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

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Abstract

Prior 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 that, I develop an asset pricing model with uncertain expectations about the future cash flows of fossil fuels firms. The price-dividend ratio increases with uncertainty about a climate policy regime shift. This proposition is confirmed empirically using data on analysts' forecasts. I find that analysts' forecasts disagreement - as a proxy for climate policy uncertainty - might explain part of the valuations of a large sample of fossil fuels stocks. Using my model, I show with forward-looking scenarios that cash flows expectations implied in the valuations of fossil fuels firms may not be consistent with a net zero carbon transition.

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

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1 Introduction

Countries, businesses, and non-profit organizations 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 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 firms in spite of 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). But in a present value framework, (idiosyncratic) uncertainty may right-skew expected cash flows leading to higher valuations (Pástor & Veronesi, 2003, 2006). Contrary to what suggested by 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 might 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 flows expectations and explain part of the valuations of some of the most carbon intensive energy producers: fossil fuels firms. A climate policy regime shift can influence the trend of the stochastic process governing high and low carbon energy

[1] Source: Oxford net zero tracker

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 where high carbon energy will keep growing in line with the past. The uncertain occurrence of the climate policy regime shift means that the investor is unable to anticipate if and when the prospective shift will occur. That is, the sustained high levels of climate policy uncertainty affect the valuations of fossil fuels firms.

To conceptualise this effect, I develop a partial equilibrium asset pricing model with uncertainty where the long-term growth of fossil fuels firms depends on the occurrence or not of an uncertain climate policy regime shift. I show that the valuations of fossil fuels 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 absence of learning about the prospective climate policy regime shift and I refer to it 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 lower than one are less exposed to the policy *regime shift risk* while values higher 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 fuels firms with an empirical analysis of analysts' forecasts of dividends per share. I find that climate policy uncertainty might 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 future dividends' growth and the valuations of fossil fuels firms. Using analysts' forecasts disagreement as a proxy for market uncertainty in a panel regression, I find that the variance in dividends per share (DPS) forecasts - and similarly earnings per share (EPS) forecasts - is positively associated with the valuations of fossil fuels companies. This effect is generally higher for more carbon intensive firms and consistent across various dimensions explored in the robustness analysis.

I then use forward-looking climate scenarios to show that financial markets may be mispricing a net zero carbon transition. I observe that the valuations of fossil fuels stocks might be more closely aligned with the right tail of the distribution of price-dividend ratio conditional to a no climate policy regime shift estimated with my model. This suggests that either markets do not believe that policymakers will shift their climate policy to meet their pledges to prevent global warming, or they 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 flows expectations may lead to mispricing of the net zero carbon transition. In turn, high realised returns may not be a good proxy of expected returns as investors may reprice their cash flows 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 pay 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)[2]. Differently from previous research that focuses on realised returns, this paper discusses some asset pricing implications of the net zero carbon transition focusing on a forward-looking cash flows perspective[3]. In particular, it shows that the valuations of fossil fuels 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 financial markets are yet to

[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). It should also be noted that some opposite evidence also emerged (Aswani, Raghunandan, & Rajgopal, 2023; Hong, Li, & Xu, 2019)

[3]The reader should also note that changes in expectations (or news) around cash flows might explain more the variability in stock market prices of "value" stocks such as fossil fuels firms than discount rate news (Campbell & Vuolteenaho, 2004; La Porta, Lakonishock, Shleifer, & Vishny, 1997)

sufficiently 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 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 expected returns. Instead, high realised returns may be a product of mispricing generated by the effect of uncertainty on cash flows 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 the carbon premium may be a symptom of mispricing rather than of pricing of climate related transition risks and, in turn, that realised returns may not be reflective of expected returns[4].

Finally, this research 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 leaning about political costs lowers uncertainty with the passing of time leading to a higher risk premium and lower prices (Kelly, Pástor, & Veronesi, 2016; Pástor & Veronesi, 2012, 2013)[5], I argue that the inability to learn about the perspective climate policy maintains high the levels of cash flows uncertainty of carbon intensive firms. In the simple model developed in this paper, I show that this, in turn, could contribute to maintaining high the valuations of fossil fuels firms.

