Working Paper No.
2023-23

INET Oxford Working Paper Series
16th November 2023

Are financial markets pricing the net zero carbon transition?

A reconsideration of the carbon premium

Matteo Gasparini

Are financial markets pricing the net zero carbon transition? A reconsideration of the carbon premium

Matteo Gasparini*

University of Oxford

November 16, 2023

Click Here For The Most Recent Version

Abstract

Previous research has highlighted a positive correlation between realised returns and carbon emissions. This paper shows that this carbon premium might be partially due to mispricing produced by climate policy uncertainty. For this reason, realised returns may not be representative of expected returns. To show this, I develop an asset pricing model with uncertain expectations about the future cash flows of fossil-fuel firms; the price-dividend ratio increases with uncertainty about a climate policy regime shift. I confirm this proposition empirically using data on analysts' forecasts; I find that analysts' forecast disagreement, as a proxy for climate policy uncertainty, may explain part of the valuations of a large sample of fossil-fuel stocks. Using my model, I show with forward-looking scenarios that cash flow expectations implied in the valuations of fossil-fuel firms may be inconsistent with a net zero carbon transition.

Keywords: Asset Pricing, Uncertainty, Climate Finance, Climate Change

JEL Codes: G11, G18, Q51

---

*Email: matteo.gasparini@ouce.ox.ac.uk. Address: Manor Road Building, Manor Road, Oxford OX1 3UQ, United Kingdom. I would like to thank Peter Tufano, Cameron Hepburn, Doyne Farmer, Rick Van der Ploegh, Matt Ives, Patrick Bolton, John Campbell, James Stock, Marcin Kacperczyk, Stefano Giglio, Robert Pindyck, Boris Vallee, Mark Egan, Daniel Green, Massimo Guidolin, Stefano Ramelli, Oliver David Zerbib, and Fulvia Marotta for their feedback. Part of this work was conducted while I visited Harvard Business School. I am extremely grateful to Harvard D^3 Sustainability Lab, Peter Tufano, Michael Toffel, and George Serafeim for hosting me. I would like to thank Rebecca Cui, Micheal Lewis, Roy Appelman, Christian Mueller-Glissmann at Goldman Sachs for their helpful collaboration on a part of this project. I thank the participants of the JFR Symposium, the World Finance Conference and EAERE Conference for their comments on a previous version of this paper.

1 Introduction

Countries, businesses, and non-profit organisations collectively accounting for almost the entire world's GDP have pledged to reach net zero carbon emissions by 2050 in line with the objectives of the Paris Agreement[1]. If credible, these commitments represent an unprecedented financial risk for high-carbon emitting firms. Yet, various surveys show that investors believe stock markets may be mispricing climate-related transition risks (Krueger, Sautner, & Starks, 2020; Stroebel & Wurgler, 2021). This mispricing could be because the valuations of high-carbon emitting firms may not be pricing expected cash flows consistently with the increasing likelihood of a future without carbon-intensive energy sources. Extant literature has focused on realised returns, but if we were to prevent global warming in line with the climate pledges, the main effect of risk may be on the cash flows of these firms, which should arguably decline substantially by 2050 (Edmans, 2023).

Climate policy uncertainty may provide a first explanation for the current valuations of high carbon-emitting firms despite the increasing number of climate pledges. The financial economics literature concerned with climate change has highlighted that investors may be pricing the uncertainty around a transition to net zero carbon emissions through higher expected returns and lower valuations (Bolton & Kacperczyk, 2021, 2023; Hsu, Li, & Tsou, 2023). However, in a present value framework, (idiosyncratic) uncertainty may right-skew expected cash flows, leading to higher valuations (Pástor & Veronesi, 2003, 2006). Contrary to what is suggested in previous literature, the positive correlation between realised returns and carbon emissions (or *carbon premium*) may not be a sign of financial markets pricing the increasing likelihood of a transition to net zero carbon emissions through higher expected returns, but a symptom of mispricing.

In this paper, I show that the relatively high realised returns of carbon-intensive firms may be driven by climate policy uncertainty and they are unlikely to be purely reflective of a risk premium. I show that the high uncertainty surrounding climate policy may affect cash flow expectations and explain part of the valuations of some of the most carbon-intensive energy producers: fossil-fuel firms. A climate policy regime shift

[1] Source: Oxford net zero tracker

can influence the trend of the stochastic process governing high and low-carbon energy demand, shifting the respective firms' cash flows growth. A rational investor prices stocks, discounting future expected cash flows by an expected rate of return, which increases for more risky and uncertain assets. But uncertainty increases the *expected value* of future cash flows. The investor discounts a state of the world wherein high-carbon energy will continue to grow. The uncertain occurrence of a climate policy regime shift means that the investor is unable to anticipate whether and when the prospective shift will occur - that is, the sustained high levels of climate policy uncertainty affect the valuations of fossil-fuel firms.

To conceptualise this effect, I develop a partial equilibrium asset pricing model with uncertainty wherein the long-term growth of fossil-fuel firms depends on whether an uncertain climate policy regime shift occurs. I show that the valuations of fossil-fuel stocks are positively related to a rational investor's expectations about the trend of future cash flows and their variance. The latter describes the uncertainty faced by the investor in the absence of learning about the prospective climate policy regime shift, which I refer to as climate policy *regime shift uncertainty*. Moreover, I discuss how the different levels of exposure to the regime shift could exacerbate or mitigate the effects of uncertainty on assets' valuations. Firms with an elasticity of dividends to energy expenditure less than one are less exposed to the policy *regime shift risk* while values greater than one magnify the impact of possible climate policies on valuations.

To discuss the magnitude of the effect of climate policy uncertainty on stock market valuations, I test my proposition on a large sample of fossil-fuel firms with an empirical analysis of analysts' forecasts of dividends per share. I find that climate policy uncertainty may have weighed significantly on the valuations and realised returns of carbon-intensive firms. I report a positive and statistically significant relationship between analysts' estimates of growth in future dividends and the valuations of fossil-fuel firms. In a panel regression, using analysts' forecast disagreement as a proxy for market uncertainty, I find that the variance in dividends per share (DPS) forecasts - and similarly that for earnings per share (EPS) forecasts - are positively correlated with the valuations of fossil-fuel companies. This effect is generally higher for more carbon-intensive firms and is consistent across the various dimensions explored in the robustness analysis.

Employing forward-looking climate scenarios, I show that financial markets may be mispricing a net zero carbon transition. I observe that the valuations of fossil-fuel stocks may be more closely aligned with the right tail of the distribution of price-dividend ratios conditional to a no climate policy regime shift estimated with my model. This alignment suggests that either markets do not believe that policymakers will shift their climate policy to meet their pledges to prevent global warming or that markets are over-optimistic about possible technological breakthroughs that allow the continued use of fossil-fuels, such as carbon capture and storage. These results show that the effect of climate policy uncertainty on cash flow expectations may lead to a mispricing of the net zero carbon transition. In turn, high realised returns may be a poor proxy for expected returns, as investors may reprice their cash flow expectations.

This paper contributes to various strands of the recent climate finance literature (Edmans & Kacperczyk, 2022; Gasparini & Tufano, 2023; Giglio, Kelly, & Stroebel, 2021; Hong, Karolyi, & Scheinkman, 2020; Starks, 2023). Firstly, I provide a novel perspective on the extent to which financial markets price a transition to net zero carbon emissions. A growing strand of empirical literature has recently shown that market agents are paying increasing attention to global warming and this is reflected in stock market prices (Bolton & Kacperczyk, 2021, 2023; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021; Sautner, Van Lent, Vilkov, & Zhang, 2023; Wagner, Zeckhauser, & Ziegler, 2018). Unlike previous research that has focused on realised returns, this paper discusses some asset pricing implications of the net zero carbon transition, focusing on a forward-looking cash flow perspective[2]. In particular, I show that the valuations of fossil-fuel firms may not be aligned with a transition to net zero carbon emissions. I also provide a first explanation as to why surveys of professional investors indicate that financial markets are yet to suf-

[2]Similar evidence has also been found across various asset classes such as corporate and municipal bonds (Baker, Bergstresser, Serafeim, & Wurgler, 2022; Flammer, 2021; Painter, Chaifetz, & Louis, 2020), derivatives (Ilhan, Sautner, & Vilkov, 2021; Schlenker & Taylor, 2021), real estate (Bernstein, Gustafson, & Lewis, 2019), and mortgages (Nguyen, Ongena, Qi, & Sila, 2022). However, some opposite evidence has also emerged (Aswani, Raghunandan, & Rajgopal, 2023; Hong, Li, & Xu, 2019). Furthermore, it should be noted that changes in expectations (or news) around cash flows may better explain the variability in stock market prices of 'value' stocks such as fossil-fuel firms than that of discount rate news (Campbell & Vuolteenaho, 2004; La Porta, Lakonishock, Shleifer, & Vishny, 1997)

ficiently reflect the risks emerging from a net zero carbon transition residing in climate policy uncertainty.

Secondly, this paper contributes to the climate finance literature by reconsidering the recent evidence on the presence of a carbon premium. I show that, even though the realised returns of high-carbon emitting firms may have been higher than their low-carbon counterparts in the past - disclosing a carbon premium (Bolton & Kacperczyk, 2021, 2023) - they may not be representative of higher expected returns. Instead, high realised returns may be a product of mispricing generated by the effect of uncertainty on cash flow expectations. If the uncertainty around the net zero carbon transition will resolve, investors may revise their expectations about the growth of cash flows of carbon-intensive firms leading to lower future returns. As also discussed by Atilgan, Demirtas, Edmans, and Doruk (2023), this paper provides further evidence showing that the carbon premium may be a symptom of mispricing rather than of pricing of climate-related transition risks and that, in turn, realised returns may not be purely reflective of expected returns and cost of capital[3].

Finally, this study contributes to the financial economics literature on uncertainty. The net zero transition may be analogous to the early 2000s, when there was high uncertainty about the growth of the fundamentals of internet firms, which led to high valuations (Pástor & Veronesi, 2003, 2006). Even though the subsequent literature on policy uncertainty discusses how endogenous learning about political costs lowers uncertainty over time and thus leads to a higher risk premium and lower prices (Kelly, Pástor, & Veronesi, 2016; Pástor & Veronesi, 2012, 2013)[4], I argue that the inability to learn about the perspective climate policy maintains high levels of cash flows uncertainty for carbon-intensive firms. With the simple model I developed, I show that uncertainty, in turn, could contribute to maintaining high the valuations of fossil-fuel firms.

In the following section, I present a valuation framework of climate-sensitive firms and discuss some asset pricing implications. In Section 3, I outline the empirical strategy

[3] Pástor, Stambaugh, and Taylor (2022) show that using past returns as a proxy of expected returns for green stocks may not be appropriate.

[4] Similar results have also been found extending these models to the environmental policy (Hsu et al., 2023)

and the econometric specifications. In Section 4, I provide the results of the analysis and discuss the empirical evidence. In Section 5, I provide numerical simulations of the valuations of fossil-fuel stocks conditional to a set of possible climate scenarios.

2 Valuation framework

In this section, I describe a simple valuation framework of climate-sensitive firms exposed to an uncertain policy regime shift to curb carbon emissions. I consider a closed economy with two firms $i \in [d, c]$, one producing carbon-intensive energy and one low-carbon energy, a representative investor, and an infinite time horizon $t \in [0, \infty]$. Let $E_{i,t}$ denote an exogenous level of energy expenditure from firm i at time t. Energy supply matches energy demand. For all $t \in [0, \infty]$ energy expenditure for energy from firm i follows a specific and independent geometric Brownian motion with drift μ_i and standard deviation ω_i, where dW_t is a process with mean zero and unit variance $dW_t \sim \mathcal{N}(0, 1)$. The drift μ_i remains constant for all $t \in [0, \infty]$ unless the policymaker takes an irreversible decision to shift its climate policy.

$$dE_{i,t} = \mu_i E_{i,t} dt + \omega_i E_{i,t} dW_t \tag{1}$$

At time 1 the policymaker can decide to maintain its current climate policy regime a or to shift towards restricting energy expenditure in carbon-intensive energy b in order to prevent global warming. If a climate policy regime shift occurs, the drift μ_i is shifted by a known amount δ_i. This parameter for high-carbon energy δ_d is assumed to be strictly less than zero, while for low-carbon energy δ_c it is assumed to be strictly higher than zero. Loosely speaking, if the policymaker decides to take action to prevent global warming, he can implement policies for curbing high-carbon energy (e.g., carbon tax) or fostering low-carbon energy (e.g., stimulating innovation), thereby shifting the growth balance between high and low-carbon energy. For simplicity, I assume that the future path of low and high-carbon emitting energy expenditure only depends on the climate policy regime, but this can be thought of as a proxy for many unknown factors surrounding the transition[5].

[5] For example, the development of a new breakthrough energy technology, the possible continuation

I then assume that the representative investor's expectations of μ_i are distributed normally with mean g_i and variance σ_i^2. The latter term depends on the uncertainty introduced by the policymaker about the climate policy regime shift. The more uncertain is the signal from the policymaker about a possible shift in its climate policy regime from a to b, the more uncertain the representative investor is about the drift of the stochastic process governing carbon-intensive and low-carbon energy expenditure μ_i. I refer to σ_i^2 as *regime shift uncertainty* as the value of μ_i is ultimately defined by the decision of the policymaker. For simplicity, I assume that the magnitude of the possible policy is known and the decision is irreversible, but I acknowledge that these components introduce additional uncertainty and could be considered as a possible extension of the model.

I now want to use this framework in a simple present value asset pricing model. Let $D_{i,t}$ denote the dividend paid by firm i at time t. I assume that for all $t \in [0, \infty]$ the change in the level of dividends is proportional to the change in energy expenditure scaled by a known and constant firm-specific factor $dD_i = \gamma_i dE_i$. γ_i denotes the elasticity of dividends to changes in energy expenditure and represents the exposure of each firm to the regime shift. I therefore refer to γ_i as the exposure of each firm to the *regime shift risk*. Consequently, if we set $\omega_i = 0$ in Equation (1) without loss of generality, dividends grow at an exponential rate $\gamma_i \mu_i$ for all $t \in [0, \infty]$[6].

