. $*$, $**$ and $***$ indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	RegExposure
constant	21.01***
	(0.25)
carbon intensity	1.18***
	(0.22)
Observations	283123
R^2	0.16
Year FE	Yes
Industry FE	Yes

Table 10: Impact of a Change in Political Regime

This table reports the results of regressions of the risk premia time series on a dummy equal to 1 when the US president is Democrat. T-statistics are robust to heteroskedasticity. $*$, $**$ and $***$ indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Regulatory Risk Premium	Technological Risk Premium
constant	-0.004**	0.025***
	(0.002)	(0.004)
Dummy=1 if Democrat	0.014***	-0.041***
	(0.002)	(0.005)
Observations	162	162
R^2	0.254	0.341

Table 11: Impact of a Change in Political Regime

This table reports the results of regressions of the risk premia time series on dummies DD, DR and RR equal to 1 respectively when the US Democrat president has full support of the Congress (both the Senate and the House of Representatives are controlled by the Democrats), partial support of the Congress (one of the two chambers is Republican) or no support for the Congress (both chambers of the Congress are Republican). T-statistics are robust to heteroskedasticity. $*$, $**$ and $***$ indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Regulatory Risk Premium	Technological Risk Premium
constant	-0.004*	0.025***
	(0.002)	(0.004)
DD	0.019***	-0.036***
	(0.002)	(0.006)
DR	0.013***	-0.036***
	(0.002)	(0.005)
RR	0.005**	-0.055***
	(0.002)	(0.004)
Observations	162	162
R^2	0.365	0.373

Table 12: Calibration

This table indicates the values of the model's parameters in the baseline calibration used to illustrate the dynamics of the equity premia.

Parameter	Value	Interpretation
γ	5	risk aversion
ψ	1.5	intertemporal elasticity of substitution
δ	0.98	time discount factor
μ_C	0.0	average consumption growth rate
μ_D	-0.136	average dividend growth rate
μ_R	0.0	average regulation probability
μ_I	0.0	average innovation probability
μ_B	0.0	average brown consumption growth rate
μ_G	0.001	average green consumption growth rate
ξ^R	0.02	regulation jump size
ξ^I	0.02	innovation jump size
k^B_{high}	2	regulation risk exposure brown stocks
k^B_{low}	0.5	regulation risk exposure green stocks
k^G_{high}	2	technological risk exposure innovative firms
k^G_{low}	0.5	technological risk exposure non-innovative firms
ρ_B	0.96	persistence of brown economic growth
ρ_G	0.96	persistence of green economic growth
ρ_R	0.85	persistence of regulation jumps' intensity
ρ_I	0.85	persistence of innovation jumps' intensity
ϕ	2.6	dividend leverage
ν	0.1	multiplicator of brown growth on regulation probability
ϵ	2	multiplicator of regulation shock on innovation probability
α	1	multiplicator of innovation shock on regulation probability