In Section 2, I develop a valuation framework of climate-sensitive firms and discuss some asset pricing implications. In Section 3, I outline the empirical strategy and the econometric specifications. In Section 4, I provide the results of the analysis and discuss

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

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

the empirical evidence. In Section 5, I provide some numerical simulation of the valuations of fossil fuels stocks conditional to a set of possible climate scenarios. The final Section concludes.

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 for energy 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 of many unknown factors surrounding the transition[6].

[6] 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 the *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 $t \in [0, \infty]$[7].

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 flows 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

[7]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 8, 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 can have an effect on the valuations of climate-sensitive assets through cash flows 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[8]. Investors do not know whether high carbon energy will remain predominant (leading to global warming) or whether the world will move towards net zero carbon emissions thanks to a

[8]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.

policy regime shift. In such case, uncertainty around policy action might 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, the 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 is 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 first instance, proportional to carbon emissions (intensity), as highlighted by extant literature. However, it may also be influenced by a broader set of factors such as the capacity of firms to cost-effectively abate emissions, the ability to transition to net zero carbon emissions, the increasing or decreasing returns to scale, and the difference in efficiency and profitability of companies. In general, the impact of a transition to net zero carbon emissions on polluting firms may vary greatly depending on a broader set of factors and not only carbon emissions. In turn, this implies that the heterogeneous exposure of climate sensitive firms to the policy regime shift risk might be a material driver of their valuations.

In this section, I describe a simple model of valuations of climate sensitive firms exposed to an uncertain policy regime shift to curb carbon emissions. Contrary to prior research that focuses only on the required rate of return, I show that the uncertainty around cash flows expectations may right-skew the valuations of fossil fuels 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 flows expectations. This entails that past realised returns may not be representative of expected returns as cash flows expectations might 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 fuels 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 fuels. Fossil fuels 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 absence of technological breakthroughs on carbon capture and storage.

I use professional analysts' forecasts of fossil fuels firm's fundamental value to proxy investors' expectations and their uncertainty. In line with previous literature, I measure investors' uncertainty using forecasts disagreement and I focus on its time-varying component (Anderson, Ghysels, & Juergens, 2009; Diether, Malloy, & Scherbina, 2002; Johnson, 2004)[9]. 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 are news about events which may affect, directly or indirectly, the likelihood of more stringent climate policy.

I use data from CRSP/Compustat to identify a set of fossil fuels energy stocks. I select sub-industries related to oil & gas consumable fuel companies according to the Global Industry Classification Standard (GICS)[10]. 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 IBES and Refinitiv firm'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 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

[9]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)

[10]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)

gives me a total of 480 fossil fuels stocks followed by stock market analysts. The data report analysts' forecasts for different forecasting horizon (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 fuels companies. Table 1 shows some descriptive statistics.

I perform some data cleaning and transformations to ensure the data is adequate for the analysis. In line with previous literature, I set a threshold of minimum required number of analyst's forecasts. I set the threshold to 10 in order to achieve the highest number possible of underlying estimates 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 between the beginning of 2010 and the end of 2019 as it is particularly suitable for the empirical analysis, but also because of data limitations in 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 would 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 forecasts (or forecasts disagreement about mean 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 forecasting 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 forecasting 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 of earnings - rather than understanding whether firms more exposed to uncertainty show higher prices[11]. 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[12].

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

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 (forecasts disagreement). This allows for a better identification of climate policy uncertainty. If forecasts 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-

[11] 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)

[12] The reader should note that in most cases fossil fuels stocks are not "growth" companies and generally pay dividends with a constant payout. Consequently, EPS and DPS results are expected to be similar

tion between my metric and climate policy uncertainty for fossil fuels firms by exploiting this instrument and I corroborate this 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 A, 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 forecasts disagreement tracks the average implied option volatility of fossil fuels firms[13]. These analyses, jointly with the empirical set up described in this section, should reassure that the results capture, at least to a certain extend, 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 fuels 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 fuels 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 fuels firms could be material.

