Stock valuation and climate change uncertainty: Is there a carbon bubble?*

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Abstract

We develop a valuation framework for climate-sensitive stocks in the presence of uncertainty around a policymaker action to prevent global warming. The price-dividend (P/D) ratio of climate-sensitive stocks depends on investors expectations about an ambiguous path of future energy generated by a high carbon emitting and a low carbon emitting firm, and conditional on a climate policy regime shift. We show theoretically and empirically that, given a required rate of return, the higher the uncertainty the higher the valuation of climate-sensitive stocks. Moreover, we discuss a broader set of asset pricing implications in the context of climate change uncertainty.

JEL Codes: G11, G18, Q51

Keywords: Financial Economics, Climate Finance, Asset Pricing, Climate change, Uncertainty

1 Introduction

Technological transitions are oftentimes associated with financial bubbles. The introduction of steam-powered railroads in the 1860s is perhaps one of the first examples in history. Modern examples are the internet bubble of the late 1990s, or the more recent experience of crypto-currencies. While oftentimes bubbles are associated with new technologies, a recently debated and controversial question is whether fossil fuel firms are carrying a bubble. The maximum amount of cumulative carbon dioxide (CO2) emissions that would result in limiting global warming to the most ambitious objective of the Paris agreement of 1.5C with a 50% chance was around 500GtCO2 in 2020, according to the IPCC sixth assessment report (AR6). This figure is in stark contrast with the around 2800 GtCO2 carbon emissions that would result from burning all known Earth's fossil fuel reserves and the around 750 GtCO2 that would result from burning fossil fuel reserves held by the 100 largest coal and 100 largest oil and gas companies[1]. This "carbon budget" is also depleting very fast at a rate of about 40 GtCO2 per year, raising the question of whether the current high valuations of fossil fuel stocks are rational.

A possible explanation for the bubble-like pattern of technological revolutions may reside in their uncertainty. Pástor and Veronesi (2006) argue that time-varying idiosyncratic uncertainty about the growth and profitability of specific firms might justify high valuations, including those observed in the late 1990s for internet firms. Ex-post prices might seem irrational, but a sufficiently high level of uncertainty might justify ex-ante valuations. Similarly, the future of "old economy" technologies, such as fossil fuels, might be highly uncertain, because they might be replaced by new energy technologies, such as renewables, but also because governments have the tools to act to stimulate the transition, introducing political uncertainty.

In the context of global warming much of the uncertainty about the future of fossil fuels might emerge from unpredictable climate policy (e.g., carbon taxation, green subsidies). On the one hand, if governments follow through their net zero carbon emission pledges to fight global warming, energy from high emitting firms should be limited decisively in the near future. On the other hand, if there is continuous government inaction, fossil

[1] Source: CarbonTracker.org

fuel energy might keep growing in line with the past decades. Climate policy, and its uncertainty, might have a material effect on the cash flows and the valuation of fossil fuel firms.

Previous literature has highlighted two different effects of uncertainty on asset prices. A first, *discount rate*, effect emerges from investors uncertainty-aversion. Investors require a higher rate of return for holding assets negatively correlated with systematic uncertain, depressing prices. For example, political uncertainty commands a risk premium because of the inability of investors to learn and fully anticipate costly government actions (Kelly, Pástor, & Veronesi, 2016; Pastor & Veronesi, 2012; L. Pástor & Veronesi, 2013). Similarly, empirical analyses show that investors are willing to pay higher prices, accepting lower returns, for stocks which perform well in periods of higher economic uncertainty (Bali, Brown, & Tang, 2017).

A second, *cash flow*, effect emerges from the option value of volatility. There is a positive relationship between asset prices and idiosyncratic uncertainty because it increases future expected cash flows (Pastor & Veronesi, 2009). For example, investors are uncertain about the profitability of newly listed firms which show higher valuations compared to mature companies. Learning oftentimes leads to a resolution of uncertainty which results in the convergence of valuation ratios with the passing of time (Pástor & Veronesi, 2003). Pástor and Veronesi (2006) argue that in technological transitions, at first, risk about the new technology is idiosyncratic pushing up prices, and then gradually turns into systematic depressing valuations.

In this paper, we take a cash flow view to investigate the effect of time-varying idiosyncratic uncertainty on the valuation of climate sensitive assets. Although uncertainty may impact the required rate of return, fossil fuel firms fundamental value in the low carbon energy transition will ultimately be affected by their long-term cash flows trajectory. We also argue that the climate policy regime is the most material driver affecting future fossil fuel energy demand, and cash flows. Governments climate policy ambiguity generates idiosyncratic uncertainty about the future of fossil fuel firms by sending contrasting signals to market agents who cannot fully learn about the prospective policy regime. Similarly, the future of renewable energy will ultimately depend on the speed of the transition. If fossil fuels are used for longer because no strong climate policy is introduced, renewable energy growth will be slower. On the contrary, if government action stimulates the deployment of renewable energy, fossil fuels will disappear faster. The future of low and high emitting energy technologies is inherently intertwined due to their complementary role in the economy and largely depends on the climate policy regime.

We develop a valuation model which links investors climate expectations, and their uncertainty about a climate policy regime shift, with the price-dividend ratio of low and high carbon emitting firms. The basic idea could be summarised as follows. Let μ_i be the subjective probability distribution of a representative investor's believes about the growth rate of future dividends of a low carbon and a carbon intensive asset i, and that this is conditional on a climate policy regime. Let assume that this is normally distributed with mean g_i and variance σ_i^2. Within the traditional present value framework, if we assume that the price of an asset is the expected present value of its future payoffs, or dividends, discounted at a rate specified by a known model of expected returns r_i, the price-dividend ratio today is:

$$\frac{P_i}{D_i} = \int_{t=0}^{T} exp\Big\{ \big[(g_i + \sigma_i^2/2) - r_i\big]\, t \Big\} dt$$

The previous equation shows the well known convex relationship between the price-dividend ratio, the growth rate g_i and the uncertainty about the growth rate σ_i^2. The price of a stock today is the present value of its future dividends which grow at an expected rate of g_i from today's level of D_i and are discounted at a known rate r_i. From the above equation, we can infer that the higher the uncertainty about climate change, the higher the valuation of climate sensitive assets today[2]. Uncertainty right-skews the distribution of future expected dividends increasing possible values of future cash flows. Loosely speaking, there is value in the possibility that fossil fuels might remain the predominant source of energy in the future. We build on this idea and discuss a richer set of asset pricing implications, focusing on low-carbon and carbon-intensive assets.

[2]This can be thought as the volatility component of a "real options" valuation. This intuition can be found in Pástor and Veronesi (2003) where the M/B ratio is defined as $M/B = exp[(\bar{g} + \sigma^2/2 - r)T]$ where the uncertainty of newly listed companies is discussed. Pastor and Veronesi (2009) also reviews this concept in the context of the more traditional Gordon Growth Model

In our model, stocks valuations depend on investors mean dividends growth expectations, and their uncertainty. The higher the mean growth expectation (g_i), the higher the price-dividend ratio. But, also the uncertainty (σ_i^2) around climate policy increases stocks valuations. The higher the climate policy *regime shift uncertainty*, the higher the price-dividend ratio. Moreover, we discuss how the elasticity of dividends to energy demand (γ_i) could have effects on assets valuations. We assume that firms with a value of γ_i lower than one are less exposed to the policy *regime shift risk* while values higher than one magnify the impact of a possible climate policy on prices.

In our empirical analysis, we find evidence that uncertainty might explain a portion of the valuation of climate sensitive-assets. We test the analytical model predictions with an empirical analysis of professional analysts dividends per share forecasts with monthly snapshots over the decade 2010-2020. We find a statistically significant relationship between analysts' estimates of future dividends growth and the valuation of climate sensitive assets. If we use as a proxy of uncertainty analysts forecasts disagreement, we find, in a cross section regression, that dividends per share (DPS) idiosyncratic volatility seems to increase the valuation of climate-sensitive companies. The higher our measure of uncertainty the higher the price-dividend ratio of the firms in our sample. More in general, we find that financial markets are sensitive to climate ambiguity valuing assets. This result is consistent across various dimensions explored in our robustness analysis such as: gross profit margin, price to book, debt to ebitda, debt to asset.

Our paper suggests that the valuation of climate sensitive assets will ultimately depend on the predominant climate policy regime. However, not divesting from high carbon emitting energy companies has an intrinsic option value until inaction from the policy-maker is possible. The higher the likelihood of no climate policy regime shift, the higher the option value of not divesting from fossil fuel firms. Similarly, low carbon emitting companies have an intrinsic option value discounting the possibility that governments will meet their targets of limiting global warming. Regardless of the world that will materialise, high levels of political uncertainty might have effects on assets valuations. These might also be real effects, the status quo might lower the cost of financing of high carbon emitting firms affecting the allocation of resources. In the absence of clear climate policy, financial markets might not be able to fully internalise environmental externalities, even though more climate information becomes available. This paper shows how the role of finance in preventing global warming might only be a necessary, but not sufficient, condition to the problem, which ultimately resides in governments action. Political uncertainty might also generate systemic risks, such as a carbon bubble, given that the option value of either low or high carbon emitting firms must ultimately disappear as a cleaner or a dirtier future materialises.