The investor has to price both firms at time 0 before the policy decision is taken. I assume that the price of firm i is the expected present value of future dividends discounted by an exogenous rate r_i given by a known model of expected returns. Importantly, differently from previous research that focuses on realised returns, I use my model to discuss the asset pricing implications of climate policy uncertainty from a cash flows perspective. I argue the effect of uncertainty on cash flow expectations in this context could be considerable given that, if we were to reach net zero carbon emissions, high-

of the decline in the costs of renewable energy and storage

[6]The reader should note that the model can be generalised to values of ω_i greater than zero. The motivation for this assumption is that I am interested in considering the uncertainty that investors face about the probability distribution of the drift (i.e., the long-term path of energy demand) rather than the volatility around it. The reader should also note that the previous step is only a useful construct to link climate policy with asset valuations, but from a theoretical standpoint, assuming uncertainty about the drift of the diffusion process of dividends is equivalent.

carbon energy may need to be almost entirely replaced by low-carbon energy.

$$P_{i,t} = \mathbb{E}_0 \int_0^\infty D_{i,t} exp(-r_i t) dt \tag{2}$$

Following some simple manipulations described in Appendix A, I find a convex relationship between four parameters and the price-dividend ratio. Substituting $D_{i,t}$ in the present value Equation (2) with the growth process of dividends emerging from the energy expenditure path in Equation (1), the price of firm i at time t depends on a dividend stream growing at a rate $\mu_i \gamma_i$ and discounted at a rate r_i. If we take the expectations, dividends $D_{i,t}$ are log-normally distributed, and μ_i has mean $exp(g_i + \sigma_i^2/2)$. For $r_i > g_i$, the price-dividend ratio of either low or carbon-intensive firm i at time $t = 0$ is positively related to the energy growth expectations, described by its mean g_i and variance σ_i^2, a known constant representing the elasticity of dividends to changes in energy expenditure γ_i and negatively related to the required rate of return $r_{i,t}$:

$$P_i/D_i = 1/[r_i - (g_i + \sigma_i^2/2)\gamma_i] \tag{3}$$

This simple model shows that the uncertainty about climate policy action might have an effect on the valuations of climate-sensitive assets through cash flow expectations. The higher the uncertainty about the growth of the fundamentals of climate-sensitive firms the higher the prices, everything else being equal. Contrary to the case where learning is possible and uncertainty decreases with the passing of time (e.g., Pástor and Veronesi (2012)), here uncertainty remains high until it is fully resolved[7]. Investors do not know whether high-carbon energy will remain predominant (leading to global warming) or whether, thanks to a policy regime shift, the world will move towards net zero carbon

[7]This situation is similar to the case of internet companies in the dot.com bubble (Pástor & Veronesi, 2006) or the uncertainty about the future profitability of newly listed firms (Pástor & Veronesi, 2003) and more generally common in real option approaches (Mcdonald & Siegel, 1986; Paddock, Siegel, & James, 1988). However, it should by noted that in this model, uncertainty emerges from the unknown level of the drift rather than the volatility around it. See Pastor and Veronesi (2009) for a review of learning in a context of uncertainty.

emissions. In such a case, uncertainty around policy action may lead to higher valuations by right-skewing expected cash flows. For a sufficiently high difference δ_i in the expected values of μ_i conditional to either state of the world, this effect could possibly lead to miscpricing due to the very different possible pathways of future cash flows. In particular, mispricing may occur, whereas an event may lead to a substantially lower level of future cash flows than the expected value (e.g., a climate policy regime shift).

A second observation is that the price-dividend ratio can be impacted by growth expectations and uncertainty, depending on the level of exposure of firms to the *policy regime shift risk* γ_i. The exposure of firms to the policy regime shift risk could be, in the first instance, proportional to carbon emissions (intensity), as highlighted by extant literature (e.g., Bolton and Kacperczyk (2023)). However, it may also be influenced by a broader set of factors such as the capacity of firms to cost-effectively abate emissions, the increasing or decreasing returns to scale of production, and the difference in efficiency and profitability of companies. In general, the impact of a transition to net zero carbon emissions on high carbon firms may vary greatly depending on a broader set of factors than just carbon emissions. In turn, this implies that the heterogeneous exposure of climate-sensitive firms to the policy regime shift risk may be a material driver of their valuations.

Contrary to prior research that focuses only on the required rate of return, I show that the uncertainty around cash flow expectations may right-skew the valuations of fossil-fuel firms. This, in turn, may lead to mispricing compared to a state of the world where a net zero carbon transition unfolds and hence lower future returns as investors may reprice their cash flow expectations. This entails that past realised returns may not be representative of expected returns, as cash flow expectations may have weighed significantly on valuations. In order to study the magnitude of this effect, in the next section, I turn to an empirical analysis.

3 Empirical specifications

In this section, I outline an empirical strategy to study the magnitude of the effect of climate policy uncertainty on the valuations of fossil-fuel firms. Even though the theoretical framework described in the previous section allows for a more general assessment of climate policy uncertainty on climate-sensitive firms, I focus on companies involved in the extraction, refinement, and commercialisation of fossil-fuel. Fossil-fuel firms are arguably some of the most exposed businesses to the risks of a net zero carbon transition given that carbon-intensive energy would need to be almost entirely replaced by low-carbon energy in the absence of technological breakthroughs on carbon capture and storage.

I use professional analysts' forecasts of fossil-fuel firm's fundamental value to proxy investors' expectations and their uncertainty. In line with previous literature, I measure investors' uncertainty using forecast disagreement and focus on its time-varying component (Anderson, Ghysels, & Juergens, 2009; Diether, Malloy, & Scherbina, 2002; Johnson, 2004)[8]. Specifically, I am interested in testing whether investors' expectations about future cash flows and their time-varying uncertainty affect valuations. In the context of climate change, the levels of uncertainty may vary when there is news about events that affect, directly or indirectly, the likelihood of more stringent climate policy.

I use data from CRSP/Compustat to identify a set of fossil-fuel energy stocks. I select sub-industries related to oil & gas consumable fuel companies according to the Global Industry Classification Standard (GICS)[9]. This gives me a large set of stocks and their respective market data, including prices, earnings, and dividends. I then merge this data with Refinitiv's IBES and Refinitiv's carbon emissions. IBES reports data about analysts' forecasts of financial indicators monthly (e.g., Dividends per share, Earnings per share). I use the summary dataset, which reports the mean, standard deviation, high and low of analysts' estimates (including the number of underlying forecasts) as well as a set of aggregated statistics about the detailed estimates. Joining IBES with CRSP gives me a total of 480 fossil-fuel stocks, followed by stock market analysts. The data report analysts'

[8]Various methods have been used in the literature to proxy investors' (climate) uncertainty: *i.* ARCH conditional variance discussed by Engle (1983), *ii.* market-based methods (Bekaert & Hoerova, 2014; Brenner & Izhakian, 2018), *iii.* text-mining methods (Baker, Bloom, & Davis, 2016; Bloom, 2009), of which some applied to climate policy uncertainty (Berestycki, Carattini, Dechezleprêtre, & Kruse, 2022; Gavriilidis, 2022; Noailly, Nowzohour, & Van Den Heuvel, 2022)

[9]GICS Sub-industries selected: Integrated Oil & Gas (10102010), Oil & Gas Exploration & Production (10102020), Oil & Gas Refining & Marketing (10102030), Oil & Gas Storage & Transportation (10102040), Oil & Coal & Consumable Fuels (10102050)

forecasts for different forecast horizons (FH) in the future, from 1 to 3 years. For example, estimates could be for the next fiscal year (FH 1) or for 3 years in the future (FH 3). This data has monthly records (forecast date) corresponding to more than 800,000 underlying estimates, which summarise analysts, and arguably investors' beliefs, of a representative sample of fossil-fuel companies. Table 1 shows some descriptive statistics.

I perform the following data cleaning and transformations to ensure the data is adequate for the analysis. In line with previous literature, I set a threshold for the minimum required number of analyst's forecasts. I set the threshold at 10 to ensure enough estimates are included without reducing substantially the number of records. I also remove stocks with a price lower than 5 USD at the forecast date. Further, I select the decade starting at the beginning of 2010 and ending in 2019 as it is particularly suitable for the empirical analysis, but also because of data limitations and major global upheavals in the surrounding years. Firstly, if we consider a minimum number of analysts' forecasts for each forecast date, the number of estimates before 2010 is low. Secondly, the period between the global financial crisis and COVID-19 has been relatively stable from a macroeconomic standpoint while various major climate policy events occurred (e.g., Paris agreement in 2015, Trump's election in 2016) without being overly influenced by other exogenous events. This limits the concerns about the influence of other major economic and policy developments on the valuations of the stocks in the sample that might bias the results (e.g., global financial crisis).

I construct two metrics of analysts' forecasts as a proxy for market's expectations and uncertainty. First, I define: *i.* mean earnings per share (EPS) growth forecasts relative to the most recent earnings per share at forecast date ($EPS\_G_{i,t}^{FH}$). Secondly, I define: *ii.* the standard deviation of EPS growth forecast (or forecast disagreement about the growth of earnings) relative to the most recent absolute value of earnings per share at forecast date ($EPS\_STD_{i,t}^{FH}$). I use the latter metric as a proxy of analyst's uncertainty. More formally, I define $EPS_{i,t,k}^{FH}$ as the EPS forecast for the forecast horizon FH for firm i at time t of analyst k (where K is the total number of analyst estimates). Further, I define $EPS_{i,t}$ as the most recent earnings per share at forecast date t and $\overline{EPS_{i,t}^{FH}}$ as the arithmetic average of the K analysts' forecasts for firm i for each forecast horizon.

$$EPS\_G_{i,t}^{FH} = \frac{\overline{EPS_{i,t}}^{FH}}{EPS_{i,t}} - 1$$

$$EPS\_STD_{i,t}^{FH} = \frac{\sqrt{\sum_{k=1}^{K}(EPS_{i,t,k}^{FH} - \overline{EPS_{i,t}}^{FH})^2/K}}{|EPS_{i,t}|}$$

In the first specification, I estimate a panel regression model between the price-earnings ratio and the two metrics. I control for firm-fixed effects because I am interested in the time-varying level of uncertainty. Loosely speaking, I am interested in understanding whether, during a period of higher climate policy uncertainty, the relative valuations of climate-sensitive assets are higher, given a certain level of expected growth in earnings, rather than understanding whether firms that are more exposed to uncertainty show higher prices[10]. Moreover, I replicate the same specification for the price-dividend (P/D) and dividends per share (DPS) forecasts in the dataset. Earnings per share allow us to avoid concerns about non-dividend paying stocks and use a larger number of data points, but results are generally equivalent[11].

$$P/E_{i,t} = \beta_1 * EPS\_G_{i,t}^{FH} + \beta_2 * EPS\_STD_{i,t}^{FH} + Controls_{i,t} + \epsilon_{i,t} \tag{1}$$

In the second specification, I estimate a panel regression model between the price-earnings ratio and the interaction of total carbon emissions (Scope 1,2,3), and the standard deviation of analysts' forecasts (forecast disagreement). This allows for a better identification of climate policy uncertainty. If forecast disagreement at least partially represents climate policy uncertainty, firms with higher carbon emissions should have a higher coefficient for the interaction term. I provide some reassurance about the correla-

[10]It is already postulated in the financial economics literature that firms more exposed to idiosyncratic uncertainty tend to have higher stock market valuations all else being equal (Pástor & Veronesi, 2003)

[11]The reader should note that, in most cases, fossil-fuel stocks are not "growth" companies and generally pay dividends with a constant pay-out. Consequently, EPS and DPS results are expected to follow a similar pattern

tion between my metric and climate policy uncertainty for fossil-fuel firms by exploiting this instrument. I corroborate this evidence with further identification analyses.

$$
\begin{aligned}
P/E_{i,t} = \beta_1 * EPS\_STD_{i,t}^{FH} + \beta_2 * TOTAL\_EMIS_{i,t} \\
+\beta_3 * TOTAL\_EMIS_{i,t} * EPS\_STD_{i,t}^{FH} + Controls_{i,t} + \epsilon_{i,t}
\end{aligned}
\tag{2}
$$

In Appendix B, I report some additional identification analyses. Firstly, I show the two metrics described above are, in aggregate, sensitive to climate policy events. Secondly, I show the metric of uncertainty broadly correlates with other climate policy uncertainty measures in the literature but not substantially with general uncertainty metrics. Finally, I show that forecast disagreement tracks the average implied option volatility of fossil-fuel firms. These analyses, together with the empirical set-up described in this section, should ensure that the results capture, at least to a certain extent, the effects of climate policy uncertainty on investors' expectations.

4 Empirical results

In the first part of this section, I investigate some of the determinants of uncertainty around the fundamentals of fossil-fuel firms, particularly focusing on elements that may increase climate policy uncertainty. In this part, I also investigate some of the drivers of the changes in mean analysts' expectations. In the second part, I turn to the main results of my empirical analysis, reporting first the effects of uncertainty on the valuations of fossil-fuel firms and then exploring the interaction between carbon emissions and climate policy uncertainty. With this analysis, I show that the effect of climate policy uncertainty on the valuations of fossil-fuel firms could be material.

4.1 Some determinants of analysts' expectations and climate policy uncertainty

To get a better understanding of the drivers of the valuations of fossil fuel firms, I regress some possible factors of uncertainty on my measure of forecast disagreement

(EPS_STD). The objective of this analysis is to first describe what may drive uncertainty around fossil-fuel stocks' fundamentals before turning to its effects on the valuations of firms. In particular, I focus on three elements: climate policy events, climate disasters, and political beliefs proxied using analysts' locations in Democratic or Republican-leaning states in the United States.

I first consider a set of climate policy events. In order to do that, I retrieve a list of climate policy events collected by Barnett (2023). I then create a dummy variable that equals one if, in the month the forecast was published, a climate policy event occurred, and equals zero otherwise. In Table 2, I show that there seems to be a weak positive correlation between my measure of uncertainty and climate policy events. The regression is not significant for a one and two-years forecast horizons but it is significant and positive for a three-years forecast horizon. This may indicate that during periods of climate policy events, analysts are generally more uncertain about the medium- and long-term future performance of fossil-fuel firms. The list of climate policy events is provided in Appendix A10.

I then consider a set of climate disasters that may increase the salience of climate change. I use data from Spatial Hazard Events and Losses Database for the United States (SHELDUS)[12] which reports historical property damages and fatalities of natural hazards. I classify a major disaster as an occurrence that led to either fatalities or property damages (expressed in terms of inflation adjusted Dollars at 2021 values) above the 90th percentile of the decade 2010-2020. I consider Coastal Flood, Drought, Flooding, Heat, Hurricane/Tropical Storm, Severe Storm/Thunder Storm, Tornado, and Wildfire. I focus on the US as most analysts in my sample reside in this country. Similarly, for climate policy events, I create a dummy variable tracking whether an event occurs in the month the estimate was published. In Table 2, I show that there is a weak positive correlation between my measure of uncertainty and the occurrence of physical climate events. The coefficient is positive and significant for the one-year forecast horizon. The list of events is provided in Appendix A11.