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

4.1 Some determinants of analysts' expectations and climate policy uncertainty

In the first part of this subsection, I regress some possible factors of uncertainty on my measure of forecasts disagreement (EPS_STD). The objective of this analysis is to first describe what may drive uncertainty around fossil fuels 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' location 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 if in the month the forecast was published a climate policy event occurred. 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 one and two years forecasting horizon but it is significant and positive for three years forecasting horizon. This may indicate that in periods of climate policy events, analysts are generally more uncertain about the medium-long term future performance of fossil fuels firms. The list of climate policy events is provided in Appendix A10.

I then consider a set of climate disasters which may increase the salience of climate change. I use data from Spatial Hazard Events and Losses Database for the United States (SHELDUS)[14] which reports historical property damages and fatalities of natural hazards. I classify a major disaster as an occurrence which 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, Wildfire. I focus on the US as most analysts in my sample reside in this country. Similarly to climate policy events, I create a dummy if such 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 one year forecasting horizon. The list of events is provided in

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

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 future of fossil fuels firms. I use this as a proxy of political beliefs which may indicate different views about climate change. I use data from Gerken and Painter (2023)[15] about analysts' location and classify Democratic/Republican states depending on the outcome of the previous four elections. I classify as Democratic/Republican leaning states where the respective party consistently won the election between 2004 and 2020. I do not consider the 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., New York) tend to be more uncertain about the future performance of fossil fuels 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 occurred, the mean analysts' forecast is generally lower than in other periods. The coefficients of the regressions are negative and significant. Specifically, for policy events the coefficients are significant for two and three years ahead forecasting horizon. For climate disasters the only significant coefficients is for two years ahead forecasting horizon. Turning to political beliefs, the results suggest that analysts located in Democratic leaning states, not only are 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., New York, California) as opposed to Republican leaning states (e.g., Texas).

These analyses show some of the drivers of analysts' uncertainty about fossil fuels firms. The salience of climate policy events and climate disasters shows a weak correlation with my measure of uncertainty and a negative correlation with mean forecasts. Even though analysts headquartered in Democratic/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

[15] I thank the authors for sharing the data

tend to be more uncertain about the future of fossil fuels 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 are generally lower in the months such events occur.

4.2 The effects of uncertainty on the valuations of fossil fuels firms

In this subsection, I provide the results of the main empirical analysis. I start by averaging the forecasts across the three forecasting horizons in order to capture a stronger signal. Table 4 shows a positive and statistically significant relationship between analysts' forecasts disagreement and the price-earnings ratio (Specification 1). I show that given a mean forecast growth, periods with higher forecasts disagreement tend to have a higher price-earnings ratio, consistently with my model's prediction. This result seems to indicate that financial markets discount climate policy uncertainty through their cash flows 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 fuels 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 in line with expectations and significant. 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' forecast by different forecasting horizons (FH 1,2,3). The signs of the coefficients are consistently positive across the three forecasting horizon and highly significant. The coefficients are also economically significant: an expectation of doubling of the EPS in a three years forecasting 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. The variance explained by the regression model is high. 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 2 years 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 forecasting horizon of 2 years and log absolute emissions where the coefficient is not significant. Without considering the effects of uncertainty on cash flows expectations, higher carbon emissions entail lower price-earnings ratio in line with other empirical studies (Bolton, Halem, & Kacperczyk, 2022)[16].

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 Debt. The only exception is the EPS growth estimate EPS_G for 1 forecast horizon (FH 1) where the coefficient turns negative. But the R^2 also decreases substantially in this case to around 7%. On the opposite, the variance explained by the regression models for 2 and 3 years forecasting 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[17].

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

[16]It should be noted that - in line with previous literature - this result is based on Scope 1 emissions that are relatively low for fossil fuels firms. The exposure of fossil fuels 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 analysis I consider total emissions.

[17]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

and earnings per share forecasts 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 not winsorized sample. Scope 1 emission coefficients also remain negative and significant with the only exception of three years forecasting horizon and log absolute emissions which become not significant.