This paper contributes to two strands of financial economics literature. Firstly, this paper speaks to the recent literature on climate finance (Gasparini & Tufano, 2023; Giglio, Kelly, & Stroebel, 2021; Hong, Karolyi, & Scheinkman, 2020). Bolton and Kacperczyk (2021) investigate whether financial markets price climate related risks by looking at the cross section of stock returns and firms carbon emissions. They find a statistically significant carbon premium related to the absolute level in carbon emissions and the year-on-year change. Engle, Giglio, Kelly, Lee, and Stroebel (2020) use textual analysis of newspapers climate news to develop a climate news index. They use the index to construct a "mimicking" portfolio which allows to dynamically hedge against climate change innovations. Pástor, Stambaugh, and Taylor (2021) develops a theoretical model to explain asset valuations as investors want to hedge against climate change, but might also want to invest in green stocks for non-pecuniary motives. Their model is an augmented CAPM where green (brown) stocks have negative (positive) alpha, but green (brown) stocks have also a positive (negative) exposure (beta) to an "ESG factor".

This paper is most closely related to Hsu, Li, and Tsou (2022). They seek to explain an environmental pollution premium in a general equilibrium model whereas polluting firms' future profits depend on a environmental policy regime. They assume that if the policy maker tightens environmental regulation the profitability of firms with high toxic emissions intensity declines more than low toxic emissions. The explanation for a premium which emerges from their model is that investors require a compensation for an uncertain environmental policy regime shift risk. In our model, the valuation of climate-sensitive assets is related to an uncertain climate policy regime. However, differently from their model, we take a cash-flow perspective and investigate how time-varying idiosyncratic uncertainty affects assets valuations, rather than the expected rate of return, which has been the focus of most of the climate finance literature so far.

This paper is also close to Ilhan, Sautner, and Vilkov (2021) that provide evidence that option markets price climate policy uncertainty. Carbon intensive firms options are more expensive than low carbon firms ones and this increases in periods of climate sensitive political events. In our empirical analysis, by using professional analysts forecast, we find evidence that time-varying idiosyncratic uncertainty affects assets valuations and it is priced in stock markets.

Secondly, this paper speaks to the financial economics literature on uncertainty and asset prices. A first theoretical work is Pástor and Veronesi (2006) who discuss whether the high valuation of internet companies in the late 1990s represented an asset bubble. They use a Gordon growth model with uncertain expectations about the stochastic process of the growth rate, similarly to Pástor and Veronesi (2003), to explain that high levels of uncertainty might justify high valuations. They use their model to calculate a value of implied volatility which might justify assets valuations. They argue that the late 1990s was not a bubble, but it was justified by high uncertainty about the performance of technology stocks. This paper borrows some of this concepts and applies them to the context of the net zero carbon transition.

Similarly, Pastor and Veronesi (2012) and L. Pástor and Veronesi (2013) investigate the effect of political news on financial markets. They develop a model where profitability follows a stochastic process affected by government policy. The policy is uncertain, but investors learn in a Bayesian fashion. However, investors cannot fully anticipate the costs of the policy and, for this reason, political uncertainty commands a risk premium (in terms of higher expected returns). Their model mostly takes a discount rate view, as opposed to the cash flow view of this model.

This literature has also a variety of empirical works. Kelly et al. (2016) use option prices around political events to investigate market pricing of political uncertainty. They find that around political events options are more expensive because of higher implied volatility and conclude that political uncertainty is priced in option markets. Bali et al. (2017) investigate the pricing of economic uncertainty in the cross section of stock returns. The estimate and uncertainty beta by regressing an index of economic uncertainty on stocks excess returns and then calculate stock returns by beta decile. They find that the lowest uncertainty decile generates 6% higher excess returns compared to the higher decile. A portfolio long in stocks in the lowest uncertainty and short stocks in the higher uncertainty beta generate positive average returns. Consistently with theory, they find that uncertainty averse investors are willing to pay higher prices for stocks with positive uncertainty beta.

The remainder of the paper proceeds as follows. In Section 2 we develop a valuation framework of climate-sensitive assets and discuss some asset pricing implications. In Section 3 we outline our empirical strategy and the econometric specifications for testing our theoretical propositions. In Section 4 we provide the results of the analysis and discuss the empirical evidence. The last section concludes.

2 Valuation framework

We consider an economy with two firms $i \in [1, 2]$, 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 produced by firm i at time t. Energy supply matches energy demand. For all $t \in [0, \infty]$ energy demand for firm i follows a firm-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 $t \in [0, \infty]$.

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

The value of μ_i is not known and depends on the policymaker decision about its climate policy regime. The policymaker can decide to maintain its current policy regime a or to make an irreversible decision to change its climate policy towards restricting energy demand from carbon-intensive sources b, in order to prevent global warming. All possible values of $\mu_{i=1}$ conditional to a are higher than the values conditional to b, for carbon-intensive energy, $f(\mu_{i=1}|a) > f(\mu_{i=1}|b)$. The opposite is true for low-carbon energy $f(\mu_{i=2}|a) < f(\mu_{i=2}|b)$. If the policymaker decides to take action to prevent global warming, she can implement policies for curbing carbon intensive energy (e.g., carbon tax) or fostering low carbon energy (e.g., stimulating innovation). For simplicity, we assume that the future path of low and high carbon emitting energy only depends on the uncertain climate policy regime.

The representative investor expectations of μ_i are distributed normally with mean g_i and variance σ_i^2. The latter term depends on the ambiguity introduced by the policymaker about the climate policy regime and describes the uncertainty of the representative investor about its mean expectation. The more ambiguous the policymaker is about a possible shift in its climate policy regime from a to b, the more uncertain the representative investor is about the drift in energy demand μ_i for each firm i. The investor has to price a climate-sensitive asset at time $t = 0$, before the policy decision is taken. We assume that the policymaker decision, once taken, is irreversible, but we acknowledge that the reversibility of the climate policy regime introduces additional uncertainty. We refer to σ_i^2 as the *regime shift uncertainty.*

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

We now want to link the uncertainty about climate action to the ambiguity about the payoff, or cash flows, of climate-sensitive stocks[3]. Let $D_{i,t}$ denote the dividend paid by firm i at time t. We assume that for all $t \in [0, \infty]$ the change in the level of dividends is proportional to the change in energy demand, scaled by a known and constant firm-specific factor $dD_i = \gamma_i dE_i$. 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 $t \in [0, \infty]$.

$$D_{i,t} = D_{i,0} exp(\gamma_i \mu_i t) \tag{3}$$

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 we are interested in considering the ambiguity that investors face about the probability distribution of the drift (i.e., the long-term path of energy demand) rather than the short-term volatility around it.

[3]The reader should note that the previous step is a useful construct to link climate policy with asset valuations, but from a theoretical standpoint assuming uncertainty about the drift of the dividends diffusion process is equivalent

Climate policy might impact dividends in the short-term, but the impact on valuations is greatest if it shifts the growth of the future stream of dividends. For this reason, we focus only on the drift component.

The parameter γ_i denotes the elasticity of dividends to changes in energy demand and represents the exposure of each firm to the regime shift. On the one hand, if μ_i is negative, for values of γ_i greater than one the decline in future dividends is larger. On the opposite, for values of γ_i lower than one the decline in dividends is smaller. On the other hand, if μ_i is positive, values of γ_i greater than one lead to a larger increase in dividends while values lower than one to a smaller increase. This parameter represents how sensitive each firm is to changes in energy demand and to the policymaker climate policy regime[4]. This parameter magnifies the effects of a positive policy regime shift on companies dividends, but also increases their exposure to the risk of a policy negatively impacting cash flows. We refer to γ_i as the exposure of each firm to the *regime shift risk*.

We then assume that the price of firm i at time t is the expected present value of future dividends from $t = 0$ to infinity discounted by a rate r_i, based on an exogenous and known model of expected returns for which $\mathbb{E}_t[r_i] = r_i$. Although previous literature discuss how systemic uncertainty might also affect the required rate of return, in this paper we focus on the effect of climate policy idiosyncratic uncertainty on future cash flows, assuming a constant rate of return. We argue that the fundamental value of climate sensitive assets in the long-term is mostly impacted by the effect of the climate policy regime on future dividends.

$$P_{i,t} = \mathbb{E}_0 \int_0^{\infty} D_{i,t} exp(-r_i t) dt \tag{4}$$

We acknowledge that uncertainty might have a dichotomous effect on asset prices through both the discount rate and cash flow channels. On one side, a higher rate of return required by uncertainty-averse investors might have a depressing effect on assets

[4] In a context with more than two firms, the heterogeneity of companies might generate different levels of exposure to the policymaker decision. A diversified utility might be less exposed than a pure fossil fuel company. In the stylised version of the model, we only consider the different exposure between low and high carbon emitting firms, but not the heterogeneity within each type of firm

valuations. On the contrary, higher uncertainty might right-skew the distribution of future dividends. Nevertheless we argue that in this context the latter effect might be stronger than the former. In this regards, we take a different view compared to the previous literature which focuses on the expected rate of return and explore a broader set of effects of climate policy uncertainty.