Thirdly, I consider whether analysts' headquartered in states that are leaning towards the Democratic or Republican party disclose differences in their uncertainty about the

[12] https://sheldus.asu.edu/SHELDUS/index.cfm?page=members

future of fossil-fuel firms. I use this as a proxy for political beliefs, which may indicate different views about climate change. I use data from Gerken and Painter (2023)[13] about analysts' location and classify Democratic and Republican states depending on the outcome of the previous four elections. I classify states as Democratic or Republican-leaning where the respective party consistently won the election between 2004 and 2020. I do not consider states where there have been mixed results in the past four elections. In Table 2, I show that analysts headquartered in Democratic-leaning states (e.g., California) tend to be more uncertain about the future performance of fossil-fuel firms than analysis in Republican-leaning states (e.g., Texas). The classification of states is provided in Appendix A12.

In Table 3, the analysis is extended to the mean earnings growth forecast (EPS_G). I find that in months when climate policy events or climate related disasters occur, the mean analysts' forecast is generally lower than in other periods. The coefficients for the variables in the regressions are negative and significant. Specifically, for policy events, the coefficients are significant for a two and three-years forecast horizons. For climate disasters, the only significant coefficient is for a forecast horizon of two years ahead. Turning to political beliefs, the results suggest that analysts located in Democratic-leaning states are not only more uncertain about their forecasts but tend to have higher mean estimates than their counterparts in Republican-leaning states. However, it should be noted that more than two-thirds of analysts are located in Democratic-leaning states (e.g., California) as opposed to Republican-leaning states (e.g., Texas).

These analyses show some of the drivers of analysts' uncertainty about fossil-fuel firms. When climate policy events and climate disasters occur, and arguably become more salient, my measure of uncertainty is generally higher and mean earnings' growth forecasts lower. Even though analysts headquartered in Democratic or Republican states may not share the predominant political belief of their geographical area, analysts in states where the predominant political orientation is towards the more climate-conscious Democratic party tend to be more uncertain about the future of fossil-fuel firms as opposed to states with a predominant orientation towards the Republican party. Analysts seem also to pay attention to climate policy and climate disasters in revising their mean forecasts, which

[13] I thank the authors for sharing the data

are generally lower in the months such events occur.

4.2 The effects of uncertainty on the valuations of fossil-fuel firms

I now provide the results of the main empirical analysis. I start by averaging the forecasts across the three forecast horizons in order to capture a stronger signal. Table 4 shows a positive and statistically significant relationship between analysts' forecast disagreement and the price-earnings ratio (Specification 1). I show that given a mean forecast growth, periods with higher forecast disagreement tend to have a higher price-earnings ratio, consistent with my model's prediction. This result seems to indicate that financial markets discount climate policy uncertainty through their cash flow expectations with higher average prices, everything else being equal (e.g., expected cash flows growth).

In Table 4, I show that in months when climate policy events or climate disasters occurred, the valuations of fossil-fuel firms are generally lower. The coefficients of the regressions are significant and negative. Introducing dummy variables on the date of the occurrence of such events does not affect the results, which remain significant and in line with expectations. Complementing these results with the findings in the previous subsection, it seems that analysts revise their expectations and their levels of uncertainty when climate policy or climate disasters occur, and, in turn, these beliefs have a significant impact on the valuations of firms.

In Table 5, I break down analysts' forecasts by different forecast horizons (FH 1,2,3). The signs of the coefficients are consistently positive across the three forecast horizons and highly significant. The coefficients are also economically significant: an expectation of doubling of the EPS in a three-years forecast horizon leads to around 14-points increase in the price-earnings ratio. A 50% standard deviation (i.e., EPS remaining constant or doubling in the next three years) leads to around 5 points increase in the price-earnings ratio. Similar results are also confirmed using the price-dividend ratio (P/D) in Table A1. The only exception is the standard deviation of forecasts for a two-years forecast horizon where the sign turns negative, although this model has a much lower explanatory power compared to the regression with earnings per share.

In Table 5, I show a negative and statistically significant relationship between Scope 1 emissions and the price-earnings ratio. I report that the coefficients for Scope 1 emissions expressed as intensity of revenues, assets, and log absolute emissions are negative and significant. The only exception is again for a two-years forecast horizon and log absolute emissions where the coefficient is not significant. Without considering the effects of uncertainty on cash flow expectations, higher carbon emissions entail lower price-earnings ratio in line with other empirical studies (Bolton, Halem, & Kacperczyk, 2022)[14].

In Table 6, I show the results are robust to a set of control variables representing firms' characteristics. The relationships outlined above remain in line with expectations and significant after introducing ROE, liquidity, profit margin, market to book, leverage, and cash to debt ratio. The only exception is the EPS growth estimate (EPS_G) for one-year forecast horizon (FH 1) where the coefficient turns negative. But the R^2 also decreases substantially in this case, to around 7%. Alternatively, the variance explained by the regression models for the two and three-years forecast horizons remains high (around 30% and 70% respectively). Interestingly, after controlling for firms' characteristics, the longer the time horizon of the estimate, the higher the variance explained by the model. The coefficients for Scope 1 emissions also remain generally negative and significant. Similar results could be found for dividends per share in Table A2[15].

In Table A3, I show that the results hold after removing outliers. I winsorize to the 5th/95th percentile all variables in the sample and re-estimate the model to ensure my results are not sensitive to outliers. The coefficients for earnings per share growth forecast and earnings per share forecast disagreement remain positive and strongly significant. The explanatory power of the model slightly decreases, but remains broadly in line with the results based on a non-winsorized sample. Scope 1 emission coefficients also remain negative and significant with the only exception of three-years forecast horizon and log absolute emissions, which becomes not significant.

In Table A5, I show the results are robust to different thresholds of minimum number

[14]It should be noted that, this result is based on Scope 1 emissions that are relatively low for fossil-fuel firms. The exposure of fossil-fuel firms to the risks of a transition could be better captured by the total emissions of their products (i.e., including Scope 3). For this reason, in subsequent analyses, I consider total emissions.

[15]The only exception in the DPS case are the coefficients of the standard deviation of analysts forecasts which become non-significant for a three-years forecast horizon

of analysts' forecasts. To test the sensitivity of the results to the cut-off I use for the minimum number of estimates. I increase it from 10 to 15 and decrease it to 5 to test the sensitivity of the results to this parameter. The results generally persist in increasing the minimum number of estimates, although with a few exceptions. The sample size decreases substantially when considering only records with at least 15 estimates, thereby decreasing the robustness of the model. Alternatively, decreasing the minimum number of estimates increases the sample size, but the metrics are less robust. The results are confirmed also in this case, with a few exceptions, but I am cautious when using my metrics with fewer than 10 analysts' forecasts because it may not be sufficiently robust. These results are reported only for comparison with the baseline model. Nevertheless, this robustness analysis shows that the results are not particularly sensitive to the cut-off threshold above a certain level.

In Table 7, I find a positive and significant relationship between the interaction term of total emissions (Scope 1, 2, and 3) and forecast disagreement and the price-earnings ratio (Specification 2). This may indicate that the valuations of firms that are more exposed to the policy regime shift risk (i.e., those with higher emissions) might be more impacted by the effect of uncertainty. This result also shows that at least a portion of forecast disagreement may be due to climate policy uncertainty. In line with the previous finding, the coefficient of forecast disagreement remains generally positive and significant, although the sign turns negative for absolute emissions.

In Table A7, I report on additional robustness analyses. I find that in some instances, the relationship between the interaction term of total emissions and uncertainty and the price-earnings ratio does not hold to the set of control variables. However, after including firms' characteristics, the R^2 of the model decreases substantially, and in some instances, the coefficients of the interaction term turn negative or not significant. Such results suggest that there could be only a limited relationship between the interaction of emissions and uncertainty. Broader political and economic uncertainty may also contribute to the effects described in this paper. I am indeed aware that climate policy may only be one source of uncertainty that may affect cash flow expectations of fossil-fuel stocks. But I argue this analysis is sufficient to show it may, at least partially, contribute to this broader uncertainty[16].

These results show that there may be a positive relationship between time-varying uncertainty and the valuations of fossil-fuel stocks. Although some anomalies emerge in the robustness analysis, my results suggest that this effect might be stronger for carbon-intensive firms - indicating that, at least in part, it could be attributed to climate policy uncertainty. Such findings highlight how climate policy uncertainty may have weighed significantly on the valuations of fossil-fuel firms and on their realised returns. In turn, this result suggests that realised returns may be a poor proxy for expected returns and cost of capital.

In the next section, I discuss some of the implications of the effect of climate policy uncertainty on cash flow expectations for the valuations of fossil-fuel firms. Particularly, I discuss how uncertainty may lead to mispricing compared to a state of the world where a net zero carbon transition unfolds.

5 The valuations of fossil-fuel firms and the net zero carbon transition

To calculate some numerical results of the valuations of fossil-fuel stocks conditional to a world with a climate policy regime shift and without, I calibrate the model described in Section 2 with some climate scenarios. In order to find a representative basket of fossil-fuel stocks, I run the model on a stock index representing high-carbon emitting energy sources: the S&P 1200 Global Energy Index. This index represents investments in traditional energy companies involved in the extraction, refinement, and commercialisation of fossil-fuel. I follow an approach similar to Campbell and Shiller (1989) and use my model to estimate a distribution of price-dividend ratios conditional to a set of climate scenarios. Specifically, I use climate scenarios to generate projections of dividends rather than using their historical realisations as proposed by Campbell and Shiller (1989). I use a set of climate scenarios from the the Network for Greening the Financial System (NGFS, 2021)

[16]Previous literature has also shown that a part of uncertainty in the S&P 500 may be due to climate change. Arguably, the share of climate policy uncertainty is even higher for fossil-fuel stocks (Rocciolo, 2022)

to calculate the yearly growth rate of global energy expenditure on fossil-fuel energy (projected energy demand multiplied by energy prices) g_d and its standard deviation σ_d^2 [17]. I then use a sensitivity parameter γ_d to link the change in carbon-intensive energy expenditure to the change in dividends.

I calibrate the discount rate r_d equal to 6.3%, the growth rate of carbon-intensive energy expenditure conditional to no climate regime shift $g_{d,a}$ equal to 1.37% and the standard deviation of the energy expenditure growth conditional to no climate regime shift $\sigma_{d,a}^2$ equal to 1.13%. The growth rate of carbon-intensive energy expenditure conditional to a climate regime shift $g_{d,b}$ equal to -0.92% and the standard deviation of the energy expenditure growth conditional to a climate regime shift $\sigma_{d,b}^2$ equal to 1.41%[18]. In the baseline model, I set the elasticity of dividends to energy expenditure γ_d=1. This is the only parameter that is not possible to calibrate due to data limitations, but I use a range of plausible parameters ranging from 0.5 to 1.5 to show that the results do not change[19].

It should be noted that the calibration of my model conditional to a climate policy regime shift is fairly conservative. A decrease in primary energy expenditure of around 1% per year results in only around 30% lower levels of energy expenditure in 2050 compared to 2020. The total fossil-fuel expenditure in such a scenario decreases from around 4 trillion USD in 2020 at 2010 prices to only around 3 in 2050 in real terms. This is because the NGFS scenarios consider a sizeable use of carbon capture and storage (CCS) which allows for an extended use of carbon-intensive energy. Arguably less conservative scenarios would put the decline in high-carbon energy expenditure higher. Further, the estimates consider a linear and smooth decline in dividends, but a sharper drop in high-carbon

[17] NGFS Scenarios used: Climate regime shift: Below 2°C, Net Zero 2050, Delayed transition, Divergent Net Zero. No climate regime shift: Current Policies. Models used: GCAM 5.3+ NGFS, MESSAGEix-GLOBIOM 1.1-M-R12, REMIND-MAgPIE 3.0-4.4.

[18] Consider that in the period between 2010 and end of 2019 this value increased by around 2% per year in real terms

[19] Consider the total value of carbon-intensive energy expenditure (coal, oil and gas) between 2010 and end of 2019 increased around 20%, similarly to the total value of dividends of companies in the index in the same period. This entails an elasticity of dividends to energy expenditure of around 1:1. It seems reasonable to assume that firms dividends cannot increase substantially more than their revenues, except for relatively limited economies of scale. It should also be noted that the relative comparison is not affected by a changing r or γ_d, but purely by different levels of μ.

emitting energy may be required to meet the ambitious goals of the Paris Agreement. This implies that the estimates conditional to a climate policy regime shift are likely to be on the high-end of possible values and conservative, but are already sufficiently different to illustrate the results.

To examine the potential impact of climate policy uncertainty, I generate two probability distributions of the price-dividend ratio conditional to the two set of scenarios (climate policy regime shift and no climate policy regime shift). I use the two conditional probability distributions of μ_d to calibrate the model. In Figure 1, I show the resulting probability distribution of yearly global energy expenditure growth μ_d and the price-dividend ratio conditional to a no climate policy regime shift (brown curve) and to a climate policy regime shift scenario (green curve). In line with expectations, the price-dividend ratio distribution conditional to a climate policy regime shift scenario is to the left of the one conditional to a no climate policy regime shift scenario. We would expect that in a world with climate policy high-carbon emitting firms will grow slower or decline, as opposed to scenarios where climate policies lead to a transition to low-carbon energy. I also show the range of the price-dividend ratio in the period after the Paris agreement (2016-2019) and the price-dividend ratio at the end of 2019. This ratio is fairly stable for "value" stocks such as fossil-fuel with a standard deviation of around 2.5.

To control for model misspecification, I then generate the conditional probability distributions of the price-dividend ratio by varying selectively some of the baseline parameters. This approach is useful because it allows me to make some observations on actual prices as long as it covers a wide range of plausible calibration parameters. It is possible that the baseline model might also be misspecified, but I argue at least one model calibration might be plausible. I test various levels of discount rate r_d, uncertainty around the growth rate of carbon-intensive energy expenditure σ_d^2, and elasticity of dividends to energy expenditure γ_d. In Table 9, I show the mean and the standard deviation of the distribution while in Figure A4 I show the respective probability distributions. Reassuringly, the analysis shows that the mean values of the model are not substantially sensitive to the only parameter not calibrated empirically, γ_d, but rather that the unknown level of μ_d is the key driver of the results[20].

[20] It should be noted that it is likely that the baseline calibration of the discount rate is in the lower

In this analysis, the average valuations of fossil-fuel firms in the period 2016-2019 (after the Paris Agreement) and at the end of 2019 have been at the right of the distribution of the price-dividend ratio conditional to no climate policy regime shift. This result is consistent across the set of plausible model calibrations. Loosely speaking, high-carbon energy stocks have been broadly pricing a high likelihood of a no climate policy regime shift scenario. Depending on the model calibration, the valuations of the S&P 1200 Global Energy Index moved historically either in the range of the probability distribution conditional to no climate policy regime shift or to the right of it. If we assume that at least one of these model calibrations is plausible, the results show that it is unlikely that carbon-intensive stocks over the period following the Paris agreement priced dividends, or cash flows, growth rates substantially different than a no climate policy regime shift scenario.