In Table A5, I show the results are robust to different thresholds of minimum number of analysts' forecasts. I test the cut-off I use for the minimum number of estimates, increasing it from 10 to 15 and decreasing it to 5 to test the sensitivity of the results to this parameter. The results generally persist increasing the minimum number of estimates, although with a few exceptions. The sample size decreases substantially considering only records with at least 15 estimates, decreasing the robustness of the model. On the opposite side, 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 in using my metrics with fewer than 10 analysts' forecasts because the measure 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 forecasts disagreement and the price-earnings ratio (Specification 2). This might 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 forecasts disagreement might be due to climate policy uncertainty. In line with the previous finding, the coefficient of forecast's disagreement remains generally positive and significant, although the sign turns negative for absolute emissions.

In Table A7, I report the robustness analysis. 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 might also contribute to the effects described in this paper. I am indeed aware that climate policy may only be one source of uncertainty that might affect cash flows expectations of fossil fuels stocks. But I argue this analysis is sufficient to show it might, at least partially, contribute to this broader uncertainty.

In this section, I show that there might be a positive relationship between time-varying uncertainty and the valuations of fossil fuels 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. These findings highlight how climate policy uncertainty might have weighed significantly on the valuations of fossil fuels firms and on their realised returns. In the next section, I discuss some of the implications of the effect of climate policy uncertainty on cash flows expectations for the valuations of fossil fuels 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 Discussion

In this section, I calibrate the model described in Section 2 to calculate some numerical results of the valuations of fossil fuels stocks conditional to a world with a climate policy regime shift and without. 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 fuels. I follow the approach of Campbell and Shiller (1989) and use my model to estimate a distribution of price-dividend ratio 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) to calculate the yearly growth rate of global energy expenditure on fossil fuels energy (energy demand multiplied by energy prices) g_d and its standard deviation σ_d^2 [18]. 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%[19]. In the baseline model, I set the elasticity of dividends to energy expenditure γ_d=1. This is the only parameter which 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[20].

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 in 2050 compared to 2020. The total fossil fuels expenditure in this scenario decreases from around 4 trillion USD in 2020 at 2010 prices to only 3.5 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 emitting energy might be

[18] 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.

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

[20] 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.

required. This implies that the estimates conditional to a climate policy regime shift are likely on the high-end of possible values and conservative, but they are already sufficiently different to illustrate the results.

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 is to the left of the one conditional to no climate policy regime shift. We would expect that in a world with climate policy high carbon emitting firms will grow slower or decline as opposed to a scenarios where climate policies lead to a transition to low carbon energy. I also show that the range of price-dividend ratio in the period after the Paris agreement 2016-2019 and the price-dividend ratio at the end of 2019. These ratios are fairly stable for "value" stocks such as fossil fuels with a standard deviation of around 2.5.

I then generate the conditional probability distributions of price-dividend ratio by varying selectively some of the baseline parameters to control for model mis-specification. This approach is useful because as long as it covers a wide range of plausible calibration parameters I am able to draw some observations on actual prices. I am aware of the possible mis-specification of the baseline model, but I argue at least one of the models simulated 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 the unknown level of μ_d is the key driver of the results[21].

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

I observe that the average valuations in the period 2016-2019 (after the Paris Agreement) and at the end of 2019 have been at the right of the distributions 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 fuels 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 entailing a world with only 30% less fossil fuels 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)[22]. Nevertheless, these results show that investors' uncertainty about climate policy might at least partially explain the valuations of fossil fuels 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 may be mispricing a net zero carbon transition.

and uncertainty the required rate of return might arguably tend to increase moving both price-dividend distributions to the left. It is more likely than not that the model is under-estimating the required rate of return r. This further corroborates my hypothesis

[22] According to the latest IPCC assessment report the likely of a possible future scenario where fossil fuels energy may be combined with Carbon Capture and Storage (CCS) has decreased substantially due to the increasingly lower price of renewable energy

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 light of climate policy uncertainty. In a present value framework, the main effect of transition risk on the valuations of carbon intensive firms may be on 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 carbon intensive 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 flows expectations might be material, possibly limiting the extent to which financial markets reflect in their valuations a transition towards lower carbon emissions. The future growth of carbon intensive firms may strongly depend on an uncertain climate policy regime shift affecting cash flows expectations. I showed that uncertainty may have weighed significantly on the valuations of some of the most carbon intensive businesses: fossil fuels firms. I provided evidence showing that part of this uncertainty may be due to climate policy. I then showed that it is unlikely that financial markets following the Paris Agreement priced expected cash flows consistently 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 a transition to net zero carbon emissions.