Substituting $D_{i,t}$ in the present value Equation (4) with the dividends growth process in Equation (3), 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 $exp(g_i + \sigma_i^2/2)$. With some further manipulations, we find the following convex relationship between four parameters and the price-dividend ratio which we will use throughout the paper to make some considerations about climate change and asset prices. For $r_i > g_i$, in Equation (5), the price-dividend ratio of either low or carbon-intensive firm i at time $t = 0$ depends on the distribution of energy growth expectations described by its mean g_i and variance σ_i^2 - i.e., *regime shift uncertainty* -, the expected required rate of return $r_{i,t}$ and a known constant representing the sensitivity of dividends to changes in energy demand γ_i - i.e., *regime shift risk*.

$$P_i/D_i = 1/[r_i - (g_i + \sigma_i^2/2)\gamma_i] \tag{5}$$

Our simple analytical model describes how the uncertainty about climate policy action might have effects on the valuation of climate-sensitive assets. The policymaker can influence the future trajectory of carbon intensive and low carbon energy, and consequently the respective firms dividends or cash flows. The fundamental value of climate sensitive assets depends on the growth of energy produced by each technology that is the primary source of income of energy firms. Uncertainty right-skews the distribution of future cash flows by increasing the expected value and positively affecting valuations, for both low and high carbon emitting firms.

While the required rate of return is assumed constant in our model, a strengthening of climate concerns might increase the discount rate for carbon-intensive assets reducing prices. Systemic uncertainty might also increase the rate of return required by an uncertainty-averse investor. Nevertheless, given the possibility that carbon intensive energy might be, in a substantial part, replaced by low carbon energy, we argue the cash flow effect in such case could be considerable. For this reason, our model focuses on the possible trajectory of cash flows rather than the expected returns. It should be noted that the uncertainty in our approach emerges from the unknown policymaker decision about an irreversible policy decision affecting the drift of the stochastic process governing the energy demand. Contrary to the real option approaches, the uncertainty in our model emerges from an unknown drift of the process rather than the volatility around it.

		g -0.03			g 0			g 0.03		
		r 0.06	r 0.09	r 0.12	r 0.06	r 0.09	r 0.12	r 0.06	r 0.09	r 0.12
γ 0.5	σ^2 0	13.33	9.52	7.41	16.67	11.11	8.33	22.22	13.33	9.52
	σ^2 1%	13.79	9.76	7.55	17.39	11.43	8.51	23.53	13.79	9.76
	σ^2 3%	14.81	10.26	7.84	19.05	12.12	8.89	26.67	14.81	10.26
γ 1	σ^2 0	11.11	8.33	6.67	16.67	11.11	8.33	33.33	16.67	11.11
	σ^2 1%	11.76	8.7	6.9	18.18	11.76	8.7	40	18.18	11.76
	σ^2 3%	13.33	9.52	7.41	22.22	13.33	9.52	66.67	22.22	13.33
γ 1.5	σ^2 0	9.52	7.41	6.06	16.67	11.11	8.33	66.67	22.22	13.33
	σ^2 1%	10.26	7.84	6.35	19.05	12.12	8.89	133.33	26.67	14.81
	σ^2 3%	12.12	8.89	7.02	26.67	14.81	10.26	NA	44.44	19.05

Table 1: Sensitivity of Price-Dividend ratio and model parameters. The table shows the values of the Price-Dividend ratio in output of the valuation model varying input parameters.

Our model is broadly in line with previous financial economics literature on asset pricing. In line with the framework proposed by Campbell (2019), stock valuations depend on the expected dividends growth and the expected required rate of return. This model shares common features with the present value relation models where the price-dividend ratio depends on the expected required rate of return and the expected dividends growth rate (Campbell & Shiller, 1987, 1989). Perhaps our modelling framework is most similar to Pástor and Veronesi (2003) and Pástor and Veronesi (2006) which links firms' valuations with a stochastic process of investors' uncertainty about profitability. The difference with their model is that investors are not able to learn with the passing of time because climate uncertainty is guided by unpredictable policy action. Although with significant differences, this model is also close to the real option valuation framework developed by Schwartz and Moon (2001) in the context of the dot.com bubble where high valuations of companies are explained by the high uncertainty around revenue growth. While our focus is on the uncertainty about the drift of the cash flows, the philosophy of this model is akin to real option modelling approaches, some of them also used in environmental economics (Kolstad, 1996; Paddock, Siegel, & James, 1988; Pindyck, 1991).

No uncertainty about climate policy

We now turn to some of the implications arising from this model and make two propositions about the relationship between investors' expectations, their uncertainty, and assets valuations. Before we discuss the more realistic case where investors face ambiguity about climate action, we focus on a simpler context without uncertainty to draw some initial observations. We first assume that the representative investor knows with certainty the future energy demand path of low-carbon and carbon-intensive energy and there is no ambiguity about the climate policy regime. In this case, σ^2 is equal to zero and the expected value of μ is g.

$$P_i/D_i = 1/[r_i - g_i\gamma_i]$$

In this context without uncertainty, the higher the expected growth of future dividends the higher the price relative to its dividends today. Investors know which energy production technology (either low-carbon or carbon-intensive) will be predominant in the future and they can forecast dividends accordingly. In this hypothetical case, the price-dividend ratio of a stock is positively related to investors' expectations about climate-sensitive firms' dividends growth and negatively related to the required rate of return. The economic interpretation of this relationship is straightforward. Investors are willing to pay more today for a climate-sensitive stock which is expected to pay more in the future given a known and certain payoff distribution and an uncertainty-neutral required rate of return.

This interpretation of the model is equivalent to the traditional framework proposed by Gordon (1962) and in line with the subsequent financial economics literature (Campbell, 2019; Campbell & Shiller, 1989). The only difference with this previous literature is that the growth rate of dividends depends on investors' climate expectations, which in turn, depend on the policymaker climate policy regime. Until now, the contribution of the model is limited to conceptualising the link between investors climate expectations and climate-sensitive assets valuations.

PROPOSITION 1: The price-dividend ratio (P/D) increases with investors mean expectation about the growth of carbon-intensive/low carbon energy demand, and consequently dividends from carbon-intensive/low-carbon firms, given a known level of expected rate of return

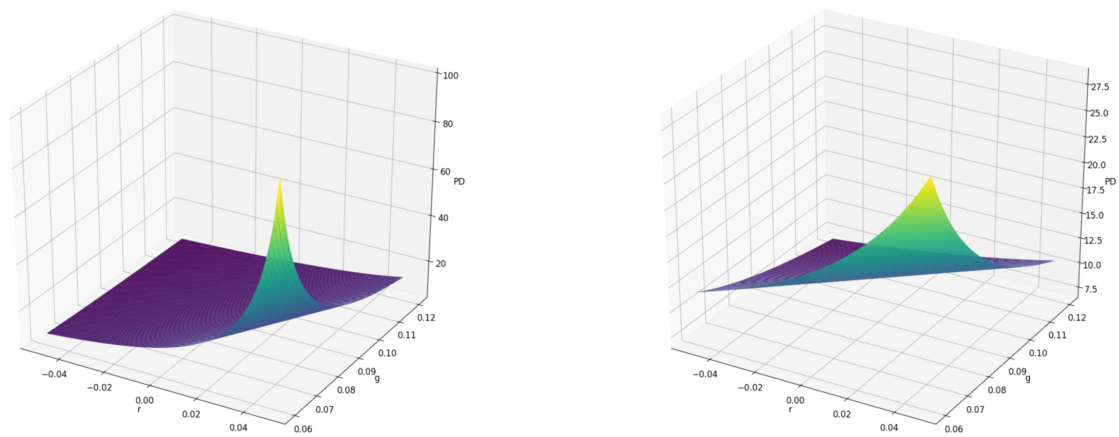

Figure 1: Price-Dividend ratio, discount rate and growth rate. Price-dividend ratio for different levels of discount rate r (x-axis), energy growth rate g (y-axis) and arbitrary levels of sensitivity of dividends to energy demand γ. Left-hand side chart $\gamma = 1$, right-hand side chart $\gamma = 0.5$

The convexity of this relationship depends on the level of *policy regime risk*, which we quantified with the parameter γ_i. On the one hand, if $g < 0$ then γ_i is negatively related with the price-dividend ratio (the higher γ_i the lower the price-dividend ratio). On the other hand, if $g > 0$ then γ_i is positively related with the price-dividend ratio (the higher γ_i the higher the price-dividend ratio). Further, the lower the discount rate the higher the sensitivity of the price-dividend ratio to changes in γ_i due to the higher convexity of the present value relation. A higher discount rate gives less weight to higher dividends in the future as opposed to a lower discount rate. The different exposure of energy firms to the policy regime risk might be a material driver of their valuations. Although we do not estimate this parameter empirically, we argue that carbon intensive firms might have higher values of γ given that low carbon energy is likely to be less susceptible to climate policies compared to carbon intensive energy, especially on the downside risk.

This simplified version of the model allows to link investors' climate expectations with the valuations of low-carbon and carbon-intensive firms today, but it disregards the high uncertainty of climate change and the net zero transition. If strong policy action to fight global warming was taken, investors would be able to estimate the trajectory of dividends for climate-sensitive assets and price them accordingly. But, until strong action is taken, investors remain uncertain about a possible policy regime shift and ambiguous about the conditional distribution of μ_i. In the following part of this section, we discuss how the above proposition might be affected by investors' uncertainty about future climate policy.

Uncertainty about climate policy

We now turn to the more realistic case where investors do not know whether the policymaker will act to curb carbon emissions. The growth rate of energy demand μ_i is not known, but investors can observe the distribution of μ_i conditional to each climate policy regime. This can be done, for example, by looking at climate mitigation scenarios such as The Intergovernmental Panel on Climate Change (IPCC). We assume that the investors information set contains such data and it is available to market agents. The representative investor, however, does not know the policymaker decision, and she remains ambiguous about the policy regime shift. In this case, in our model, the valuation of low and carbon-intensive assets not only depends on the required rate of return and the expected growth rate of dividends, but also the uncertainty around the expected growth rate.