The numerical simulations show that climate policy uncertainty may lead to mispricing compared to a net zero carbon transition. It would be sensible to expect the valuations of fossil-fuel firms to discount, at least to a certain extent, the possible effect of a net zero carbon transition on cash flows. Governments worldwide have made various commitments to fighting climate change, and the NGFS estimates are quite conservative given they entail a world with only 30% less fossil-fuel energy expenditure in 2050. An alternative explanation for these results may be that markets discount the low probability outcome of technological breakthroughs that could allow for an extended use of fossil-fuels (e.g., carbon dioxide removal)[21]. Nevertheless, these results show that investors' uncertainty about climate policy may, at least partially, explain the valuations of fossil-fuel stocks in light of the increasing number of climate pledges. But also that it is unlikely that realised returns are reflective of expected returns as financial markets

range of possible values in light of the recent literature showing increasing levels of expected returns for carbon-intensive firms (Bolton & Kacperczyk, 2023). In a context of higher climate related risks and uncertainty, the required rate of return might arguably have a tendency to increase, moving both price-dividend ratios distributions to the left. It is also more likely than not that the model is under-estimating the required rate of return r.

[21]According to the latest IPCC assessment report the likelyhood of a possible future scenario where fossil-fuel energy may be combined with Carbon Capture and Storage (CCS) has decreased substantially due to the increasingly lower prices for renewable energy

may be mispricing a net zero carbon transition.

6 Conclusion

This paper investigates the extent to which financial markets price a transition to net zero carbon emissions. I reconsider the evidence around a correlation between realised returns and carbon emissions (*carbon premium*) in the light of climate policy uncertainty. In a present value framework, the main effect of transition risk on the valuations of high-carbon emitting firms may be on the expected cash flows rather than on the discount rate. Uncertainty may right-skew the expected value of future cash flows, maintaining high the valuations of high-carbon emitting firms relative to a state of the world where a transition to net zero carbon emissions unfolds. In turn, the carbon premium may be a product of financial markets mispricing the net zero carbon transition rather than a symptom of pricing of transition risk. This implies that past realised returns may not be representative of expected returns, as uncertainty may have weighted significantly on past valuations.

The results presented in this paper suggest that the effect of uncertainty on cash flow expectations may be material, possibly limiting the extent to which financial markets reflect in their valuations a transition towards lower carbon emissions. The future growth of high-carbon emitting firms may strongly depend on the occurrence or not of an uncertain climate policy regime shift affecting cash flow expectations. I showed that uncertainty may have weighed significantly on the valuations of some of the most carbon-intensive businesses: fossil-fuel firms. I provided evidence showing that part of this uncertainty may be due to climate policy. I then showed that it is unlikely that following the Paris Agreement financial markets consistently priced expected cash flows in line with a transition to net zero carbon emissions. In conclusion, a better understanding of the reasons underlying the carbon premium may be required in order to shed light on the extent to which financial markets price the risk of a transition to net zero carbon emissions.

References

Anderson, E., Ghysels, E., & Juergens, J. (2009). The impact of risk and uncertainty on expected returns. *Journal of Financial Economics*, *94*(2), 233–263.

Aswani, J., Raghunandan, A., & Rajgopal, S. (2023). Are carbon emissions associated with stock returns? *Review of Finance*, *1*(32).

Atilgan, Y., Demirtas, O., Edmans, A., & Doruk, G. (2023). Does the Carbon Premium Reflect Risk or Mispricing? *Working paper*.

Baker, M., Bergstresser, D., Serafeim, G., & Wurgler, J. (2022). The Pricing and Ownership of US Green Bonds. *Annual Review of Financial Economics*, *14*, 415–437.

Baker, M., Bloom, N., & Davis, S. (2016). Measuring economic policy unceirtanty. *Quarterly Journal of Economics*, *131*(4), 1593–1636.

Barnett, M. (2023). Climate Change and Uncertainty: An Asset Pricing Perspective. *Management Science*, *(Forthcoming)*.

Bekaert, G., & Hoerova, M. (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics*, *183*(2), 181–192.

Berestycki, C., Carattini, S., Dechezleprêtre, A., & Kruse, T. (2022). Measuring and assessing the effects of climate policy uncertainty. *Working paper*.

Bernstein, A., Gustafson, M., & Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, *134*(2), 253–272.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, *77*(3), 623–685.

Bolton, P., Halem, Z., & Kacperczyk, M. (2022). The financial cost of carbon. *Journal of Applied Corporate Finance*, *34*(2), 17–29.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517–549.

Bolton, P., & Kacperczyk, M. (2023). Global Pricing of Carbon-Transition Risk. *The Journal of Finance*, *78*(6), 3677–3754.

Brenner, M., & Izhakian, Y. (2018). Asset pricing and ambiguity: Empirical evidence. *Journal of Financial Economics*, *130*(3), 503–531.

Campbell, J., & Shiller, R. (1989). The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *The Review of Financial Studies*, *1*(3), 195–228.

Campbell, J., & Vuolteenaho, T. (2004). Bad beta, good beta. *American Economic Review*, *94*(5), 1249-1275.

Chan, K. F., & Malik, I. (2022). Climate policy uncertainty and the cross section of stock returns. *Working paper*.

Diether, K., Malloy, C., & Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance*, *57*(5), 2113–2141.

Edmans, A. (2023). Applying economics—not gut feel—to esg. *Financial Analysts Journal*, *0*(0), 1-14.

Edmans, A., & Kacperczyk, M. (2022). Sustainable Finance. *Review of Finance*, *26*(6), 1309–1313.

Engle, R. (1983). Estimates of the variance of u. s. inflation based upon the arch model. *Journal of Money, Credit and Banking*, *15*, 286-301.

Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*, *142*(2), 499–516.

Gasparini, M., & Tufano, P. (2023). The Evolving Academic Field of Climate Finance. *Working paper*.

Gavriilidis, K. (2022). Measuring Climate Policy Uncertainty. *Working paper*.

Gerken, W. C., & Painter, M. O. (2023). The Value of Differing Points of View: Evidence from Financial Analysts' Geographic Diversity. *The Review of Financial Studies*, *36*(2), 409–449.

Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate Finance. *Annual Review of Financial Economics*, *13*, 15–36.

Hong, H., Karolyi, A., & Scheinkman, J. (2020). Climate finance. *The Review of Financial Studies*, *33*(3), 1011–1023.

Hong, H., Li, F., & Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics*, *208*(1), 265–281.

Hsu, P., Li, K., & Tsou, C. (2023). The pollution premium. *The Journal of Finance*, *78*(3), 1343-1392.

Ilhan, E., Sautner, Z., & Vilkov, G. (2021). Carbon Tail Risk. *The Review of Financial Studies*, *34*(3), 1540–1571.

Johnson, T. (2004). Forecast dispersion and the cross section of expected returns. *The*

Journal of Finance, *59*(5), 1957–1978.

Kelly, B., Pástor, L., & Veronesi, P. (2016). The Price of Political Uncertainty: Theory and Evidence from the Option Market. *The Journal of Finance*, *71*(5), 2417–2480.

Krueger, P., Sautner, Z., & Starks, L. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, *33*(3), 1067–1111.

La Porta, R., Lakonishock, J., Shleifer, A., & Vishny, R. (1997). Good news for value stocks: Further evidence on market efficiency. *The Journal of Finance*, *52*(2), 859-874.

Mcdonald, R., & Siegel, D. (1986). The value of waiting to invest. *The Quarterly Journal of Economics*, *101*, 707-728.

NGFS. (2021). *Scenarios in Action: a progress report on global supervisory and central bank climate scenario exercises.*

Nguyen, D., Ongena, S., Qi, S., & Sila, V. (2022). Climate change risk and the cost of mortgage credit. *Review of Finance*, *26*(6), 1509-1549.

Noailly, J., Nowzohour, L., & Van Den Heuvel, M. (2022). Does environmental policy uncertainty hinder investments towards a low-carbon economy? *Working paper*.

Paddock, J., Siegel, D., & James, S. (1988). Option valuation of claims on real assets: The case of offshore petroleum leases. *The Quarterly Journal of Economics*, *103*(3), 479–508.

Painter, M., Chaifetz, R., & Louis, S. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*, *135*(2), 468–482.

Pástor, L., Stambaugh, R., & Taylor, L. A. (2022, 11). Dissecting green returns. *Journal of Financial Economics*, *146*(2), 403–424.

Pástor, L., & Veronesi, P. (2003). Stock Valuation and Learning about Profitability. *The Journal of Finance*, *58*(5), 1749–1790.

Pástor, L., & Veronesi, P. (2006). Was there a nasdaq bubble in the late 1990s? *Journal of Financial Economics*, *81*(1), 61–100.

Pastor, L., & Veronesi, P. (2009). Learning in Financial Markets. *Annual Review of Financial Economics*, *1*(1), 361–381.

Pástor, L., & Veronesi, P. (2012). Uncertainty about Government Policy and Stock Prices. *The Journal of Finance*, *67*(4), 1219–1264.

Pástor, L., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, *110*(3), 520–545.

Ramelli, S., Wagner, A. F., Zeckhauser, R. J., & Ziegler, A. (2021). Investor Rewards to Climate Responsibility: Stock-Price Responses to the Opposite Shocks of the 2016 and 2020 U.S. Elections. *The Review of Corporate Finance Studies*, *10*(4), 748–787.

Rocciolo, F. (2022). Pricing climate change ambiguity. *Working paper*.

Sautner, Z., Van Lent, L., Vilkov, G., & Zhang, R. (2023). Firm-level climate change exposure. *The Journal of Finance*, *78*(3), 1449-1498.

Schlenker, W., & Taylor, C. A. (2021). Market expectations of a warming climate. *Journal of Financial Economics*, *142*(2), 627–640.

Starks, L. (2023). Presidential Address: Sustainable Finance and ESG Issues—Value versus Values. *The Journal of Finance*, *78*(4), 1837–1872.

Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics*, *142*(2), 487–498.

Wagner, A. F., Zeckhauser, R., & Ziegler, A. (2018). Unequal Rewards to Firms: Stock Market Responses to the Trump Election and the 2017 Corporate Tax Reform. *AEA Papers and Proceedings*, *108*, 590–596.

7 Tables

	FH	P/E	EPS_G	EPS_STD
	1	27.2895	0.0993	0.5778
Mean	2	31.8017	0.5507	1.1493
	3	33.8423	0.5518	1.7515
	1	460.9999	10.0607	5.6415
Standard dev.	2	855.1199	39.8871	15.1574
	3	1073.6872	44.5025	16.1923
	1	-41.5	-1.6878	0.0199
5th Percentile	2	-47.6731	-4.0534	0.0351
	3	-58.8291	-6.1899	0.0373
	1	99.5296	1.4664	1.6207
95th Percentile	2	101.737	3.6	2.9583
	3	95.5333	5.45	4.4
	1	68822	68809	60848
N	2	60092	60081	54053
	3	39038	39028	29755

Table 1: Descriptive statistics Sample descriptive statistics. Values between January 2010 and December 2019. From top to bottom: mean, standard deviation, 5th percentile, 95th percentile and number of observations. FH refers to different forecast horizons from 1 fiscal year ahead up to 3 fiscal years ahead.

	(1)			(2)			(3)		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
Policy Event	0.0184	-0.0284	7.6375***						
	(0.1152)	(0.3515)	(2.5396)						
Climate Disaster				0.3949***	0.0638	1.9637			
				(0.156)	(0.4844)	(3.5334)			
Democratic leaning							5.0871***	10.8242***	13.5304***
							(0.6255)	(1.0582)	(2.8844)
Republican leaning							1.0901	0.558	0.8337
							(3.0861)	(5.1662)	(27.4018)
R^2	0.00	0.00	0.0031	0.0009	0.0000	0.0001	0.0333	0.0546	0.0572
N	7467	8145	2909	7467	8145	2909	1924	1811	363

Table 2: Panel regression of forecast disagreement. Panel regression of earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and the absolute value of the latest earnings per share - (EPS_STD) and a dummy variables representing: (1) if in the month of the forecast a major global policy event occurred (e.g., COP); (2) if in the month of the forecast the US experienced a major climate disaster (Coastal Flood, Drought, Flooding, Heat, Hurricane/Tropical Storm, Severe Storm/Thunder Storm, Tornado, Wildfire); (3) if the analyst publishing the forecast is headquartered in a Democratic or Republican leaning state. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	(1)			(2)			(3)		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
Policy Event	-0.035	-1.4015***	-18.5299***						
	(0.1818)	(0.5119)	(6.3945)						
Climate Disaster				0.0469	-2.2958***	-0.3256			
				(0.2462)	(0.7052)	(8.8961)			
Democratic leaning							36.1986***	43.9854***	46.7472***
							(3.9326)	(4.6419)	(10.1583)
Republican leaning							17.9902	5.3912	3.9158
							(19.4024)	(22.6627)	(96.5035)
R^2	0.0000	0.0013	0.0000	0.0000	0.0009	0.0029	0.0426	0.0473	0.0551
N	7467	8145	2909	7467	8145	2909	1924	1811	363

Table 3: Panel regression of mean earnings growth forecast. Panel regression of earnings per share growth mean forecast (EPS_G) and a dummy variables representing: (1) if in the month of the forecast a major global policy event occurred (e.g., COP); (2) if in the month of the forecast the US experienced a major climate disaster (Coastal Flood, Drought, Flooding, Heat, Hurricane/Tropical Storm, Severe Storm/Thunder Storm, Tornado, Wildfire); (3) if the analyst publishing the forecast is headquartered in a Democratic or Republican leaning state. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. Controlling for firm fixed effect. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	(1)	(2)	(3)	(4)	(5)
	Emission intensity revenues	Emission intensity assets	Log absolute emission		
EPS_G	10.9458***	11.2541***	11.519***		0.8627***
	(0.2847)	(0.2807)	(0.2767)		(0.0296)
EPS_STD	17.7839***	16.8048***	15.987***		1.6472***
	(0.7799)	(0.7674)	(0.7565)		(0.0711)
$SCOPE\_1$	-0.0024***	-0.0024***	-3.887***		
	(0.0003)	(0.001)	(1.1323)		
$SCOPE\_2$	0.0362***	0.1014***	3.4302*		
	(0.0082)	(0.055)	(2.497)		
$SCOPE\_3$	-0.0002***	-0.0007	0.7659		
	(0.0001)	(0.0008)	(1.0117)		
Policy Event D				-8.7912***	-7.6727**
				(4.0842)	(3.9767)
Physical Event D				-10.5935***	-10.6058**
				(5.5972)	(5.4478)
R^2	0.9374	0.9366	0.9359	0.0002	0.0533
N	4269	4314	4395	18524	18524
Firm FE	Yes	Yes	Yes	Yes	Yes