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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 forecasting 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	0.0000	0.0000	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 forecasts disagreement. Panel regression of earnings per share forecasts 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 fuels 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)
N	7467	8145	2909	7467	8145	2909	1924	1811	363
R^2	0.0000	0.0013	0.0000	0.0000	0.0009	0.0029	0.0426	0.0473	0.0551

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 fuels 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)
N	4269	4314	4395	18524	18524
R^2	0.9374	0.9366	0.9359	0.0002	0.0533
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 forecasts 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 forecasting 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 fuels 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)
N	0.8945	0.9828	0.9418	0.889	0.9828	0.9386	0.8842	0.9815	0.9389
R^2	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 forecasting horizon. Panel regression of price-earnings ratio, earnings per share growth mean forecast (EPS_G), earnings per share forecasts 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 fuels 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 forecasts disagreement regression. Panel regression of earnings per share growth mean forecast (EPS_G), earnings per share forecasts 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 fuels 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 forecasts 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 forecasts 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 fuels 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 forecasts 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 forecasts 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 fuels companies. *** significant at 5% confidence level, ** significant at 10% confidence level, * significant at 15% confidence level. Standard errors in brackets.

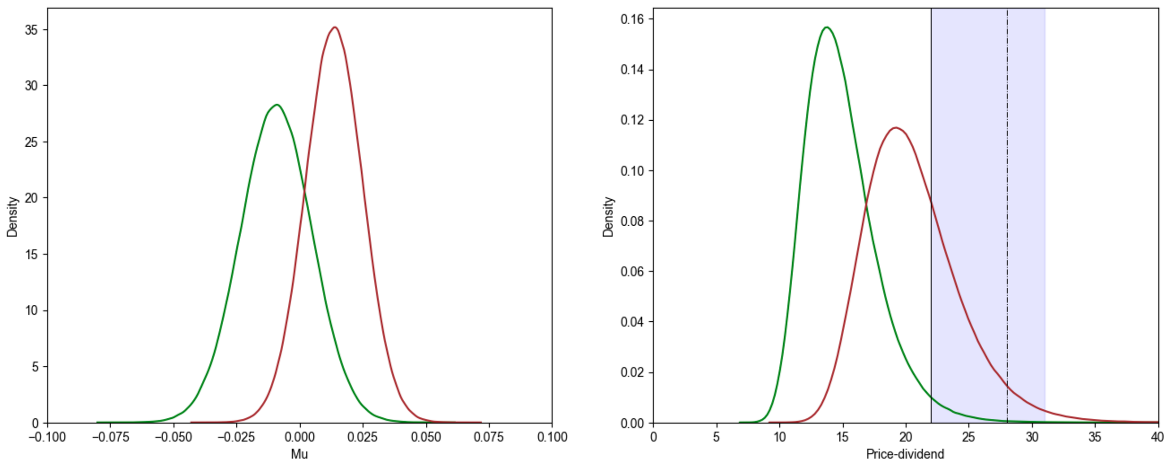

Figure 1: Scenario energy expenditure growth probability distributions and Price Dividend ratio. Left hand side chart shows yearly energy expenditure growth distribution (μ) from Network for Greening the Financial System (NGFS) scenarios. Right hand side chart shows distribution of price-dividend ratio 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

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.