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

In this context of ambiguity, higher uncertainty about the growth of climate-sensitive firms leads to higher prices. Investors do not know whether carbon-intensive energy will remain predominant (leading to global warming) or whether the world will move towards net zero carbon emissions thanks to low-carbon energy and the policy regime shift. In such case, uncertainty around policy action might lead to higher valuations, 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). Not divesting from the carbon intensive energy firm has an intrinsic option value until inaction from the policymaker is possible. The higher the likelihood of no regime shift, the higher the option value of not divesting from carbon-intensive energy.

PROPOSITION 2: The price-dividend ratio (P/D) increases with the uncertainty about growth expectations of carbon-intensive/low carbon energy demand, and consequently dividends from carbon-intensive/low carbon firms, given a known level of expected rate of return r_i and a mean expected growth g_i

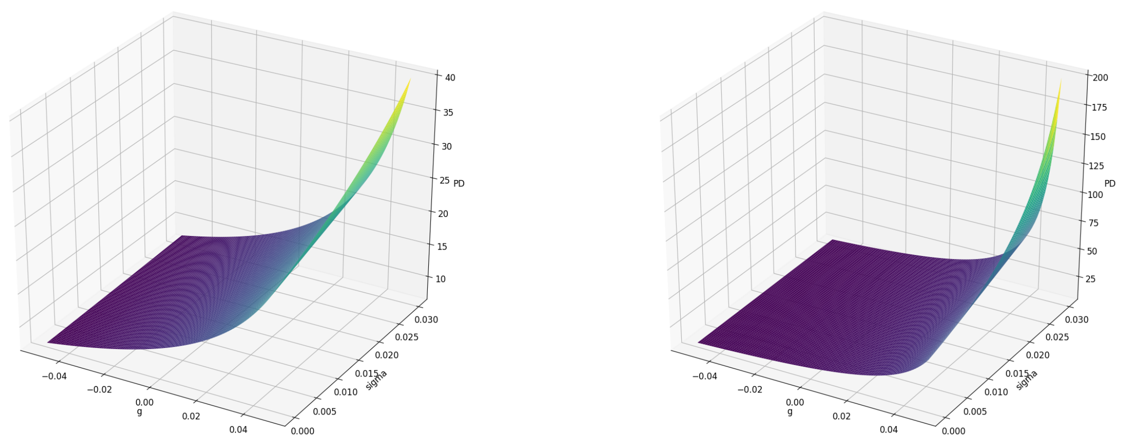

Figure 2: Price-Dividend ratio and uncertainty. Price-dividend ratio for different levels of energy growth rate g (x-axis) and uncertainty σ (y-axis) assuming sensitivity of dividends to energy demand $\gamma = 1$ and arbitrary levels of discount rate. Left-hand side chart discount rate $r = 0.09$, right-hand side chart discount rate $r = 0.07$

The status quo generated by climate political uncertainty might have effects on the valuations of climate-sensitive assets by right-skewing the expected value of future dividends. This, in turn, might have real effects by lowering the cost of financing for low carbon, but also carbon-intensive, firms and affecting the allocation of resources. Arguably the option value is higher for high-emitting assets given the larger potential downside in case of strong climate policy action. In the absence of resolution of climate policy uncertainty, financial markets might not be able to fully price environmental externalities, even if more information about firms' exposure to climate related risks becomes available. From a policy perspective, the largest part of climate finance policies rely on the assumption that financial markets are able to price environmental externalities, if sufficient information is provided. In contrast, our model shows that climate information is less important in a context of high climate political uncertainty. Ambiguity about future climate policies reduces the value of climate information.

In this section, we described a theoretical framework of stock market valuations of firms exposed to an uncertain policy regime shift to curb carbon emissions and prevent global warming. Our first two propositions are aligned with previous financial economics literature, but they are extended to the context of global warming. Moreover, our model provides us with two testable propositions that could help us in understanding to what extent current climate-sensitive assets valuations are explained by the uncertainty around climate policy and by investors expectations regarding low and high carbon emitting energy firms. This will be the focus of the next sections.

3 Empirical Analysis

In the empirical analysis we use professional analysts forecasts, or estimates, of climate-sensitive firms fundamental value to proxy investors' expectations and climate policy uncertainty. Using analysts forecasts is appealing for assessing investors' time-varying expectations because it allows to compute statistical moments summarising investors' consensus. In line with previous literature, it also allows the estimation of a proxy of uncertainty based on forecast disagreement (Anderson, Ghysels, & Juergens, 2009; Diether, Malloy, & Scherbina, 2002; Johnson, 2004). It seems reasonable to assume that if all analysts agreed on the same fundamental value, uncertainty would be low. On the opposite, if the disagreement about the future fundamental value of a firm was high, uncertainty might be high. This approach allows us to calculate investors idiosyncratic uncertainty about climate-sensitive firms, which we assume depends mostly on climate policy uncertainty[5].

In order to identify the largest universe possible of climate-sensitive energy stocks we use international data from CRSP/Compustat merged stock dataset where we select sub-industries related to energy oil & gas consumable fuels and utility renewable energy companies[6]. This gives us a large set of stocks and their respective market data such as daily prices, earnings and dividends from 1994. We then merge this data with Refinitiv IBES through IBES/CRPS mapping table available at Wharton Research Data Services (WRDS). We use the code PERMNO as main unique identifier for firms between the tables. IBES reports data about analysts forecasts of financial indicators monthly (e.g., Dividends per share, Earnings per share). We use the summary dataset which reports mean, standard deviation, high, low of analysts estimates (including the number of underlying forecasts) as well as a set of aggregated statistics about the detailed estimates. IBES detailed file also allows to retrieve information about each analysts estimate underlying the aggregated statistics.

Joining IBES with CRPS dataset gives us a total of 495 stocks that are followed by analysts of which 15 renewable energy and 480 fossil fuel from 1994. This data has monthly records (forecast date) corresponding to more than 800,000 underlying estimates which summarise investors' believes of a representative sample of climate-sensitive companies worldwide. We recognise that our sample is skewed towards fossil fuel firms, being predominantly large and concentrated firms, as opposed to renewable energy companies. Table 2 shows some descriptive statistics.

[5]There are different methods for assessing uncertainty in financial markets proposed in the literature. To cite some: *i.* ARCH conditional variance discussed by Engle (1983), *ii.* market-based methods Bekaert and Hoerova (2014); Brenner and Izhakian (2018), *iii.* text-mining methods Baker, Bloom, and Davis (2016); Bloom (2009), of which some applied to climate policy uncertainty Berestycki, Carattini, Dechezleprêtre, and Kruse (2022); Gavriilidis (2022); Noailly, Nowzohour, and Van Den Heuvel (2022)

[6]GIC 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) and Renewable Energy (55105020)

Our data reports analysts forecasts for different forecasting horizon (FH) in the future, from 1 to 5 years, allowing us to construct our measures for different temporal horizons. For example, estimates could be for next fiscal year (FH 1) or for 5 years in the future (FH 5). The number of analysts estimates for 4 and 5 years in the future is quite limited. For this reason we disregard forecasts of more than 3 years ahead. Further, considering combinations of firm-date with a low number of underlying analysts forecasts would decrease the robustness of our measures. In line with previous literature, we set a threshold of minimum required number of analysts. We set the threshold to 10 in order to achieve the highest number possible of underlying estimates without reducing substantially the number of snapshots. We test in the robustness analysis that this does not affect our key results.

	FH	P/D	DPS_G	DPS_STD	P/E	EPS_G	EPS_STD
	1	38.72	0.03	0.07	23.18	0.11	0.2
Mean	2	42.44	0.33	0.14	15.25	-0.37	0.11
	3	25.81	0.37	0.14	15.95	-1.18	-0.17
	1	65.7	0.25	0.25	477.22	15.08	6.89
Std	2	125.29	1.66	0.58	207.04	11.39	5.22
	3	26.18	1.3	0.46	286.91	22.89	20.94
	1	0.46	-1	0	-1583	-156.83	-272.85
Min	2	0.45	-1	0	-2810	-320.00	-203.53
	3	0.45	-1	0	-4526	-365.40	-850.33
	1	843	5.1	6	29820	979	440
Max	2	3399	24	11	3410	319.2	62.24
	3	394.75	14.98	6.35	3188	663.27	99.02
	1	5291	5291	5291	8895	8895	8895
N	2	4556	4556	4556	10040	10040	10040
	3	1212	1212	1212	3365	3365	3365

Table 2: IBES Descriptive statistics CRSP/IBES sample descriptive statistics. Values between January 2010 and December 2019. From top to bottom: mean, standard deviation, minimum, maximum and number of observations. FH refers to different forecasting horizons from 1 year forward until 3 years ahead.

We select the decade between the beginning of 2010 and the end of 2019 because particularly suitable for our empirical analysis, but also for data limitations. Firstly, if we consider a minimum number of analysts forecasts for each forecast date, data before 2010 is scattered. Secondly, between the global financial crisis and Covid 19, this period has been relatively stable from a macroeconomic standpoint while various climate policy events occurred (e.g., Paris agreement, Trump election) without being influenced by other macroeconomic factors. This allows us to avoid to worry about the influence of other major economic and policy developments on the valuations of the stocks in our sample that would affect our results (e.g., Global financial crisis). This period give us a sufficient number of monthly forecast dates, analysts forecasts across three forecasting horizon and heterogeneity of climate policy events to estimate a regression model (Table 7 and 8).