Table 4: Panel regression of price-earnings ratio. From 1 to 3, panel regression of price-earnings ratio, earnings per share growth mean forecast (EPS_G), earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and the absolute value of the latest earnings per share - (EPS_STD), Scope 1,2,3 GHG emissions expressed in absolute and relative term (revenue and asset intensity). From 4 to 5, panel regression of price-earnings ratio on dummy variables indicating whether in the month of the forecast was published policy events (e.g., COP) or climate disasters occurred. Mean values across three forecast horizons from 1 fiscal year ahead up to 3 fiscal years ahead. Controlling for firm fixed effect. Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	Emission intensity revenues			Emission intensity assets			Log absolute emissions		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
EPS_G	17.2967***	12.98***	13.7058***	16.6831***	13.0224***	14.1021***	17.8769***	13.2896***	14.2496***
	(0.6355)	(0.1166)	(0.136)	(0.6346)	(0.1151)	(0.1261)	(0.5862)	(0.1193)	(0.1196)
EPS_STD	26.6804***	6.5801***	10.8526***	27.2408***	6.454***	11.37***	24.2669***	5.7001***	11.7554***
	(1.4345)	(0.3245)	(0.37)	(1.4405)	(0.3187)	(0.3833)	(1.3306)	(0.3298)	(0.3799)
$SCOPE\_1$	-0.0026***	-0.0006***	-0.004***	-0.0063***	-0.0013***	-0.0458***	4.4049***	-0.6993	-4.2443***
	(0.0006)	(0.0002)	(0.0006)	(0.0023)	(0.0006)	(0.0079)	(1.8606)	(0.6258)	(1.0644)
$SCOPE\_2$	-0.1652***	-0.0015	-0.036***	-0.6457***	-0.0207	0.0742	-15.008***	-0.5093	5.3516***
	(0.0129)	(0.0045)	(0.0096)	(0.091)	(0.0295)	(0.0576)	(4.0411)	(1.3719)	(2.2089)
$SCOPE\_3$	0.0017***	0.0001	-0.0003***	0.0028***	0.0003	-0.0021***	5.5713***	0.8104	-1.2405
	(0.0002)	(0.0001)	(0.0001)	(0.0013)	(0.0004)	(0.001)	(1.611)	(0.5528)	(0.8759)
R^2	0.8945	0.9828	0.9418	0.889	0.9828	0.9386	0.8842	0.9815	0.9389
N	3419	4004	1346	3438	4043	1348	3508	4116	1366
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Panel regression of price-earnings ratio by forecast horizon. Panel regression of price-earnings ratio, earnings per share growth mean forecast (EPS_G), earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and the absolute value of the latest earnings per share - (EPS_STD), Scope 1,2,3 GHG emissions expressed in absolute and relative term (revenue and asset intensity). Controlling for firm fixed effect. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	Emission intensity revenues			Emission intensity assets			Log absolute emissions		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
EPS_G	-5.9818***	9.156***	10.0781***	-5.9823***	9.1595***	10.0377***	-5.6565***	9.1349***	9.9935***
	(1.1138)	(0.2746)	(0.2055)	(1.1115)	(0.2745)	(0.2072)	(1.0935)	(0.2716)	(0.205)
EPS_STD	9.7193***	2.8072***	7.7574***	9.3767***	2.7101***	7.7124***	8.5685***	2.628***	7.7015***
	(1.7533)	(0.6202)	(0.3773)	(1.7438)	(0.6195)	(0.3814)	(1.7162)	(0.6149)	(0.3767)
$SCOPE\_1$	-0.0011***	-0.0006***	-0.0025***	-0.0105***	-0.0077***	-0.0093	0.0621	0.9973	-3.617***
	(0.0003)	(0.0003)	(0.0006)	(0.0035)	(0.0038)	(0.0096)	(1.1531)	(1.0902)	(1.3278)
$SCOPE\_2$	0.0063	0.0104	0.0138	-0.0042	0.0009	0.0588	-2.2137	-2.3698	4.1329***
	(0.0092)	(0.0089)	(0.01)	(0.0456)	(0.0422)	(0.0558)	(1.7632)	(1.7122)	(1.9595)
$SCOPE\_3$	0.0001	0.0001**	0.000	0.0023***	0.0017***	0.0002	2.6191***	1.5062***	-0.8795
	(0.0001)	(0.0001)	(0.0001)	(0.0007)	(0.0007)	(0.0009)	(0.643)	(0.6362)	(0.7416)
ROE	13.159**	-13.7406**	9.1733	11.5323*	-15.1511***	11.4629	13.7655***	-11.4116**	12.6821
	(7.0958)	(7.1305)	(9.9804)	(7.2646)	(7.353)	(10.7163)	(6.8544)	(6.8847)	(10.0069)
Liquidity	-0.6898***	0.6429***	0.0955	-0.7145***	0.6118***	0.1126	-0.7719***	0.586***	0.1293
	(0.1019)	(0.1)	(0.0946)	(0.102)	(0.1003)	(0.0937)	(0.1022)	(0.1008)	(0.0934)
Profit Margin	-0.3498	23.0589***	-23.5791***	1.1262	24.3493***	-24.0866***	-0.3925	22.1099***	-22.2324***
	(4.4942)	(4.5884)	(5.4822)	(4.5518)	(4.6522)	(5.7136)	(4.4237)	(4.5331)	(5.5078)
M/B	0.9747	0.4465	2.4517*	0.8564	0.4259	2.8574**	0.6531	0.5024	2.5215*
	(0.6852)	(0.7097)	(1.6169)	(0.6877)	(0.7119)	(1.6796)	(0.6751)	(0.7021)	(1.6377)
Leverage	-86.478***	19.2268**	-20.5334	-91.5516***	17.7566**	-28.4941**	-96.6882***	8.0353	7.8166
	(10.356)	(10.1505)	(14.7254)	(10.5015)	(10.4688)	(15.6561)	(15.9301)	(15.1902)	(20.6833)
Cash to Debt	105.3083***	-115.3787***	-10.0038	105.0166***	-112.0413***	-13.6987	81.9258***	-126.5316***	23.6891
	(12.948)	(12.603)	(14.9239)	(13.4048)	(13.1935)	(15.6913)	(17.2169)	(16.6157)	(21.1556)
R^2	0.0671	0.3398	0.7116	0.0704	0.3401	0.7074	0.0751	0.3383	0.707
N	2366	2479	1043	2366	2479	1043	2418	2532	1060
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Robustness analysis of price-earnings ratio on forecast disagreement regression. Panel regression of earnings per share growth mean forecast (EPS_G), earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and the absolute value of the latest earnings per share - (EPS_STD) and the price-earnings ratio. Including as control variables: Return on Equity (ROE), Interest coverage rate (Liquidity), Profit Margin, Market to Book (M/B), Assets to debt ratio (Leverage), and Cash to Debt. Controlling for firm fixed effects. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	Emission intensity revenues			Emission intensity assets			Log absolute emissions		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
EPS_STD	58.9609***	38.1219***	9.4497***	21.2152***	23.4367***	-0.301	-280.7932***	-129.6253***	-192.1518***
	(1.0358)	(0.295)	(0.8938)	(2.0554)	(0.5306)	(0.5886)	(6.7288)	(2.3791)	(4.2255)
TOT_EMISS	-463.4163***	-50.1747**	-539.8365***	-7255.9721***	-472.6214***	-2507.1871***	-0.7676***	-0.5625***	-2.4857***
	(53.42)	(27.1214)	(219.3579)	(607.1296)	(232.4031)	(929.4158)	(0.2072)	(0.1095)	(0.2624)
TOT_EMISS_STD	10.9375***	16.1093***	235.0278***	1694.9267***	913.0794***	4213.7354***	17.4751***	8.6794***	13.7564***
	(2.1538)	(1.3115)	(6.8984)	(80.6763)	(26.3322)	(54.4091)	(0.3416)	(0.121)	(0.2603)
R^2	0.8661	0.9307	0.6862	0.8802	0.9446	0.8803	0.9158	0.9667	0.7709
N	3421	4006	1348	3440	4045	1350	3510	4118	1368
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Panel regression of price-earnings ratio with emissions and forecast disagreement interaction. Panel regression of price-earnings ratio, Scope 1,2,3 GHG emissions expressed in absolute and relative term (USD mln revenues and assets) and interaction term between earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and absolute value of latest earning per share - (EPS_STD) and total emissions $EMISS\_STD$. Controlling for firm fixed effect. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	Emission intensity revenues			Emission intensity assets			Log absolute emissions		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
EPS_STD	-144.9668***	17.2523***	79.0991***	6.6337***	-1.9701***	7.6546***	11.4046***	-2.0635***	4.4649***
	(18.6816)	(6.9441)	(7.8942)	(2.1868)	(0.9511)	(1.0198)	(2.0249)	(0.883)	(0.8813)
TOT_EMISS	0.9471***	0.9494***	0.8876	1694.2122***	1119.5393**	3877.4815***	162.2697***	173.0214**	413.732***
	(0.3428)	(0.4058)	(0.6985)	(551.2063)	(650.9953)	(1484.9827)	(77.3247)	(100.2057)	(195.3629)
TOT_EMISS_STD	10.3639***	-1.3157***	-5.2424***	1849.2289	-195.1936	-5759.0534***	-234.1549***	-16.154	-238.4999***
	(1.2652)	(0.4671)	(0.5407)	(1284.9045)	(647.3618)	(944.0303)	(78.7568)	(52.299)	(86.7956)
ROE	13.8686***	-20.9593***	-30.3121**	12.603**	-22.5162***	-44.5367***	17.2699***	-19.0173***	-29.5146**
	(6.7981)	(8.206)	(16.7672)	(7.1708)	(8.6291)	(18.31)	(7.0454)	(8.4301)	(17.6469)
Liquidity	-0.4449***	0.862***	0.7805***	-0.6069***	0.9129***	0.81***	-0.6341***	0.9419***	0.7976***
	(0.1061)	(0.1202)	(0.1591)	(0.1042)	(0.12)	(0.1647)	(0.1023)	(0.1197)	(0.1685)
Profit margin	-0.3932	21.476***	-5.049	2.9232	23.3105***	-3.3259	0.1967	20.8166***	-6.5806
	(4.3367)	(5.3536)	(9.3553)	(4.5136)	(5.5224)	(9.8724)	(4.4827)	(5.4684)	(9.9053)
M/B	1.0849*	0.579	-2.1039	0.8802	0.38	-6.079***	1.1504**	0.398	-3.795
	(0.6656)	(0.8348)	(2.6995)	(0.6921)	(0.8568)	(2.9889)	(0.6884)	(0.8547)	(2.8924)
Leverage	-105.1858***	-20.563	-38.3963	-92.3705***	2.5909	-3.766	-92.1502***	5.6423	1.6264
	(13.9495)	(16.6605)	(32.9231)	(10.56)	(12.369)	(26.107)	(10.3969)	(12.0416)	(26.2242)
Cash to Debt	43.6282***	-110.4863***	1.877	79.7646***	-95.0741***	-14.1229	90.7292***	-94.2473***	-28.0553
	(15.3307)	(18.1628)	(32.5835)	(12.9072)	(15.1379)	(26.549)	(12.7333)	(15.0395)	(26.6984)
R^2	0.0817	0.0441	0.1253	0.0544	0.0419	0.0774	0.0526	0.042	0.052
N	2420	2534	1062	2368	2481	1045	2368	2481	1045
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Panel regression of price-earnings ratio with emissions and forecast disagreement interaction robustness. Panel regression of price-earnings ratio, Scope 1,2,3 GHG emissions expressed in absolute and relative term (USD mln revenues and assets) and interaction term between earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and absolute value of latest earning per share - (EPS_STD) and total emissions ($EMISS\_STD$). Including as control variables: Return on Equity (ROE), Interest coverage rate (Liquidity), Profit Margin, Market to Book (M/B), Assets to debt ratio (Leverage), and Cash to Debt. Controlling for firm fixed effect. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

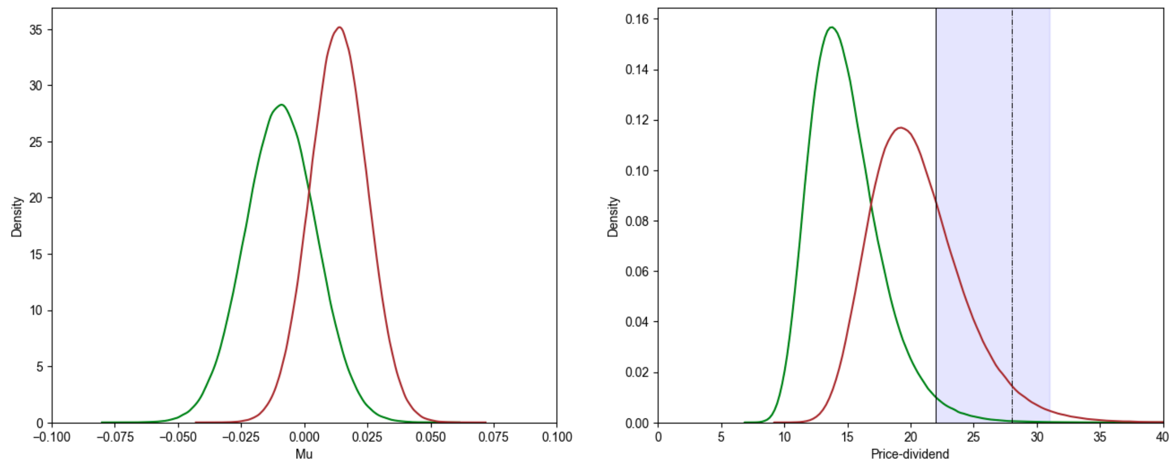

Figure 1: Scenario energy expenditure growth probability distributions and Price Dividend ratio. Left hand side chart shows yearly energy expenditure growth distribution (μ) from Network for Greening the Financial System (NGFS) scenarios. Right hand side chart shows distribution of price-dividend ratio simulated with the model. Green lines are distributions conditional to a set of scenarios assuming a climate policy shift (Net zero emissions by 2050 target). Brown lines are distributions conditional to a set of scenarios with no climate policy shift (Business as usual target). Values generated from parameters estimated based on an ensemble of NGFS climate scenarios. Full vertical line represents price-dividend ratio in Q4 2019, dashed line represents price-dividend ratio of the period 2016-2019 following the Paris Agreement. Shadow area shows the range of values in the period following the Paris Agreement. NGFS Scenarios used: Policy shift: Below 2°C, Net Zero 2050, Delayed transition, Divergent Net Zero. No policy shift: Current Policies. Models used: GCAM 5.3+ NGFS, MESSAGEix-GLOBIOM 1.1-M-R12, REMIND-MAgPIE 3.0-4.4