A Additional identification analyses

Firstly, I control the metrics are sensitive to climate policy events. The average expected growth rate of earnings across all firms in the sample $EPS\_G_{i,t}^{FH}$ and their uncertainty $EPS\_STD_{i,t}^{FH}$ 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 the measures of uncertainty, demonstrating the sensitivity of this variable to climate policy. Similarly the measure increases around the UN Climate action summit in 2019 and the release of the fourth IPCC report in late 2014. The measure for the forecasting horizon (FH) of 1 year is more volatile than longer term expectations of a FH of 3 years, which reacts more slowly. Analysts' expectations 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 average measures of earnings growth for the firms in the sample start decreasing, although the metric for FH 3 is more stable.

Secondly, I compare my metric of uncertainty with general uncertainty. In Figure A2, I compare the measure of climate policy uncertainty for 3 years forecasting horizon with two general uncertainty indexes: the VIX of the S&P 500 index and the measure proposed by Bloom (2009). The measure 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 measure of climate policy uncertainty 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 forecasts disagreement index 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 measure of CPU showing how it might 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 forecasts disagreement ($EPS\_STD_{i,t}^{FH}$) relative to the absolute value of EPS. 480 Fossil fuels 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 forecasting 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 metric of uncertainty with other climate policy uncertainty measures. In Figure A2 I compare the measure of climate policy uncertainty for 3 years forecasting 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 measure co-moves with these indexes of climate policy uncertainty, especially in the first part of President Trump term. All measures of climate policy uncertainty increase in the periods around and after President Trump election, consistently with the measure of forecasts disagreement.