We define two measures of analysts forecast as follows: *i.* Mean Dividend Per Share (DPS) growth forecast ($DPS\_G_{i,t}^{FH}$) relative to the most recent payed dividend per share at forecast date and *ii.* Standard deviation of DPS growth forecasts ($DPS\_STD_{i,t}^{FH}$) relative to the most recent payed dividend per share at forecast date (or forecast disagreement about dividends mean growth). We use the latter measure as a proxy of analysts uncertainty. Consistently with previous literature, we assume that the larger the forecast disagreement ($DPS\_STD_{i,t}^{FH}$), the higher the uncertainty. More formally, we define $DPS_{i,t,k}^{FH}$ as the DPS forecast for the forecasting horizon FH of analyst k for firm i at time t (where K is the total number of analyst estimates). Further, we define $DPS_{i,t}$ as the most recent payed dividend at forecast date t and $\overline{DPS_{i,t}^{FH}}$ as the arithmetic average of the K analysts forecasts for firm i for each forecasting horizon FH. Firm i could be either carbon intensive or low carbon.

$$DPS\_G_{i,t}^{FH} = \frac{\overline{DPS_{i,t}}^{FH}}{DPS_{i,t}} - 1$$

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

We estimate a cross section model between the price-dividend ratio, analysts Mean DPS growth forecast ($DPS\_G_{i,t}^{FH}$) and Standard deviation of DPS growth forecasts ($DPS\_STD_{i,t}^{FH}$) across firm i and time t, where ϵ_i is the error term. In this specification we remove the firm-fixed effect because we are interested in the time-varying level of idiosyncratic uncertainty. We de-mean both the firm level P/D in our time-frame and the two measures of analysts forecasts. By de-meaning these variables we remove the known effect of idiosyncratic uncertainty on asset valuations (e.g., Pástor and Veronesi (2003)) and only investigate how the time-varying idiosyncratic uncertainty affects climate sensitive assets valuations. Loosely speaking we are interested if in period of higher climate policy uncertainty, climate sensitive assets relative valuations are higher rather than understanding whether more uncertain firms show higher prices. Moreover we replicate the same specification for the Price-Earnings and Earnings Per Share (EPS) forecast in our dataset in order to avoid the concern of not dividends paying stocks and use a larger number of datapoints.

$$PD_{i,t} = \alpha_t + \beta_1 * DPS\_G^{FH}_{i,t} + \beta_2 * DPS\_STD^{FH}_{i,t} + \epsilon_{i,t}$$

Before we proceed with our empirical analysis, we verify that our measures, in aggregate, are sensitive to climate policy events. In order to have a more stable measure we use earnings per share rather than dividends per share in this comparison. The average expected growth rate of earnings across all firms in our sample $EPS\_G^{FH}_{i,t}$ and their uncertainty $EPS\_STD^{FH}_{i,t}$ varies throughout time in line with key policy events (Figure 3). In the period around the announcement of the Paris agreement and following President Trump's subsequent withdrawal, we observe spikes in our measures of uncertainty, demonstrating the sensitivity of this variable to climate policy. Similarly our measure increases around the more recent 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. Interestingly, all three measures of uncertainty are at their highest around the period of the Paris Agreement, arguably the major climate policy event of the decade.

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 our sample start decreasing, although the metric for FH 3 is more stable. The average earnings growth estimate for FH 1 and FH 2 seem to reverse following President Trump withdrawal from the Paris agreement gradually increasing afterwards. The measure for FH 3 starts decreasing towards the end of Trump mandate, perhaps anticipating a change in climate policy.

Figure 3: Average forecast estimates time series. Average Mean DPS growth forecast ($DPS\_G_{i,t}^{FH}$) and average Standard deviation of DPS growth forecasts ($DPS\_STD_{i,t}^{FH}$) relative to the absolute value of EPS. Only fossil fuel companies in our sample, excluding the 15 renewable energy companies. 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.

We are aware that other types of uncertainty might be captured in our measure (e.g., broader political uncertainty), but we argue global warming might be the largest source of uncertainty for the long term future of climate-sensitive stocks, such as fossil fuels. In order to better understand if this is the case, we compare our measure of climate policy uncertainty (CPU) based on analysts disagreement with other measures of CPU and general macroeconomic uncertainty. Our measure of CPU correlates with similar metrics in the literature, but not substantially with measures of general economic uncertainty.

Nevertheless, we are conscious of the fact that in some periods there could be a certain level of correlation between Climate policy uncertainty and macroeconomic uncertainty. For example, the election of President Trump resulted in political uncertainty because of economic reforms, but also because of his declarations about withdrawing from the Paris Agreement.

In Figure 4, we compare our 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). Our 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 our 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 forecast 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 our measure of CPU showing how it might not be substantially biased by general uncertainty.

Furthermore, in Figure 4 we compare our 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, our 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 our measure of forecast disagreement. Interestingly, the text-based methods of climate policy uncertainty do not increase in the periods around the Paris Agreement, as opposed to our measure, 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 fuel industry. Nevertheless, with the exception of the Paris Agreement, our measure seems to track fairly well the trend of the EnvPU index proposed by Noailly et al. (2022) giving comfort that our proxy is, to a good extent, capturing climate policy uncertainty.

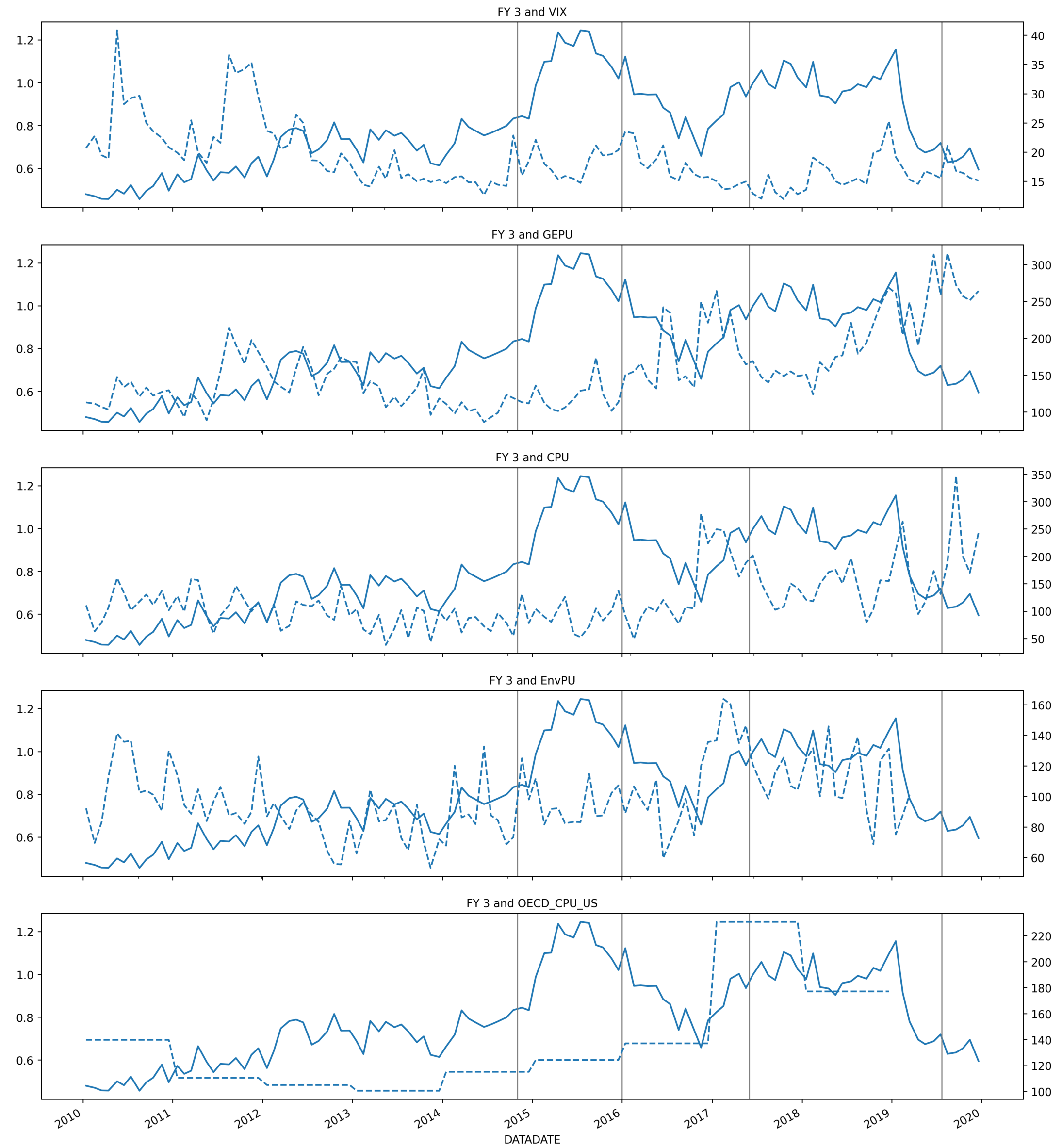

Figure 4: Uncertainty indexes comparison. Comparison of average Standard deviation of DPS growth forecasts ($DPS\_STD^{FH}_{i,t}$) relative to the absolute value of EPS (Full line, left axis) and three indexes of uncertainty (Dashed lines, right axis). From top to bottom Vix of the S&P 500 index retrieved 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 our sample.