	Value	Mean Price-Dividend		Std Price-Dividend	
		No policy scenario	Policy scenario	No policy scenario	Policy scenario
Baseline		19.7249	14.9237	3.0995	2.8669
r_i	0.05	29.2781	19.9925	6.2523	4.6582
	0.07	17.6959	13.2081	2.9093	2.2933
	0.09	12.689	10.0354	1.6725	1.381
	0.11	9.8684	8.1313	1.0582	0.922
σ_i^2	0.02	21.5722	15.3742	7.382	4.4199
	0.03	23.7984	16.6053	13.9412	8.1763
	0.04	27.6246	18.7428	25.9365	14.924
	0.06	45.6795	28.441	115.54	61.4787
γ_i	0.5	18.198	15.5276	1.5155	1.4913
	0.7	19.0611	15.2486	2.289	2.0398
	1.3	22.2754	14.6574	5.5039	3.7066
	1.5	23.6145	14.5426	6.9424	4.2835
2016-2020			25.7681	2.68	
Q4 2019			22.1188		

Table 9: Price and μ probability mean and standard deviation sensitivity. Model generated mean and standard deviation of price-dividend ratio using different calibration parameters. From top to bottom: simulation of three levels of discount rate (r) from 0.05 to 0.11, simulation of three levels of uncertainty (σ^2) from 0.02 to 0.06, simulation of three levels of elasticity of dividends to energy expenditure (γ) from 0.5 to 1.5. NGFS Scenarios used: Policy shift: Below 2°C, Net Zero 2050, Delayed transition, Divergent Net Zero. No policy shift: Current Policies. Models used: GCAM 5.3+ NGFS, MESSAGEix-GLOBIOM 1.1-M-R12, REMIND-MAgPIE 3.0-4.4

8 Appendix

A Full derivation of the model

Let $E_{i,t}$ denote the level of energy expenditure for energy produced by firm i. Energy supply matches energy demand. Let $E_{i,t}$ follow the process in (1), where dW_t is a process with mean zero and unit variance $dW_t \sim \mathcal{N}(0, 1)$

$$dE_{i,t} = \mu_i E_{i,t} dt + \omega_i E_{i,t} dW_t \tag{1}$$

The drift μ_i in (1) remains constant for all $t \in [0, \infty]$. The level of μ_i is not known a priori and depends on an exogenous decision from the policy-maker about climate action. The representative investor expectations of μ_i are distributed normally with mean g_i and variance σ_i^2 as in (2)

$$\mu_i \sim \mathcal{N}(g_i, \sigma_i^2) \tag{2}$$

I assume that the change in the level of dividends D_i is proportional to the change in energy expenditure E_i for the respective energy production technology of firm i. Therefore the parameter γ_i denotes a known and constant scaling factor between the change in the energy expenditure and the change in dividends for firm i. In (1), I set $\omega_i = 0$ without loss of generality.

$$dD_i = \gamma_i dE_i \tag{3}$$

With the assumptions in (3), dividends grow at an exponential rate $\gamma_i \mu_i$ for all $t \in [0, \infty]$

$$D_{i,t} = D_{i,0} exp(\gamma_i \mu_i t) \tag{4}$$

Let $D_{i,t}$ denote the dividend paid by firm i at time t. The price of an asset at time 0 is the expected present value of future dividends from 0 to infinity discounted by a known rate r_i as in (5):

$$P_i = \mathbb{E}_0 \int_0^{\infty} D_{i,t} exp(-r_i t) dt \tag{5}$$

I assume that the discount rate r_i is based on an exogenous and known model of expected returns $\mathbb{E}_t[r_i] = r_i$. Substituting $D_{i,t}$ in equation (5) with the process in equation (4) and taking the expectations:

$$P_i = \mathbb{E}_0 \int_0^{\infty} D_{i,0} exp\left[(\mu_i \gamma_i)t\right] exp\left[(-r_i)t\right] dt \tag{6}$$

$$P_i = \mathbb{E}_0 \int_0^{\infty} D_{i,0} exp\left[(\mu_i \gamma_i - r_i)t\right] dt \tag{7}$$

$$\frac{P_i}{D_{i,0}} = \mathbb{E}_0 \int_0^{\infty} exp\left[(\mu_i \gamma_i - r_i)t\right] dt \tag{8}$$

$$\frac{P_i}{D_{i,0}} = \int_0^{\infty} exp\Big\{ \left[(g_i + \sigma_i^2/2)\gamma_i - r_i\right] t \Big\} dt \tag{9}$$

Equation (9) is a perpetuity growing at the rate $\alpha = (g_i + \sigma_i^2/2)\gamma_i$ and discounted at the rate r_i. Solving the integral between 0 and infinity results in the following equation:

$$P_i/D_i = 1/[r_i - (g_i + \sigma_i^2/2)\gamma_i] \tag{10}$$

Equation (10) shows a relationship between the price-dividend ratio and the four parameters discussed in the paper.

B Additional identification analyses

Firstly, I control analysts' forecasts are sensitive to climate policy events. The average forecast of the growth rate of earnings across all firms in the sample ($EPS\_G^{FH}_{i,t}$) and the average disagreement ($EPS\_STD^{FH}_{i,t}$) varies throughout time in line with key policy events (Figure A1). In the period around the announcement of the Paris agreement and following President Trump's subsequent withdrawal, I observe spikes in forecast disagreement, demonstrating the sensitivity of this metric to climate policy. Similarly this measure increases around the UN Climate action summit in 2019 and the release of the fourth IPCC report in late 2014. The forecast disagreement for one year ahead forecast horizon is more volatile than three years ahead which reacts more slowly. Analysts' forecasts about the growth of earnings also seem to react to policy events such as the Paris agreement and President Trump withdrawal. Following the former, all three measures of average earnings' growth start decreasing, although the metric for three years ahead forecast horizon is more stable.

Secondly, I compare the average forecast disagreement with general economic uncertainty. In Figure A2, I compare the average forecast disagreement for a three years ahead forecast horizon with two general uncertainty indexes: the VIX of the S&P 500 index and the measure proposed by Bloom (2009). This analysis highlights that the average forecast disagreement has a low correlation with general political and economic uncertainty. The VIX and the GEPU indexes are low in the period between the release of the IPCC Fourth Assessment report and the Paris agreement, contrary to the average forecast disagreement which peaks in the months preceding the Paris Agreement. The VIX is also low around the election of President Trump, although the GEPU spikes in the months preceding the nomination and then returns to normal levels around the elections. In this period, the average forecast disagreement does not spike in the months preceding the election, but only around and after the election when discussions about the US withdrawal from the Paris Agreement started. Although the VIX index is flat for most of the periods where climate policy developments unfolded, the GEPU index shows a somewhat negative correlation with the average forecast disagreement showing how it may not be substantially biased by general uncertainty.

Figure A1: Average forecast estimates time series. Average Mean EPS growth forecast ($EPS\_G_{i,t}^{FH}$) and earnings per share forecast disagreement ($EPS\_STD_{i,t}^{FH}$) relative to the absolute value of EPS. 480 fossil-fuel companies in the sample. Blue line on left hand side axis represents EPS_G^{FH} and orange line on right hand side axis represents EPS_STD^{FH} for forecast horizons (FH) 1,2,3. Vertical lines from left to right represent Fourth IPCC assessment report release, Paris Agreement, President Trump withdrawal from it and 2019 UN Climate action summit.

Thirdly, I compare the average forecast disagreement with other climate policy uncertainty (CPU) measures. In Figure A2, I compare the average forecast disagreement for three years ahead forecast horizon with three CPU indexes: the text mining approaches of Gavriilidis (2022), Noailly et al. (2022) and Berestycki et al. (2022). Opposite to general macroeconomic uncertainty indexes, the average forecast disagreement co-moves with the indexes of climate policy uncertainty, especially in the first part of President Trump's term. All measures of climate policy uncertainty increase in the periods around and after President Trump election, consistently with the measure of forecast disagreement.

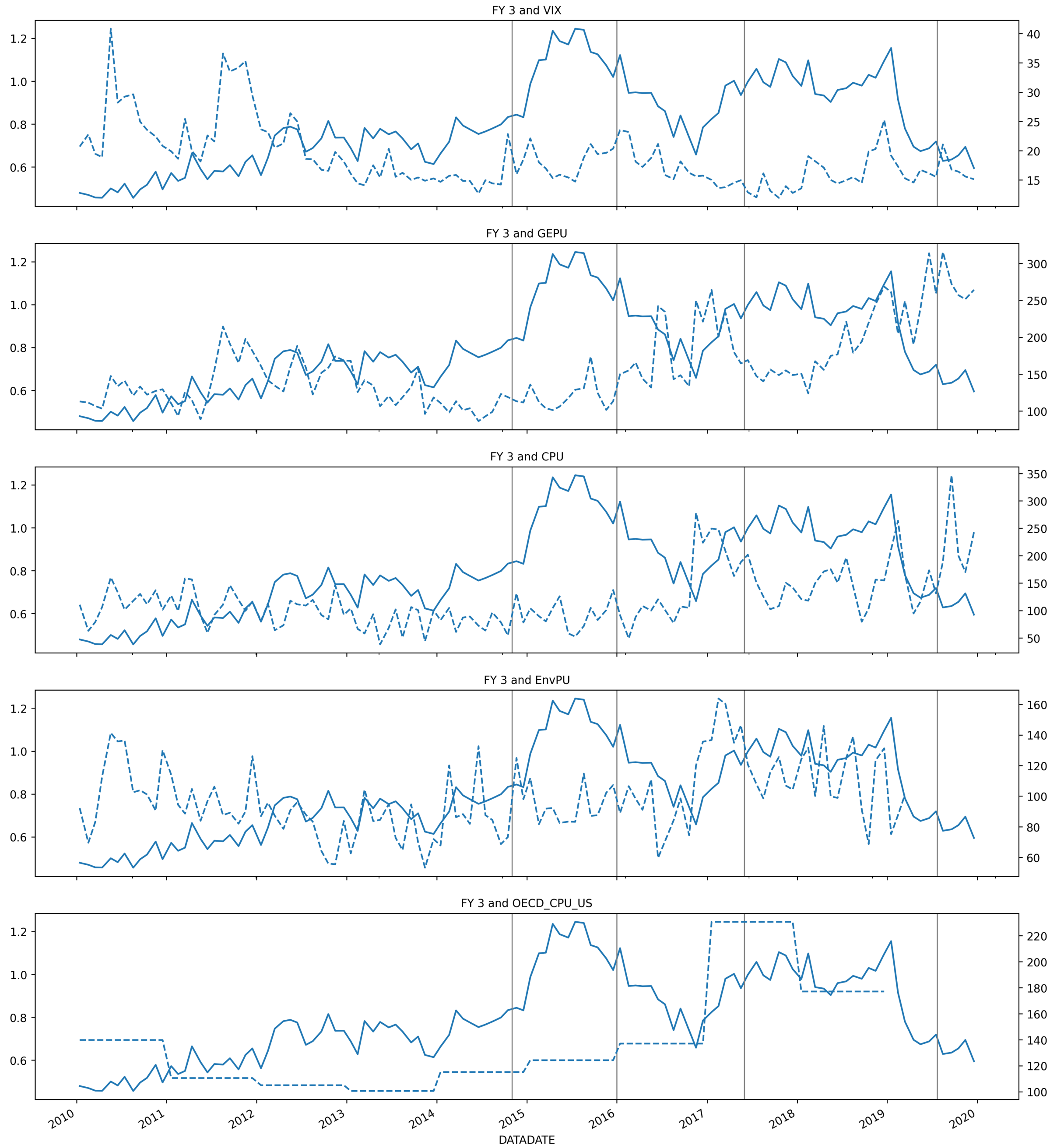

Figure A2: Uncertainty indexes comparison. Comparison of earnings per share forecast disagreement ($EPS\_STD^{FH}_{i,t}$) relative to the absolute value of EPS (Full line, left axis) and three indexes of uncertainty (Dashed lines, right axis). From top to bottom Vix of the S&P 500 index retrieved from Fred Database, Global Economic Uncertainty Index of Bloom (2009), Climate Policy Uncertainty index of Gavriilidis (2022) used by Chan and Malik (2022), EnvPU from Noailly et al. (2022) and OECD CPU index of Berestycki et al. (2022). Vertical lines from left to right represent Fourth IPCC assessment report release, Paris Agreement, President Trump withdrawal from it and 2019 UN Climate action summit. Excluding the 15 renewable energy companies in the sample.

Interestingly, the text-based measures of climate policy uncertainty do not increase in the periods around the Paris Agreement, as opposed to the average of forecast disagreement, which peaks in the months preceding the Paris Conference of Parties (COP). Arguably in such case uncertainty may have been high given the relevance of such accord for the future of the fossil-fuel industry. Nevertheless, with the exception of the Paris Agreement, the measure seems to track fairly well the trend of the EnvPU index proposed by Noailly et al. (2022) giving comfort that the measure used in this paper tracks, to a good extent, climate policy uncertainty.

Finally, I compare the average forecast disagreement with the average implied option volatility for the fossil-fuel firms in my sample. In Figure A3, I show that this market measure of uncertainty co-moves with the level of forecast disagreement. This suggests that analysts' forecasts may be related to actual investment decisions and market outcomes. Moreover, I remove from the average implied volatility (IMVOL) the general stock market volatility using the S&P 500 volatility index (VIX) index. This additional analysis shows that the spikes in uncertainty may emerge from fossil-fuel companies specific events as opposed to general market uncertainty. The implied volatility of the S&P 500 remains flat throughout major climate events in the sample. This provides further support to the main assumption that forecast disagreement about the fundamentals of fossil-fuel firms may be a sensible measure of market climate policy uncertainty. Correlation coefficients are reported in Table A9.

Figure A3: Investors disagreement and implied option volatility. Comparison of earnings per share forecast disagreement ($EPS\_STD^{FH}_{i,t}$) - orange line - and average implied option volatility for the 303 companies with traded options (out of 480 fossil-fuel companies) removing S&P 500 option volatility - dashed line. Vertical lines from left to right represent Fourth IPCC assessment report release, Paris Agreement, President Trump withdrawal from it and 2019 UN Climate action summit. Excluding the 15 renewable energy companies in the sample.