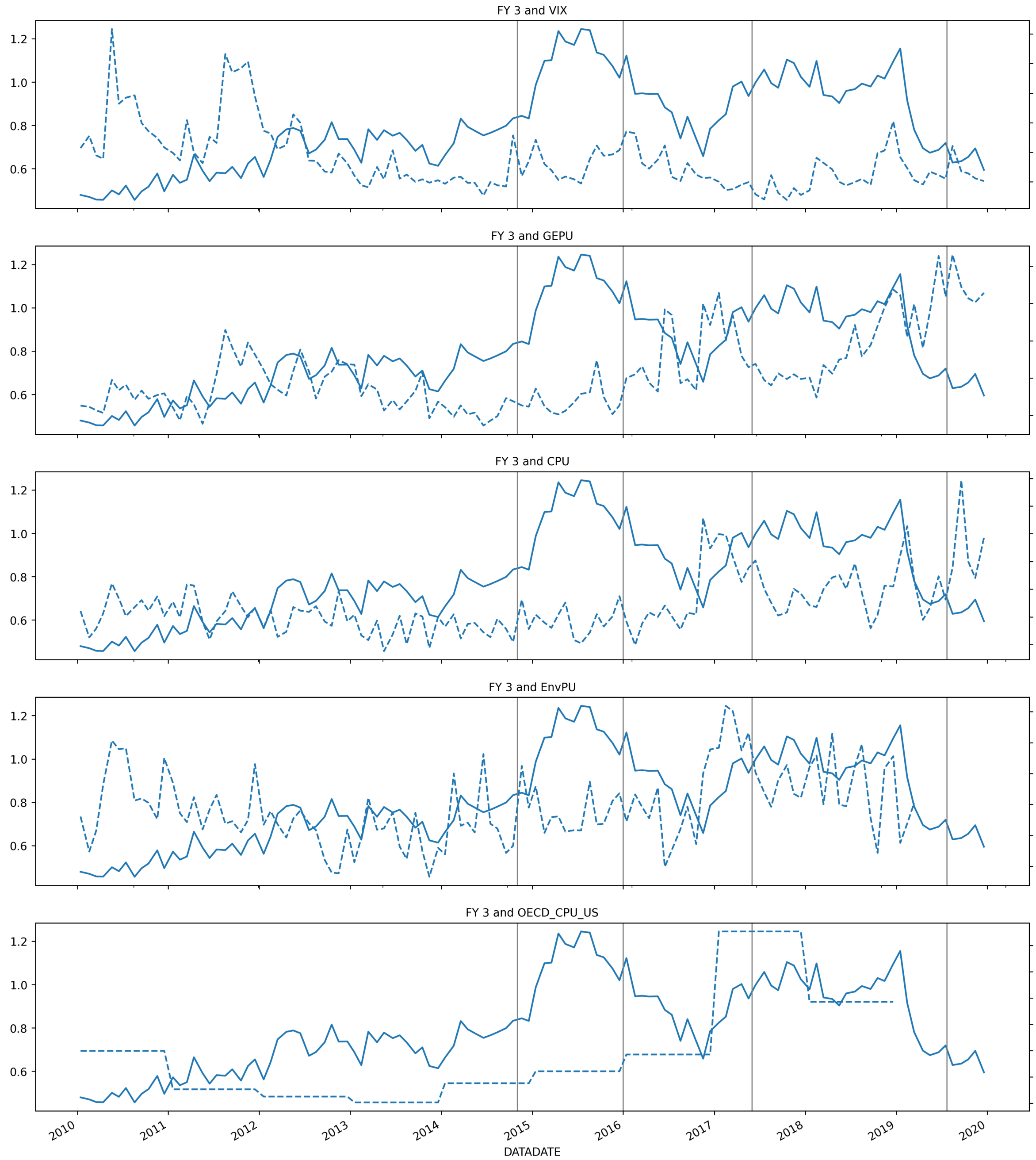

Figure A2: Uncertainty indexes comparison. Comparison of earnings per share forecasts disagreement ($EPS\_STD^{FH}_{i,t}$) relative to the absolute value of EPS (Full line, left axis) and three indexes of uncertainty (Dashed lines, right axis). From top to bottom Vix of the S&P 500 index retrieved from 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 methods of climate policy uncertainty do not increase in the periods around the Paris Agreement, as opposed to the measure of forecasts disagreement, which peaks in the months preceding the Paris Conference of Parties (COP). Arguably in such case uncertainty might have been high given the relevance of such accord for the future of the fossil fuels 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 my proxy is, to a good extent, capturing climate policy uncertainty.

Finally, I compare the forecasts disagreement with the average implied option volatility for the fossil fuels firms. In Figure A3, I show that this market measure of uncertainty co-moves with the level of forecasts disagreement. This highlights that analysts' forecasts may be related to actual investment decisions and market outcomes. Moreover, I remove from the average implied volatility (IMVOL) the IMVOL of the general stock market index, using as a proxy of the S&P 500. This additional analysis shows that the spikes in uncertainty may emerge from fossil fuels companies specific events, as opposed to general market uncertainty. The implied volatility of the S&P 500 remains flat throughout the major climate events in the sample. This analysis using option prices provides further support to the main assumption that the forecasts disagreement of fossil fuels 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 forecasts disagreement ($EPS\_STD_{i,t}^{FH}$) - orange line - and average implied option volatility for the 303 companies with traded options (out of 480 fossil fuels 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.