The empirical set up described in this section as well as the data of analyst forecasts allows to investigate empirically our theoretical model prediction about the relationship between climate-sensitive stocks valuation and investors uncertainty. Although climate policy uncertainty metrics are still emerging in the literature, we propose a novel approach based on forecast disagreement and discussed some of the limitations. In the next section we discuss some results of our empirical investigation in the context of our theoretical model.

4 Results

We now turn to discuss some empirical results testing our model propositions. Firstly, we find a statistically significant relationship between analysts dividends growth expectations (DPS_G) and the price-dividend ratio (P/D) observed at forecast date. This result is in line with our model first proposition. Table 3 shows that the regression model coefficients are positive for all three forecasting horizons (FH) and significant at 5% confidence level. The R^2 ranges between 14% and 32%. As expected, the results are stronger for the relationship between analysts earnings growth expectations (EPS_G) and the price-earnings ratio (P/E) observed at forecast date. Similarly, the regression model coefficients are positive for all three forecasting horizons and significant at 5% confidence level. The R^2 increases to between 54% and 86% because of the cleaner data and the higher number of observations compared to the dividends forecast.

We then investigate the second model proposition. We find a statistically significant relationship between analysts dividends growth uncertainty (DPS_STD) and the price-dividend ratio (P/D) observed at forecast date. The coefficients are all positive and significant. The R^2 is high for forecasting horizon 3 at around 45%, but it becomes lower for FH 1 (17%) and close to zero for FH 2 (1.5%). The sign also turns negative in FH 2 for the multivariate analysis including dividends growth expectations as additional independent variable. However, the results are more in line with expectations for the relationship between analysts earnings growth uncertainty (EPS_STD) and the price-earnings (P/E). The coefficients are positive and statistically significant at 5% confidence level. The R^2 increases substantially to between 80% and 86% for FH 1 and FH 2 respectively, although it is low for FH 3 (5%).

In Table 3, we look at the multivariate analysis with both dividends (earnings) growth expectations and uncertainty and price-dividend (earnings). For the price-dividend multivariate regression the R^2 ranges between 18% and 47% while for the price-earnings between 80% and 93% across all forecasting horizons. Moreover, the size of the coefficients is material. In the price-earnings multivariate model for FH 2, one with the highest R^2, a mean expectation of doubling of the earnings in the following 2 years leads to a 9 points increase in the price-earnings ratio. An earnings growth uncertainty, expressed in terms of standard deviation around the mean growth rate, of 50% would lead to a around 7 points increase in the price-earnings ratio. However, these figures should not be used in isolation as expectations act across different forecasting horizons. Nevertheless, this shows the statistically significant and material effect of investors climate expectations on the valuation of climate sensitive firms.

To ensure our results are not sensitive to outliers we winsorise to the 1st/99th percentile all variables in our sample and re-estimate our model. In Table 4 we show that the explanatory power of the regressions decreases following the censoring, but all parameters remain significant and the sign of the coefficients in line with our results. The only exception is the sign of analysts earnings growth expectations (EPS_G) which turns negative for FH 1. Similarly, analysts dividends growth uncertainty (DPS_STD) FH 3 turns negative, although the number of observations is particularly low, especially given that monthly snapshots are considered.

In order to ensure our results are robust, we divide the sample in different sub-samples according to various measures that include Gross profit Margin (GPM), Price to Book (PTB), Debt to Ebitda (DtE), Debt to Asset (DtA), Return of Equity (ROE), and Cash to Debt (CtD), and re-run the univariate and multivariate regressions on each sub-sample. More in details, for the financial variables, we classify companies in different quartiles and run our empirical analysis on each subset of firms. Financial information refers to the most recent quarterly data available and has been extracted from WRDS firm-level financial ratio dataset and merged with our sample. This analysis allows us to ensure our results are not susceptible to particular types of firms and a broader generalisation of our findings.

		FH 1		FH 2		FH 3	
	Dep Var	Coef	P-value	Coef	P-value	Coef	P-value
DPS_G	P/D	99.4894	$< .0001*$	39.0343	$< .0001*$	16.9548	$< .0001*$
R^2	P/D	0.1394	$< .0001*$	0.3195	$< .0001*$	0.2844	$< .0001*$
DPS_STD	P/D	110.3557	$< .0001*$	25.5029	$< .0001*$	78.6529	$< .0001*$
R^2	P/D	0.1687	$< .0001*$	0.0151	$< .0001*$	0.4445	$< .0001*$
DPS_G	P/D	41.9708	$< .0001*$	47.019	$< .0001*$	6.7857	$< .0001*$
DPS_STD	P/D	79.4654	$< .0001*$	-46.8876	$< .0001*$	63.7451	$< .0001*$
R^2	P/D	0.1803	$< .0001*$	0.3572	$< .0001*$	0.4741	$< .0001*$
N		5135		4402		1170	
EPS_G	P/E	27.115	$< .0001*$	14.6694	$< .0001*$	10.3986	$< .0001*$
R^2	P/E	0.759	$< .0001*$	0.8652	$< .0001*$	0.542	$< .0001*$
EPS_STD	P/E	64.8853	$< .0001*$	37.3005	$< .0001*$	4.1617	$< .0001*$
R^2	P/E	0.8794	$< .0001*$	0.7976	$< .0001*$	0.0535	$< .0001*$
EPS_G	P/E	1.4391	$< .0001*$	9.4191	$< .0001*$	12.9087	$< .0001*$
EPS_STD	P/E	61.9367	$< .0001*$	17.6393	$< .0001*$	9.6276	$< .0001*$
R^2	P/E	0.8797	$< .0001*$	0.9327	$< .0001*$	0.7965	$< .0001*$
N		8831		9919		3342	

Table 3: Cross section regression removing firm fixed effect. Panel regression coefficient, R^2 and P-value for DPS and EPS, removing firm fixed effect. From top to bottom: univariate regression between dividends (earning) per share growth $DPS\_G_{i,t}$ ($EPS\_G_{i,t}$) and price-dividends (price-earning ratio). Univariate regression of dividends (earnings) per share relative standard deviation (defined as the ratio between the standard deviation of analysts estimates and latest dividend (earnings)) $DPS\_STD_{i,t}$ ($EPS\_STD_{i,t}$) and the price-dividend (price-earning) ratio. Multivariate regression between relative standard deviation and mean expected growth. From left to right: analysts' estimates for next fiscal year (FH+1) up to FH in 3 years (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil fuel companies and 15 renewable energy companies. For FH 1,FH 2, FH 3 only records with underlying number of analysts estimates greater than 10. N refers to number of snapshots each with at least 10 underlying analysts' estimates. Asterisk denotes significance at 5% level.

	Dep Var	FH 1 Coef	FH 1 P-value	FH 2 Coef	FH 2 P-value	FH 3 Coef	FH 3 P-value
DPS_G	P/D	28.2869	$< .0001*$	35.4799	$< .0001*$	6.881	$< .0001*$
R^2	P/D	0.0094	$< .0001*$	0.0763	$< .0001*$	0.0319	$< .0001*$
DPS_STD	P/D	31.946	$< .0001*$	61.8057	$< .0001*$	-7.2153	$< .0001*$
R^2	P/D	0.0129	$< .0001*$	0.0291	$< .0001*$	0.003	$< .0001*$
DPS_G	P/D	16.729	$< .0001*$	31.9457	$< .0001*$	8.134	$< .0001*$
DPS_STD	P/D	24.6776	$< .0001*$	38.5307	$< .0001*$	-15.1612	$< .0001*$
R^2	P/D	0.0155	$< .0001*$	0.0869	$< .0001*$	0.0440	$< .0001*$
N	P/D		4930		3856		978
EPS_G	P/E	-9.7157	$< .0001*$	16.2482	$< .0001*$	11.7763	$< .0001*$
R^2	P/E	0.0138	$< .0001*$	0.2744	$< .0001*$	0.5067	$< .0001*$
EPS_Std	P/E	68.4154	$< .0001*$	41.7412	$< .0001*$	28.4224	$< .0001*$
R^2	P/E	0.4044	$< .0001*$	0.5085	$< .0001*$	0.4357	$< .0001*$
EPS_G	P/E	-13.0798	$< .0001*$	6.7248	$< .0001*$	8.2245	$< .0001*$
EPS_Std	P/E	69.4922	$< .0001*$	35.2739	$< .0001*$	16.2291	$< .0001*$
R^2	P/E	0.4294	$< .0001*$	0.5433	$< .0001*$	0.6026	$< .0001*$
N	P/E	8527		8656		2375	

Table 4: Cross section regression removing firm fixed effect - Winsorised results. Panel regression coefficient, R^2 and P-value for DPS and EPS, removing firm fixed effect. From top to bottom: univariate regression between dividends (earning) per share growth $DPS\_G_{i,t}$ ($EPS\_G_{i,t}$) and price-dividends (price-earning) ratio. Univariate regression of dividends (earnings) per share relative standard deviation (defined as the ratio between the standard deviation of analysts estimates and latest dividend (earnings)) $DPS\_STD_{i,t}$ ($EPS\_STD_{i,t}$) and the price-dividend (price-earning) ratio. Multivariate regression between relative standard deviation and mean expected growth. From left to right: analysts' estimates for next fiscal year (FH+1) up to FH in 3 years (FH+3). Monthly estimates between January 2010 and December 2019 for 480 fossil fuel companies and 15 renewable energy companies. For FH 1,FH 2, FH 3 only records with underlying number of analysts estimates greater than 10. N refers to number of snapshots each with at least 10 underlying analysts' estimates. Asterisk denotes significance at 5% level. Values winsorised at the 1st and 99th percentile.