C Additional figures and tables

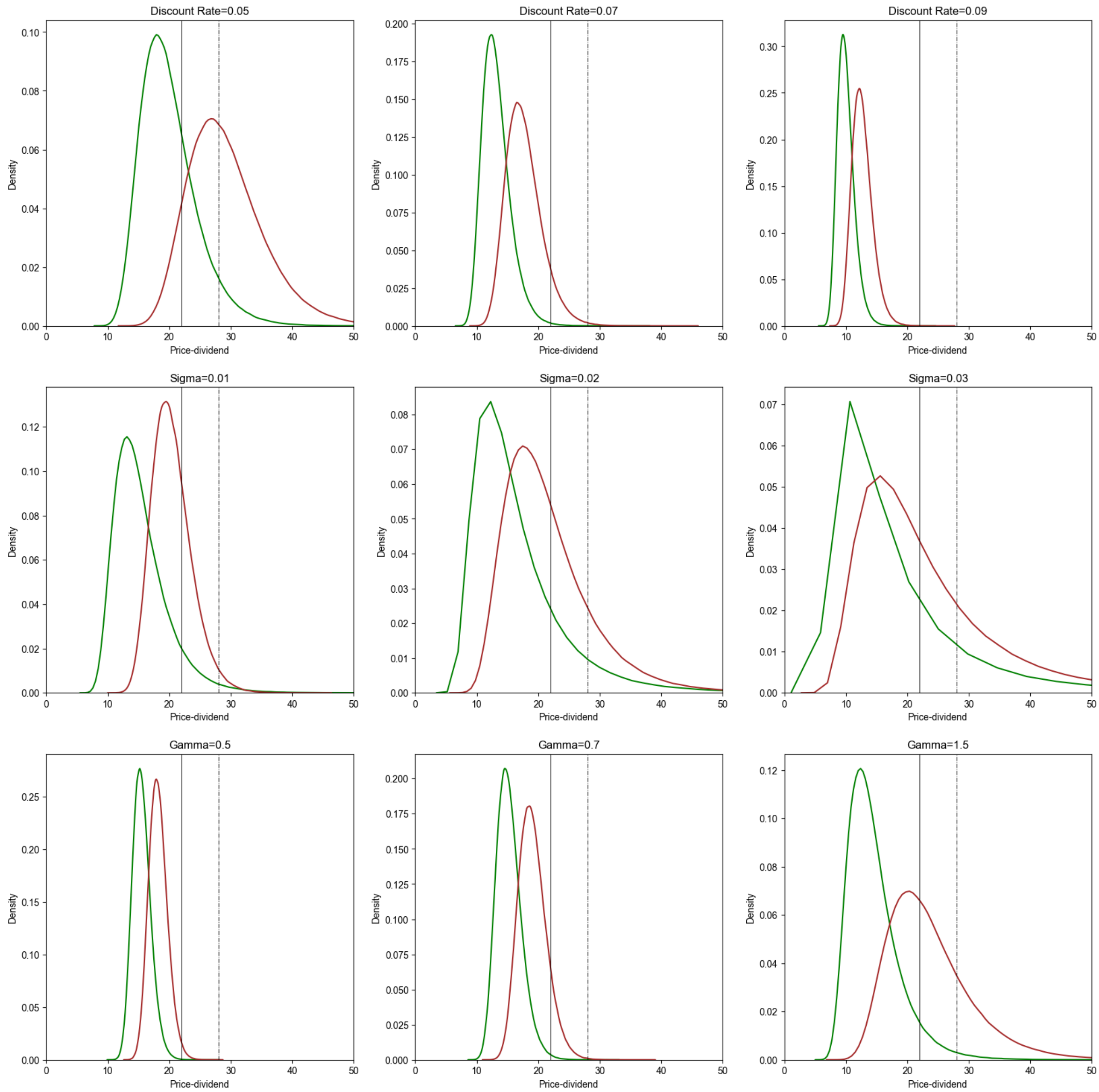

Figure A4: Price and μ probability distributions sensitivity. The chart shows the model generated distribution of price-dividend ratios using different calibration parameters. The green distribution represents climate policy shift scenarios and brown distribution represent no climate policy scenario. Values generated from parameters estimated based on an ensemble of NGFS climate scenarios conditional to the respective emission scenario. Full vertical line represents price-dividend ratio in Q4 2019, dashed line represents price-dividend ratio of the period 2016-2019 following the Paris Agreement. From top to bottom: simulation with three levels of discount rate r from 0.05 to 0.11, simulation of three levels of uncertainty σ^2 from 0.02 to 0.04, simulation of three levels of γ from 0.5 to 1.5. NGFS Scenarios used: Policy shift: Below 2°C, Net Zero 2050, Delayed transition, Divergent Net Zero. No policy shift: Current Policies. Models used: GCAM 5.3+ NGFS, MESSAGEix-GLOBIOM 1.1-M-R12, REMIND-MAgPIE 3.0-4.4

	Emission intensity revenues			Emission intensity assets			Log absolute emissions		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
DPS_G	24.299***	9.9384***	7.5175***	24.3938***	9.9013***	7.5369***	26.1994***	10.077***	7.2865***
	(2.6987)	(0.6192)	(0.3029)	(2.7126)	(0.6181)	(0.3023)	(2.6838)	(0.5966)	(0.3022)
DPS_STD	11.5108***	-7.8267***	3.1553***	12.2022***	-7.7941***	2.9109***	9.0567***	-7.4911***	3.4721**
	(3.336)	(2.1587)	(2.0133)	(3.2911)	(2.153)	(2.0166)	(3.2416)	(2.0798)	(2.0011)
$SCOPE\_1$	-0.0003***	-0.0001	-0.0001	0.0011***	0.0002	-0.0001	0.8328***	0.7727***	0.7703***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0011)	(0.3403)	(0.3379)	(0.2331)
$SCOPE\_2$	-0.0076***	-0.0092***	-0.0042***	-0.0091	-0.0314***	-0.0185***	-2.7757***	-2.6441***	-1.7497***
	(0.0019)	(0.0019)	(0.0012)	(0.0084)	(0.0083)	(0.006)	(0.8272)	(0.8179)	(0.5387)
$SCOPE\_3$	0.0001***	0.0001***	0.0001***	-0.0001	0.0002	0.0002*	1.0441***	0.9102***	0.5196***
	(0.000)	(0.000)	(0.000)	(0.0001)	(0.0001)	(0.0001)	(0.3689)	(0.3667)	(0.247)
R^2	0.0926	0.1651	0.6335	0.1098	0.1628	0.6334	0.1311	0.2179	0.6447
N	2421	2152	529	2436	2164	529	2445	2172	529
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A1: Panel regression - price-dividend and forecast disagreement regression. Panel regression of price-dividend ratio, dividends per share mean growth forecast (DPS_G), dividend per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and the latest dividend per share - (DPS_STD), Scope 1,2,3 GHG emissions expressed in absolute and relative term (revenue and asset intensity). Controlling for firm fixed effect. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	Emission intensity revenues			Emission intensity assets			Log absolute emissions		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
DPS_G	33.2981***	21.1773***	7.7613***	33.7498***	21.4658***	7.9534***	34.9199***	21.0423***	8.2046***
	(3.6959)	(1.308)	(0.3889)	(3.761)	(1.3224)	(0.4284)	(3.6524)	(1.3424)	(0.3648)
DPS_STD	7.6224**	10.3006*	1.6168	8.4008**	11.6957**	1.723	4.196	13.1327***	2.9484
	(4.5945)	(6.5555)	(2.4623)	(4.7473)	(6.4825)	(2.5508)	(4.5519)	(6.5077)	(2.7698)
SCOPE_1	-0.0004	0.0049***	0.0016	0.0369***	0.0651***	0.0094	5.722***	5.4706***	-1.066**
	(0.0013)	(0.0018)	(0.0015)	(0.0087)	(0.0093)	(0.0075)	(0.6209)	(0.6825)	(0.6145)
SCOPE_2	-0.0233***	-0.0278***	-0.0022	-0.1277***	-0.2176***	-0.0071	-11.4157***	-11.3648***	2.0791**
	(0.0052)	(0.0058)	(0.0043)	(0.0266)	(0.0279)	(0.0261)	(1.4268)	(1.5959)	(1.1271)
SCOPE_3	0	-0.0005***	-0.0001	-0.0008**	-0.0026	-0.0001	4.349***	4.083***	-0.6663
	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.0005)	(0.0005)	(0.6415)	(0.723)	(0.534)
ROE	77.528***	33.7519***	29.3699***	81.6477***	45.6709***	30.1598***	90.7101***	45.691***	25.9262***
	(6.8535)	(7.8033)	(6.8127)	(6.8106)	(7.7396)	(6.6137)	(6.5991)	(7.622)	(6.5938)
Liquidity	0.0682*	0.1172***	-0.0269	0.0975***	0.1493***	-0.0231	0.0809**	0.1628***	-0.0461**
	(0.043)	(0.0445)	(0.0274)	(0.0433)	(0.0441)	(0.0278)	(0.0421)	(0.0442)	(0.0276)
Profit Margin	-10.1111***	-4.113	20.2271***	-10.902***	-6.5535**	21.1993***	-14.2733***	-7.2457***	22.9878***
	(3.5488)	(3.8186)	(4.3397)	(3.5133)	(3.7553)	(4.3444)	(3.381)	(3.7295)	(4.3008)
MB	1.2782***	0.8824**	0.678***	1.2111***	1.4515***	0.3591	1.2796***	0.9623**	0.8321***
	(0.5222)	(0.5321)	(0.2706)	(0.6773)	(0.6831)	(0.3127)	(0.5133)	(0.5335)	(0.2666)
Leverage	3.3987	9.9118*	-27.85***	-2.9169	14.3385***	-30.2166***	-19.4244**	4.7369	-37.0031***
	(6.4159)	(6.7951)	(5.2577)	(6.6125)	(7.0163)	(7.8147)	(10.2668)	(11.5347)	(7.8575)
Cash Debt	-50.8202***	-57.9809***	-10.4426	-73.9358***	-89.5926***	-15.1901**	-98.0335***	-94.5473***	1.8338
	(7.4716)	(8.0707)	(7.7089)	(7.8679)	(8.2113)	(9.1075)	(11.3734)	(12.3614)	(11.7244)
R^2	0.3323	0.4149	0.7771	0.308	0.4053	0.7796	0.3498	0.4036	0.7787
N	1078	956	285	1078	956	285	1079	956	285
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A2: Robustness analysis - price-dividend and forecast disagreement regression. Panel regression of dividends per share growth mean forecast (*DPS_G*), dividend per share forecast disagreement (defined as the ratio between the standard deviation of analysts' estimates and the latest dividends per share - *DPS_STD*) and the price-dividend ratio. Controlling for firm fixed effects. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	Emission intensity revenues			Emission intensity assets			Log absolute emissions		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
EPS_G	27.2502***	12.98***	13.7058***	27.2028***	15.3939***	14.9817***	27.1435***	15.3985***	14.9737***
	(0.1603)	(0.1166)	(0.136)	(0.1617)	(0.0511)	(0.1401)	(0.1629)	(0.0493)	(0.1394)
EPS_STD	76.5105***	6.5801***	10.8526***	71.1351***	24.6416***	19.1861***	70.937***	27.5642***	23.9605***
	(3.5108)	(0.3245)	(0.37)	(3.5313)	(1.3739)	(2.528)	(3.6797)	(1.4774)	(2.8263)
$SCOPE\_1$	-0.011***	-0.0006***	-0.004***	-0.0917***	-0.0367***	-0.0363***	-2.5105***	-1.5041***	-0.1005
	(0.0008)	(0.0002)	(0.0006)	(0.0085)	(0.0045)	(0.0156)	(0.9262)	(0.3202)	(0.7964)
$SCOPE\_1$	-0.0355***	-0.0015	-0.036***	-0.0205	0.0597	0.0242	2.9446***	0.2718	-0.5699
	(0.0177)	(0.0045)	(0.0096)	(0.0949)	(0.0467)	(0.1148)	(1.4499)	(0.3062)	(0.7669)
$SCOPE\_3$	-0.0028***	0.0001	-0.0003***	-0.0061***	0.0013	-0.0026	-2.1393***	0.4487	-0.8871
	(0.0003)	(0.0001)	(0.0001)	(0.0018)	(0.0009)	(0.0021)	(0.6594)	(0.3157)	(0.5971)
R^2	0.7819	0.9828	0.9418	0.778	0.9174	0.7888	0.7745	0.9176	0.7898
N	8282	4004	1346	8282	9251	3172	8282	9251	3172
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A3: Price-earnings and forecast disagreement - Winsorised regression. Panel regression of price-earnings ratio, earning per share growth mean forecast (EPS_G), earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and latest earnings - (EPS_STD), Scope 1,2,3 GHG emissions expressed in absolute and relative term. Controlling for firm fixed effect. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Winsorising to the 5th and 95th percentile. Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	Emission intensity revenues			Emission intensity assets			Log absolute emissions		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
EPS_G	-45.0162***	-34.8575***	-26.9768***	7.9701***	8.1953***	9.0198***	6.2517***	5.6326***	7.6415***
	(7.4724)	(0.979)	(1.0041)	(7.5738)	(0.9473)	(1.2481)	(7.0996)	(0.8978)	(1.0991)
EPS_STD	71.7916***	56.0785	39.0953***	0.0745***	0.7899	-3.6653***	139.4269***	159.3744	106.0413***
	(9.1957)	(7.1545)	(29.4485)	(10.403)	(7.2033)	(34.6903)	(9.1495)	(6.6003)	(31.4603)
$SCOPE\_1$	0.0099	-0.0001	2.0661***	-0.0001***	-0.0005	2.4151	-0.0065***	-0.0017***	-0.4583*
	(0.0004)	(0.0005)	(0.0007)	(0.0034)	(0.0035)	(0.0052)	(0.3829)	(0.3896)	(0.3003)
$SCOPE\_2$	-0.0347***	-0.0103***	-5.0708	-0.0668***	-0.0154***	-6.185	0.0131***	0.004***	-0.915
	(0.002)	(0.0022)	(0.0032)	(0.0105)	(0.0112)	(0.0157)	(0.94)	(0.9312)	(0.6405)
$SCOPE\_3$	-0.0005***	0.0001	1.8509	0.0008*	0.0002***	2.2671	0***	0.0001***	1.027***
	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0004)	(0.4295)	(0.4393)	(0.2908)
R^2	0.1713	0.1863	0.2342	0.2664	0.2761	0.3863	0.8757	0.8879	0.9334
N	492	492	492	367	367	367	34	34	34
FE Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A4: Panel regression considering minimum number of estimates greater than 15. Panel regression of price-earnings ratio, earning per share growth mean forecast (EPS_G), earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and the absolute value of the latest earnings per share - (EPS_STD), Scope 1,2,3 GHG emissions expressed in absolute and relative term (revenue and asset intensity). Controlling for firm fixed effect. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. Considering at least 15 analysts' forecasts for each forecast date. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	Emission intensity revenues			Emission intensity assets			Log absolute emissions		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
EPS_G	15.7828***	8.1093***	11.4338***	15.2102***	7.9844***	11.4045***	14.141***	8.1621***	11.4513***
	(1.4887)	(0.3517)	(0.1841)	(1.4804)	(0.3516)	(0.1849)	(1.4593)	(0.3439)	(0.1852)
EPS_STD	36.1642***	0.5417	-11.7913***	32.2877***	1.1212	-12.644***	29.3903***	0.3254	-13.2866***
	(2.8394)	(1.4275)	(1.3773)	(2.7964)	(1.4165)	(1.3882)	(2.827)	(1.3806)	(1.3541)
$SCOPE\_1$	-0.0001***	-0.0002***	0.0003***	0.000***	0.000*	-0.0001***	0.1023	2.4821***	0.5872
	(0)	(0)	(0.0001)	(0.2886)	(0)	(0)	(0)	(0.254)	(0.4126)
$SCOPE\_2$	0.0011	-0.0022***	-0.0008	0.0089	-0.0074***	0.0006	-1.6785***	-7.6011***	-1.0468
	(0.0063)	(0.0007)	(0.0013)	(0.6802)	(0.0037)	(0.0054)	(0.0008)	(0.5963)	(0.9737)
$SCOPE\_3$	0.0000***	0.0001***	0.0000	-0.0001	0.0001***	0	1.1384***	3.5286***	0.3725
	(0.0001)	(0)	(0)	(0.2966)	(0.0001)	(0.0001)	(0)	(0.2605)	(0.4301)
R^2	0.0915	0.1853	0.6499	0.0791	0.1886	0.6444	0.088	0.2178	0.6354
N	5026	4739	2859	5131	4820	2895	5205	4878	2922
FE Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A5: Panel regression considering minimum number of estimates greater than 5. Panel regression of price-earnings ratio, earning per share growth mean forecast (EPS_G), earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and the absolute value of the latest earnings per share - (EPS_STD), Scope 1,2,3 GHG emissions expressed in absolute and relative term (revenue and asset intensity). Controlling for firm fixed effect. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. Considering at least 5 analysts' forecasts for each forecast date. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	Emission intensity revenues			Emission intensity assets			Log absolute emissions		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
EPS_G	17.1052***	6.9151***	11.2296***	28.3143***	6.9207***	11.6557***	17.8288***	13.2681***	14.2242***
	(0.6361)	(0.1191)	(0.1385)	(0.6379)	(0.1183)	(0.1283)	(0.5806)	(0.1197)	(0.1204)
EPS_STD	27.1682***	-0.0001***	-0.0031***	-0.0043***	-0.0009***	-0.0286***	24.485***	5.7348***	11.7644***
	(1.4348)	(0.33)	(0.3855)	(1.4482)	(0.3277)	(0.3886)	(1.3179)	(0.3307)	(0.3828)
$SCOPE\_1$	-0.0009*	-0.0086	-0.0358***	-0.5352**	-0.0388*	0.0446***	-40.5824***	-5.5114***	-11.0889***
	(0.0006)	(0.0002)	(0.0006)	(0.0023)	(0.0006)	(0.0099)	(8.1869)	(2.5809)	(4.2097)
$SCOPE\_2$	-0.1748***	0.0001**	-0.0002***	0.0018***	0.0006	-0.0015	9.4041*	0.5639	8.0049***
	(0.0138)	(0.0048)	(0.0105)	(0.1002)	(0.032)	(0.0663)	(5.7907)	(1.8858)	(3.0257)
$SCOPE\_3$	0.0017***	-5.3806***	-7.684*	7.6564	-5.6498*	-12.3879	-1.062	0.8697	-1.6532*
	(0.0002)	(0.0001)	(0.0001)	(0.0014)	(0.0004)	(0.0012)	(1.8816)	(0.6387)	(1.0151)
Oil & Gas Integrated	-28.6921	-12.5501*	-12.3189	-19.1706	-12.1612*	-15.7063***	553.8283***	64.5136***	84.4228**
	(10.7114)	(3.583)	(5.6183)	(11.0083)	(3.5704)	(6.1507)	(93.3896)	(29.5752)	(49.6363)
Oil & Gas Exploration & Production	6.0277***	-1.6712***	3.4812***	30.872***	-1.7374***	14.6732***	487.455***	54.8813***	76.3594**
	(5.9428)	(2.1111)	(3.6648)	(5.5961)	(1.919)	(4.1019)	(86.3388)	(27.389)	(44.8119)
Oil & Gas Refining & Marketing	-39.2344	-3.1263	-6.316	-46.3015***	-3.0683	-12.9933**	536.9284***	65.6017***	98.6779***
	(10.6681)	(3.6876)	(6.8463)	(11.3972)	(3.7567)	(8.7145)	(89.6028)	(28.2971)	(46.763)
Oil & Gas Storage & Transportation	-12.2363***	11.3516	-11.434	-12.5959***	11.6155	-5.2359**	430.0717***	61.4769***	72.1224*
	(8.3302)	(2.5497)	(5.6916)	(8.996)	(2.6562)	(6.8559)	(85.4417)	(27.1637)	(43.9035)
Coal & Consumable Fuels	12.8433	13.7574*	16.2278	12.855	14.1271*	-5.2359	495.6135***	78.3061***	82.7269**
	(23.433)	(7.4975)	(11.8621)	(23.9571)	(7.4611)	(12.699)	(89.8103)	(28.4755)	(46.4238)
R^2	0.8958	0.983	0.9424	0.8906	0.9830	0.9400	0.887	0.9815	0.9394
N	3424	4009	1351	3443	4048	1353	3513	4121	1371
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A6: Panel regression including sub-industries. Panel regression of price-earnings ratio, Scope 1,2,3 GHG emissions expressed in absolute and relative term (USD mln revenues and assets), earning per share growth mean forecast (EPS_G), earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and the absolute value of the latest earnings per share - (EPS_STD), and Sub-industries. Controlling for firm fixed effect. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 years fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	(1)			(2)		
	FH 1	FH 2	FH 3	FH 1	FH 2	FH 3
EPS_G	4.7607***	9.653***	0.0998***	5.032***	15.1348***	18.3934***
	(0.4174)	(0.1036)	(0.0298)	(1.5871)	(0.3077)	(0.3067)
EPS_STD	2.8888***	7.5983***	0.1848***	41.8321***	9.2057***	16.7057***
	(0.6759)	(0.1477)	(0.0751)	(1.9537)	(0.7782)	(0.5838)
ESG	-14.2924***	-4.256	1.5273	12.5862***	9.2866***	18.4701***
	(5.4931)	(4.8142)	(9.544)	(11.9607)	(10.7321)	(16.8017)
ROE				31.5176***	12.2061	7.2309
				(12.5583)	(10.7171)	(22.0175)
Liquidity				0.0304	0.1579***	-0.3587***
				(0.0666)	(0.0546)	(0.1727)
Profit Margin				-15.7909***	-6.1174	-10.8346
				(6.9868)	(6.1265)	(10.005)
M/B				1.8768*	0.2918***	6.8752***
				(1.2254)	(1.2897)	(2.8981)
Leverage				-76.5667***	-0.9529	-116.5636***
				(19.2522)	(17.4137)	(32.6335)
Cash to Debt				-0.1104	-100.9435***	-6.4637
				(16.8417)	(15.3721)	(25.6419)
R^2	0.0587	0.6646	0.006	0.1441	0.4578	0.7506
N	4835	5467	2124	2924	3047	1387
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A7: Panel regression robustness including ESG ratings. Panel regression of price-earnings ratio, earning per share growth mean forecast (EPS_G), earnings per share forecast disagreement - defined as the ratio between the standard deviation of analysts' estimates and the absolute value of the latest earnings per share - (EPS_STD), and Refinitiv ESG scores. Controlling for firm fixed effect. From left to right: analysts' estimates for 1 fiscal year ahead (FH+1) up to 3 fiscal years ahead (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil-fuel companies. Considering at least 5 analysts forecasts. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