B Additional figures and tables

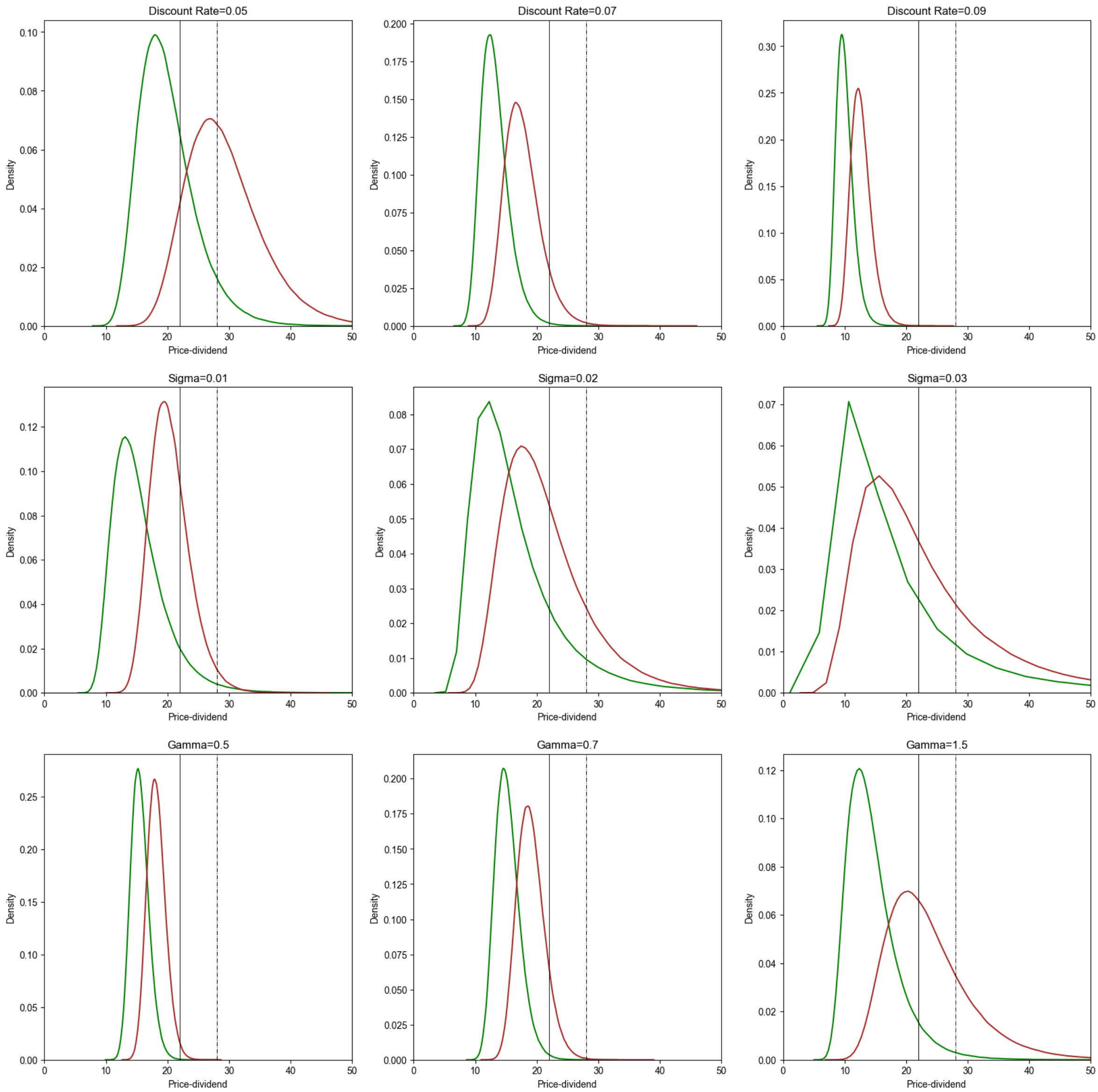

Figure A4: Price and μ probability distributions sensitivity. The chart shows the model generated distribution of price-dividend ratios using different calibration parameters. The green distribution represents climate policy shift scenarios and brown distribution represent no climate policy scenario. 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)
N	2421	2152	529	2436	2164	529	2445	2172	529
R^2	0.0926	0.1651	0.6335	0.1098	0.1628	0.6334	0.1311	0.2179	0.6447
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A1: Panel regression - Price Dividend and forecasts disagreement regression. Panel regression of price-dividend ratio, dividends per share mean growth forecast (DPS_G), dividend per share forecasts 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 fuels 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 forecasts disagreement regression. Panel regression of dividends per share growth mean forecast (DPS_G), dividend per share forecasts 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 fuels 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)
N	8282	4004	1346	8282	9251	3172	8282	9251	3172
R^2	0.7819	0.9828	0.9418	0.778	0.9174	0.7888	0.7745	0.9176	0.7898
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A3: Price Earnings and forecasts disagreement - Winsorised regression. Panel regression of price-earnings ratio, earning per share growth mean forecast (EPS_G), earnings per share forecasts 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 fuels 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 forecasts 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 fuels 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 forecasts 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 fuels 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 forecasts 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 fuels 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 forecasts 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 fuels 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 forecasts 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 fuels 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 forecasts 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 fuels firms in the sample (IVOL) and Average implied option volatility of fossil fuels 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 fuels 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.