In Table 5 we report the univariate regressions of analysts dividends growth expectations (DPS_G) and uncertainty (DPS_STD) broken down by quartiles. The signs of the coefficients are generally positive and significant, although with a few exceptions. In the lowest quartile, the coefficient DPS_STD tends to have in some occurrences negative sign. This also occurs for the highest quartile, although it is mostly limited to GpM and CtD and oftentimes these coefficients are not significant. As expected, the results are more solid for earnings per share forecast. In Table 6 we report the univariate regressions of analysts earnings growth expectations (EPS_G) and uncertainty (EPS_STD) broken down by quartiles. Similarly, the signs of the coefficients are in most cases positive and significant, although with a few exceptions. All coefficients of EPS_STD have the correct sign and only 2 out of 72 combinations are not significant. On the opposite, there are more instances where EPS_G coefficients turn negative (11 out of 72 combinations) or are not significant (7 out of 72 combinations). In any case, this effect does not seem to indicate any particular pattern or bias in our regression model, but it highlights the challenges of using forecast data.

We then ensure that our threshold of minimum analysts estimates required for each snapshot (K) does not impact our results. In Table 10, we increase the cut-off of 10 minimum number of estimates to 20 and decrease it to 5 to test the sensitivity of our results to this parameter. The results generally persist increasing the minimum number of estimates, especially for EPS forecast. As expected, the size of the sample decreases substantially for DPS and it is not sufficient for fitting a regression model. On the opposite, 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 few exceptions, although we are cautious in using our metrics with fewer than 10 analysts forecast. In such case, the metrics might have been estimated on a not sufficiently representative sample of analysts. Nevertheless this robustness analysis shows that the results are not substantially sensitive to the cut-off threshold above a certain level.

		Quartile							
		1		2		3		4	
	FH	DPS_G	DPS_STD	DPS_G	DPS_STD	DPS_G	DPS_STD	DPS_G	DPS_STD
GpM	1	52.8227	57.3577	541.428*	504.4536*	90.22*	-163.7855*	214.9057	-234.7128*
	2	174.687*	-9.5713*	167.7687*	281.6284*	69.0461*	-70.5084	144.5712*	-115.0367
	3	16.6498*	462.0239*	45.0919	251.4164*	15.2465*	-24.9879	328.5066	-1380.4112
PtB	1	66.3326*	45.1269	295.4287*	421.5916*	620.5067*	492.4462*	586.9758*	273.5026
	2	142.1021*	-5.3509	191.3892*	-377.6472*	207.9459*	575.2677*	122.0017*	-38.2852
	3	67.1339*	-87.6881	23.6299*	22.3529	34.1098*	317.3548*	12.2422*	88.555
RoE	1	91.3188	63.6379	287.5353*	646.3775*	281.1523*	560.0479*	540.7451*	867.7944*
	2	144.5849*	2.9049	199.7477*	-12.3589	137.9472*	687.2251*	227.01*	939.2452*
	3	15.9842*	24.0327	21.0598*	39.1491	40.3415*	306.1989*	29.7324*	345.3014*
DtE	1	254.0618*	227.8183*	531.4117*	627.0554*	221.1972*	746.6944*	99.8423	82.2473
	2	177.4825*	-9.0147	135.5823*	561.0598*	215.5362*	231.0026*	60.7788*	118.3451*
	3	16.662*	454.9363	19.1176	302.3469*	41.1607*	312.0763*	20.335*	11.9431*
DtA	1	400.7759*	739.7801*	857.099*	709.2959*	131.7464*	151.4767*	-15.3911	20.3184
	2	186.425*	603.6976*	221.4064*	285.9312*	94.5601*	34.196	9.0553*	-1.2376
	3	18.3681*	-132.0503*	30.9269*	321.9528*	19.1162*	161.1632	20.6765*	4.9389*
CtD	1	162.5744	127.7333	381.366*	659.7918*	100.5659*	181.5656*	33.5901	-313.6675*
	2	73.6039*	66.7532*	196.7561*	25.5559*	90.6128*	78.4098	90.9721*	-85.3032
	3	45.8424	222.8177*	22.9849*	313.8575*	12.1082*	11.7659*	30.0008*	-43.5933

Table 5: Robustness analysis - Dividends Per Share. Panel regression coefficient of univariate regression of dividends per share growth (DPS_G), dividends per share relative standard deviation (defined as the ratio between the standard deviation of analysts estimates and the mean estimate - DPS_STD) and the price-dividend ratio on quartiles sub-samples (columns) and forecast year (rows). From top to bottom: gross profit margin (GpM), price to book (PtB), Return on Equity (RoE), Debt to Ebitda (DtE) and Debt to Assets (DtA), Cash to Debt (CtD). Asterisk denotes significance at 5% level.

		Quartile							
		1		2		3		4	
	FH	EPS_G	EPS_STD	EPS_G	EPS_STD	EPS_G	EPS_STD	EPS_G	EPS_STD
GpM	1	-5.0008*	112.9525*	-14.741*	105.9097*	28.269*	107.704*	-2.7729*	100.7705*
	2	6.9528	17.1292*	27.8225*	84.6064*	29.4402*	56.9256*	30.0163*	41.1883*
	3	5.6956	4.9698*	19.7981*	28.2803*	26.0582*	30.1439*	48.905*	39.1724*
PtB	1	-22.2288*	99.2841*	8.1578*	189.838*	13.7657	185.3505*	20.1661*	99.6883*
	2	15.3363*	27.5419*	26.5443*	69.9493*	30.9442*	78.7878*	36.8359*	69.9745*
	3	6.594*	4.7321*	20.5644*	49.0402*	29.5631*	28.045*	39.0372*	88.3075*
RoE	1	-15.6531*	83.4235*	2.8319*	161.6082*	53.6435*	115.9682*	-14.3844	267.6626*
	2	11.4101*	24.2099*	32.723*	68.5964*	26.7836*	72.9188*	28.9148*	102.1837*
	3	6.1827*	5.157*	32.5066*	35.2754*	37.5687*	39.2823*	25.2263*	25.3827*
DtE	1	-43.7157*	91.7872*	4.6395*	170.4652*	15.3896	160.2649*	12.2567*	87.6546*
	2	11.0833*	21.9322*	29.7815*	80.9066*	32.7492*	54.1759*	24.3952*	52.7597*
	3	7.8546*	6.2162*	35.4586*	76.9386	25.0945*	47.6057	25.0026*	15.4121*
DtA	1	38.0079*	159.8507*	-7.036*	156.8291*	-43.4679*	163.5252*	7.5206*	51.9559*
	2	28.79*	80.2547*	29.7451*	78.354*	29.2546*	66.9892*	5.1453	13.5246*
	3	24.9284*	85.656*	32.1614*	75.649*	25.1029*	28.4684*	12.0611*	8.0253*
CtD	1	37.2597*	99.3115*	-3.3857	106.1132*	-23.0837	95.3551*	8.8786*	196.1569*
	2	22.8545*	42.3094*	10.3069*	22.7089*	25.7457*	57.7817*	33.3235*	93.3295*
	3	6.2123*	12.0242*	17.0551*	10.3863*	18.6669*	35.6528*	34.6479*	88.9322*

Table 6: Robustness analysis - Earnings Per Share. Panel regression coefficient of univariate regression of earnings per share growth (EPS_G), earnings per share relative standard deviation (defined as the ratio between the standard deviation of analysts estimates and the mean estimate - EPS_STD) and the price-earnings ratio on quartiles sub-samples (columns) and forecast year (rows). From top to bottom: gross profit margin (GpM), price to book (PtB), Return on Equity (RoE), Debt to Ebitda (DtE) and Debt to Assets (DtA), Cash to Debt (CtD). Asterisk denotes significance at 5% level.

We are aware of the limitations of this paper and a few caveats should be pointed out. Starting with our theoretical model, we recognise that we are only considering how idiosyncratic uncertainty affects future cash flows. However, systemic climate uncertainty might also impact the required rate of return, increasing the discount rate and depressing valuations. Secondly, a strengthening of climate concerns may lead to lower (higher) discount rates for low (high) carbon assets, as highlighted by some related literature (Bolton & Kacperczyk, 2021). Thirdly, our model only considers uncertainty from an unknown policymaker action, but investors might also be uncertain about endogenous technological innovation which might lead to a larger deployment of low carbon energy regardless of policy intervention. Nonetheless, we argue that our model provide a useful conceptual framework for better understanding climate uncertainty and assets valuations. Specifically, our framework suggests a novel finding in the climate finance literature, that the high uncertainty about a climate policy regime shift may increase valuations of climate sensitive firms.

The propositions of this paper are generally corroborated by empirical evidence. But we are also aware of the challenges of using professional analysts forecast data. Forecast disagreement might not necessarily represent uncertainty, but only heterogeneous expectations and investors may or may not rely on analysts forecast for their investment decisions. Nevertheless, we argue that analysts forecasts are a sufficiently representative proxy of the overall market sentiment. Moreover, uncertainty is the leading driver of more or less heterogeneous expectations or forecast disagreement. We have found reassurance in this assumption comparing our measure of uncertainty based on disagreement with other measures of uncertainty, and climate policy uncertainty in the previous section. Yet, our empirical analysis suggests that investors expectations, and their uncertainty, might have a material effect of climate sensitive assets valuations, in line with our theoretical model.