	P/E	EPS_G	EPS	ROE	Liquidity	Profit Margin	M/B	Leverage	Cash debt
P/E	1	0.106	0.1	0.02	0.00	0.00	0.00	-0.02	0.02
EPS_G	0.16	1	-0.36	0	0.00	0.03	0.02	-0.01	0.03
EPS_STD	0.10	-0.36	1	-0.08	0.00	-0.04	-0.04	0.07	-0.03
ROE	0.02	0	-0.08	1	0.02	0.38	-0.38	-0.28	0.12
Liquidity	0.00	0.00	0.00	0.02	1	0.1	0.00	0.01	0.10
Profit Margin	0.00	0.03	-0.04	0.38	0.1	1	-0.19	-0.14	0.22
M/B	0.00	0.02	-0.04	-0.38	0.00	-0.19	1	0.29	-0.02
Leverage	-0.02	-0.01	0.07	-0.28	0.01	-0.14	0.29	1	-0.40
Cash debt	0.02	0.03	-0.03	0.12	0.1	0.22	-0.02	-0.4	1

Table A8: Regression variables correlation. Pearson correlation coefficient matrix of variables in empirical analysis. From top to bottom and left to right: price earnings ratio (P/E, analysts earnings growth mean forecast (EPS_G), analysts forecast disagreement (EPS), Return on Equity (ROE), Interest coverage ration (Liquidity), Profit margin, Market to Book ratio (M/B), debt to assets (Leverage) and cash to debt. Monthly data between January 2010 and December 2019 for 480 fossil-fuel companies.

	PD	E_STD_1	E_STD_2	E_STD_3	VIX	GEPU	CPU	EnvPU	OECD	IVOL	IVOLSPX
PD	1	-0.54	-0.78	0.26	0.34	-0.67	-0.52	-0.31	-0.66	-0.52	-0.78
EPS_STD_1	-0.54	1	0.62	-0.21	-0.24	0.37	0.25	0.22	0.44	0.26	0.44
EPS_STD_2	-0.78	0.62	1	-0.34	-0.27	0.44	0.28	0.12	0.33	0.66	0.86
EPS_STD_3	-0.54	0.27	0.62	1	-0.4	0.05	0.02	0.12	0.43	0.34	0.62
VIX	0.34	-0.24	-0.27	0.09	1	0.02	-0.07	0.02	-0.31	0.35	-0.28
GEPU	-0.67	0.37	0.44	-0.27	0.02	1	0.66	0.23	0.42	0.37	0.38
CPU	-0.52	0.25	0.28	-0.01	-0.07	0.66	1	0.52	0.58	0.19	0.27
EnvPU	-0.31	0.22	0.12	0.24	0.02	0.23	0.52	1	0.59	0.13	0.15
OECD	-0.66	0.44	0.33	0.14	-0.31	0.42	0.58	0.59	1	0.09	0.33
IVOL	-0.52	0.26	0.66	-0.36	0.35	0.37	0.19	0.13	0.09	1	0.8
IVOLSPX	-0.78	0.44	0.86	-0.4	-0.28	0.38	0.27	0.15	0.33	0.8	1

Table A9: Indexes correlation. Pearson correlation coefficient matrix among climate uncertainty, general uncertainty indexes and measures of forecast disagreement for FH 1,2,3. Vix of the S&P 500 index retrieved from Fred Database, Global Economic Uncertainty Index (GEPU) of Bloom (2009), Climate Policy Uncertainty index (CPU) of Gavriilidis (2022) used by Chan and Malik (2022), EnvPU from Noailly et al. (2022) and OECD CPU index of Berestycki et al. (2022). Average implied option volatility of fossil-fuel firms in the sample (IVOL) and Average implied option volatility of fossil-fuel firms in the sample minus implied volatility of S&P 500 index (IVOLSPX).

Date	Event
20/04/10	BP Oil Rig explodes
10/12/10	COP 16
11/03/11	Fukushima
01/09/11	Solyndra bankruptcy
09/11/11	COP 17
09/02/12	US NRC approves new Nuclear Power Plants
27/03/21	EPA clean air act
17/04/12	EPA clean air act for natural gas
06/11/12	Obama election
07/12/12	COP 18
25/06/13	Obama climate action plan
20/09/13	EPA new rule to cut emissions from plants
23/11/13	COP 19
13/02/14	Ivanpah, Worlds's largest Solar power generation plant goes online
22/09/14	Rockefellers and over 800 global investors annnounce fossil fuel divestment
23/09/14	Climate submmit 2014
01/11/14	IPCC Fifth Assessment Report
12/12/14	COP 20
03/08/15	Obana annouces Clean Power Act
12/12/15	COP 21
08/11/16	Trump election
18/11/16	COP22
28/03/17	Trump sign reversal of Obama Clean power Act
01/06/17	US Withdraws from paris Agreement
31/07/17	Two nuclear plants abandoned before construction completed in NC
22/12/17	Act opens Artic Drilling
09/05/18	Solar power to be required by all New California homes by 2020
02/12/18	COP 24
22/03/19	New Mexico Commits to 100% Renewable Energy for Electricity by 2050
02/12/19	COP 25
20/10/19	Three Mile Island to Close

Table A10: Climate Policy Events. List of major climate policy events between 2010 and 2020

Date	Event	Property Damage (2021 USD)	Fatalities
30/04/11	Flooding	7,694,617,566	402
31/05/11	Coastal Flooding	7,997,691,811	202
31/08/11	Hurricane/Tropical Storm	4,083,073,551	113
31/07/12	Heat	755,061,921	121
31/10/12	Heat	24,326,399,473	49
31/05/13	Flooding	2,769,247,857	68
31/12/15	Flooding	406,764,972	61
30/06/16	Heat	206,311,372	62
31/08/16	Flooding	9,735,094,174	25
31/10/16	Coastal Flooding	4,210,043,341	37
31/08/17	Severe Storm/Thunder Storm	94,468,908,739	118
30/09/17	Hurricane/Tropical Storm	25,868,233,259	45
31/07/18	Heat	1,660,779,779	137
31/10/18	Hurricane/Tropical Storm	6,038,462,572	15
30/11/18	Wildfire	19,732,088,872	101

Table A11: Climate Physical Events. List of major climate disasters in the US between 2010 and 2020. Major disaster defined as event which caused either fatalities or property damages higher than the 90th percentile of events in the decade 2010-2020.

Democratic	Republican
BERGEN-PASSAIC, NJ	AUSTIN-SAN MARCOS, TX
BOSTON-WORCESTER-, MD	CHICAGO, IL
DENVER, CO	DALLAS, TX
FLORIDA	FORT WORTH-ARLINGTON, TX
HARTFORD, CT	HOUSTON, TX
JERSEY CITY, NJ	LOUISVILLE, KY-IN
LOS ANGELES-LONG BEACH, CA	MEMPHIS, TN-AR-MS
MIDDLESEX-SOMERSET-HUNTERDON, NJ	NASHVILLE, TN
MINNEAPOLIS-ST. PAUL, MN-WI	OKLAHOMA CITY, OK
NASSAU-SUFFOLK, NY	
NEW HAVEN-BRIDGEPORT	
NEW YORK-NEWARK, NY-NJ-PA	
NEWARK, NJ	
ORANGE COUNTY, CA	
PORTLAND-VANCOUVER,OR-WA	
RICHMOND-PETERSBURG, VA	
SAN DIEGO, CA	
SAN FRANCISCO, CA	
SAN JOSE, CA	
SEATTLE-BELLEVUE-EVERETT, WA	
WASHINGTON, DC-MD-VA-WV	

Table A12: Political orientation. Metropolitan statistical area and State political Orientation. Political orientation defined in terms of election results between 2004 and 2020 (four electoral cycles). Without considering states where election results were mixed in the four electoral cycles considered.