Regardless of the limitations, this paper provides a first useful conceptual framework for understanding climate-sensitive assets valuations in the context of climate policy uncertainty. Our propositions are supported by empirical evidence using a metrics that naturally emerge from studying investors' expectations gauged with analysts forecast. Although we are not able to conclude whether current levels of climate policy uncertainty are sufficient to justify the valuations of climate sensitive assets - or if we are living in a carbon bubble - we show that high levels of climate policy ambiguity might have perverse effects on asset prices. The key finding of the paper is that climate policy uncertainty creates a potentially material option value for both low and high carbon emitting assets. However, ultimately the valuation of climate-sensitive assets will need to align to either a cleaner or dirtier future, but both states of the world will not materialise. Yet, current valuations of climate sensitive assets seem to price a possibility that both worlds will materialise. As long as climate policy inaction is possible, climate policy ambiguity might have effects on financial markets.

Our paper also shows that the role of finance in preventing global warming might only be a necessary, but not sufficient, condition to the problem, which ultimately resides in governments action. Even if additional climate information is provided, financial markets might not be able to price environmental externalities in asset prices because of the uncertainty introduced by the policymaker. In turn, climate policy uncertainty might have real effects on resources allocation by lowering the cost of capital of high carbon emitting energy. The possibility that high carbon firms might remain profitable in the future might justify investments in those assets. This highlights that financial markets may not be able to lead the transition, but will only follow the path decided by the policymaker. Although financial markets will be important in the fight for preventing global warming, they will remain a necessary, but not sufficient, condition for achieving net zero carbon emissions.

5 Conclusion

This paper shows that the valuation of climate-sensitive assets depends on a representative investor expectations, and her uncertainty about an unknown climate policy regime shift. Our theoretical model suggests that the higher the ambiguity about the policymaker decision, the higher the valuation of climate-sensitive firms, given a certain level of required rate of return and mean expected dividends growth. Our empirical analysis supports the theoretical model predictions. We find a statistically significant relationship between analysts mean dividends (earnings) growth forecast, and their standard deviation - as a proxy of uncertainty - and the price-dividend (price-earnings) ratio of climate-sensitive firms. Although we do not conclude whether current levels of uncertainty may justify the valuations of fossil fuel firms, we provide a useful conceptual framework for better understanding climate sensitive assets valuations in the context of climate change. We argue that the results of this paper suggest that for sufficiently high levels of uncertainty around the policymaker action to curb carbon emissions and prevent global warming, financial markets might price an option value to account for the possibility of no policy regime shift. The valuation of climate sensitive assets will ultimately depend on the predominant climate policy regime, but the higher the likelihood of no climate policy regime shift, the higher the option value of not divesting from fossil fuel firms. High levels of political uncertainty might have real effects on assets valuations which might inflate asset prices. Importantly, our paper suggests that financial markets might not be able to fully internalise environmental externalities, even if more climate information becomes available. Unfortunately, the finance sector will remain a follower, but not a leader, in the fight against global warming, that will ultimately reside in government action.

6 Appendix

6.1 Full derivation of the model

Let $E_{i,t}$ denote the level of energy supply produced by firm i. Energy supply matches energy demand. Let $E_{i,t}$ follows 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 subjective expectations of μ_i are distributed normally with mean g_i and variance σ_i^2 as in (2)

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

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

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

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):

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

We 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 growing 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 four parameters

6.2 Additional tables

	Forecasting horizon (FY)				
Year	1	2	3	4	5
2010	10725	10342	6605	2211	1668
2011	13376	12841	8025	1546	1229
2012	15944	15353	9438	1940	1362
2013	18584	18135	11483	2214	1574
2014	20513	20497	13068	2918	2130
2015	22643	22194	14554	3556	2549
2016	22526	21551	14947	3180	2367
2017	20590	19827	13161	3135	1515
2018	19040	18513	12971	2603	1533
2019	15578	15133	10049	2343	1345

Table 7: Number of estimates - DPS. Number of underlying analysts dividends forecasts in the sample considered for the empirical analysis. GIC Sub-industries: Integrated Oil & Gas, Oil & Gas Exploration & Production, Oil & Gas Refining & Marketing, Oil & Gas Storage & Transportation, Oil & Coal & Consumable Fuels and Renewable Energy

	Forecasting horizon (FY)				
Year	1	2	3	4	5
2010	21317	22939	10283	3038	2220
2011	23616	26004	11174	2330	1755
2012	26238	28398	12748	2521	1726
2013	29007	32068	15339	2429	1773
2014	30534	34426	17419	3287	2316
2015	31325	37094	20419	4281	2535
2016	30931	36082	21112	3658	2583
2017	29516	32733	18084	4317	2200
2018	26170	29641	18294	3432	2022
2019	23313	26372	15721	3797	2384

Table 8: Number of estimates - EPS. Number of underlying analysts earnings forecasts in the sample considered for the empirical analysis. GIC Sub-industries: Integrated Oil & Gas, Oil & Gas Exploration & Production, Oil & Gas Refining & Marketing, Oil & Gas Storage & Transportation, Oil & Coal & Consumable Fuels and Renewable Energy

City	Count	Share	City	Count	Share
Houston	125	25.2525	Parsippany	2	0.404
Denver	36	7.2727	Pekin	2	0.404
Calgary	29	5.8586	Plano	2	0.404
Dallas	26	5.2525	Richmond	2	0.404
Tulsa	20	4.0404	Salt Lake City	2	0.404
Fort Worth	16	3.2323	Spring	2	0.404
Oklahoma City	13	2.6263	Stamford	2	0.404
Hamilton	12	2.4242	Sugar Land	2	0.404
Canonsburg	8	1.6162	Abingdon	1	0.202
London	8	1.6162	Addison	1	0.202
Midland	7	1.4141	Allentown	1	0.202
New York	7	1.4141	Ames	1	0.202
San Antonio	7	1.4141	Antwerp	1	0.202
Irving	6	1.2121	Birmingham	1	0.202
The Woodlands	6	1.2121	Bogota	1	0.202
Athens	5	1.0101	Brentford	1	0.202
Pittsburgh	5	1.0101	Bristol	1	0.202
Saint Louis	5	1.0101	Cambridge	1	0.202
Austin	4	0.8081	Casper	1	0.202
Tampa	4	0.8081	Central	1	0.202
Bethesda	3	0.6061	Cleveland	1	0.202
Buenos Aires	3	0.6061	Corpus Christi	1	0.202
Findlay	3	0.6061	Courbevoie	1	0.202
Piraeus	3	0.6061	Cupertino	1	0.202
Radnor	3	0.6061	Dalian	1	0.202
Sao Paulo	3	0.6061	Dayton	1	0.202
Vancouver	3	0.6061	Detroit	1	0.202
Aberdeen	2	0.404	East Brunswick	1	0.202
Beijing	2	0.404	Edison	1	0.202
Brentwood	2	0.404	El Segundo	1	0.202
El Paso	2	0.404	Enid	1	0.202
Englewood	2	0.404	Frisco	1	0.202
Lafayette	2	0.404	Fujairah	1	0.202
Leawood	2	0.404	Fuzhou	1	0.202
Littleton	2	0.404	Geneva	1	0.202
Mexico City	2	0.404	Gillette	1	0.202
Monaco	2	0.404	Grand Cayman	1	0.202
Moon Township	2	0.404	Greenwich	1	0.202
New Orleans	2	0.404	Indianapolis	1	0.202
Omaha	2	0.404	Inver Grove	1	0.202

Table 9: Companies headquarters. Top 80 most represented cities of company headquarter for 495 firms in our sample (out of 132 cities).

Numest (K)		Dep var	FY 1 Value	FY 1 P value	FY 2 Value	FY 2 P value	FY 3 Value	FY 3 P value
>5	DPS_G	P/D	25.4648	$< .0001*$	23.2796	$< .0001*$	8.637	$< .0001*$
	DPS_STD	P/D	50.9673	$< .0001*$	-13.6409	$< .0001*$	90.8015	$< .0001*$
	R^2	P/D	0.0469	$< .0001*$	0.0849	$< .0001*$	0.3601	$< .0001*$
	N	P/D	11538		10409		5903	
>20	DPS_G	P/D	19.2063	$< .0001*$	8.3608	$< .0001*$	NA	NA
	DPS_STD	P/D	10.7605	0.0639	-2.6337	0.6801	NA	NA
	R^2	P/D	0.1138	$< .0001*$	0.0672	$< .0001*$	NA	NA
	N	P/D	209		138		1	
>5	EPS_G	P/E	-10.201	$< .0001*$	22.7027	$< .0001*$	22.626	$< .0001*$
	EPS_STD	P/E	88.7505	$< .0001*$	-5.3869	$< .0001*$	13.9104	$< .0001*$
	R^2	P/E	0.7354	$< .0001*$	0.9241	$< .0001*$	0.952	$< .0001*$
	N	P/E	16786		17337		9273	
>20	EPS_G	P/E	11.6577	$< .0001*$	11.4268	$< .0001*$	9.2074	$< .0001*$
	EPS_STD	P/E	73.9246	$< .0001*$	24.0086	$< .0001*$	17.9008	$< .0001*$
	R^2	P/E	0.4717	$< .0001*$	0.6702	$< .0001*$	0.7433	$< .0001*$
	N	P/E	2724		3079		373	

Table 10: Robustness analysis - Minimum number of analysts forecasts. Panel regression coefficient, R^2 and P-value for DPS and EPS, removing firm fixed effect. Only records with underlying number of analysts estimates greater than NUMEST (K). Asterisk denotes significance at 5% level.

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