The Review of Financial Studies

Carbon Tail Risk

Emirhan Ilhan
Frankfurt School of Finance & Management

Zacharias Sautner
Frankfurt School of Finance & Management

Grigory Vilkov
Frankfurt School of Finance & Management

Strong regulatory actions are needed to combat climate change, but climate policy uncertainty makes it difficult for investors to quantify the impact of future climate regulation. We show that such uncertainty is priced in the option market. The cost of option protection against downside tail risks is larger for firms with more carbon-intense business models. For carbon-intense firms, the cost of protection against downside tail risk is magnified at times when the public's attention to climate change spikes, and it decreased after the election of climate change skeptic President Trump. (*JEL* G13, G32, Q54)

Received March 1, 2019; editorial decision May 17, 2020 by Editor Ralph Koijen. Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

Scientists broadly agree that strong regulatory actions are needed to avoid the potentially catastrophic consequences of climate change.[1] Climate change is mostly caused by the combustion of fossil fuels, so any regulation will have to aim at significantly curbing firms' carbon emissions. However, whether, how, and when regulatory climate policies will be implemented is highly uncertain.

We are grateful to Ralph Koijen (the editor) and two anonymous referees. We also thank Tobias Berg, Patrick Bolton, Mathijs Cosemans, Kathrin de Greiff, Philipp Krueger, Ulf Moslener, David Ng, Altan Pazarbasi, Paulo Rodrigues, Johannes Stroebel, and Jakob Thomä and seminar participants at the Western Finance Association Meetings in Huntington Beach, Frankfurt School of Finance & Management, the RSM Dynamics of Inclusive Prosperity Conference, the European Commission Conference on Promoting Sustainable Finance, the European Commission Summer School on Sustainable Finance, the New Challenges in Insurance Conference, the EFA Doctoral Workshop on ESG, the EFA Panel on Sustainable Finance, and the 2nd CUHK Derivatives and Quantitative Investing Conference for their helpful comments. Supplementary data can be found on *The Review of Financial Studies* web site. Send correspondence to Zacharias Sautner, z.sautner@fs.de.

[1] The Intergovernmental Panel on Climate Change (IPCC 2018) summarizes the current scientific consensus about climate change. The IPCC is the United Nations' intergovernmental body for providing scientific evidence related to climate change.

The Review of Financial Studies 34 (2021) 1540–1571

doi:10.1093/rfs/hhaa071 Advance Access publication June 27, 2020

Regulation to limit carbon emissions could be enforced via carbon taxes, cap-and-trade schemes, or emission limits, all of which have different impacts on firms. Even in the case of carbon taxes, it is highly uncertain what the price for carbon emissions should be (it ranges between \$15 and \$360 per ton of CO_2, depending on the model) (*Financial Times* 2019). Climate policy uncertainty is further amplified because of fundamental uncertainty about how strongly emissions have to be reduced to limit global warming (see Barnett, Brock, and Hansen 2020).

Climate policy uncertainty has heterogeneous effects across firms in the economy. Uncertainty is likely to be most relevant for carbon-intense firms, as such firms will be most affected by policies that aim at curbing emissions. For such firms, regulation that limits carbon emissions can lead to stranded assets or a large increase in the cost of doing business (Litterman 2016). Carbon-intense firms may also experience financing constraints if banks reduce funding because of climate-related capital requirements. Yet the extent to which carbon-intense firms will be affected by regulation is highly uncertain. This uncertainty makes it difficult for investors to quantify the impact that future climate regulation will have on firms in terms of large drops in stock prices or general increases in volatility.

In this paper, we test whether climate policy uncertainty is priced in the option market.[2] Specifically, we explore whether the cost of option protection against downside tail risks is larger for firms with more carbon-intense business models. We also explore whether the cost of option protection against increases in return volatility (variance risk) is larger for more carbon-intense firms. Our analysis builds on prior work documenting that political or regulatory uncertainty is priced in the option market. Notably, Kelly, Pastor, and Veronesi (2016, KPV hereafter) show that options which provide insurance against tail and variance risks are more expensive when general political uncertainty is higher. The benefit of using options-based measures is that these measures reflect forward-looking expectations of subjective or perceived risk.

Pastor and Veronesi (2013, PV hereafter) provide a theoretical framework that helps us explain why political uncertainty about climate regulation ("climate policy uncertainty") may affect asset prices. In their model, the government decides whether to change its current policy. Potential new policies are heterogeneous ex ante; that is, agents expect different policies to affect firms in unique ways and with varying degrees of uncertainty. The government decides on adopting a new policy based on investors' welfare and political costs. A new policy is more likely to be adopted if its positive impact on firms' profitability is higher and if the political costs associated with it are

[2] In this paper, the term "priced" means that option prices reflect that certain stocks are riskier than others, rather than that the market compensates investors for taking a certain risk by offering an expected return. Likewise, "uncertainty" is not to be understood strictly in the Knightian sense of the word. This wording follows the meaning used in the related literature (Pastor and Veronesi 2013; Kelly, Pastor, and Veronesi 2016).

lower. While investors can only start learning about policy impacts when a new policy is adopted, "political signals" allow them to learn about political costs before the adoption of a new policy. Asset prices are affected by shocks that originate from learning about the political costs of the new policies: as new shocks occur, investors change their beliefs about expected future policies. PV show that political uncertainty leads investors to demand compensation for political events (debates, negotiations, or elections) as such events affect beliefs about future policies. Hence, investors' expectations about future policy changes affect asset prices. A cross-sectional implication of PV's model is that the cost of protection against downside tail and variance risks associated with climate policy events depends on the sensitivity of firms to potential climate regulation.

Our analysis uses three option market measures for firms in the S&P 500 as well as for the economic sectors of the index. Our focal measure, *SlopeD*, originates from KPV and identifies downside tail risk. The measure reflects the steepness of the implied volatility slope, and it is created as the slope of a function that relates left-tail implied volatility to moneyness (with moneyness being measured by the option's delta). The measure is on average positive, because far out-of-the money (OTM) puts are typically more expensive (in terms of implied volatilities) than puts that are less OTM. An increase in *SlopeD* indicates that deeper OTM puts become more expensive, which reflects a relatively higher cost of protection against downside tail risks. *SlopeD* measures the properties of the risk-neutral probability distribution implied by option prices, and, hence, takes into account both the physical distribution of a stock's returns and an adjustment for the risk premium associated with the stock's risk.[3]

Our other two measures provide complimentary information from the option market. The model-free implied skewness (*MFIS*) quantifies the asymmetry of the risk-neutral distribution (Bakshi, Kapadia, and Madan 2003). By being the third central moment of the distribution normalized by the risk-neutral variance (raised to the power of 3/2), *MFIS* reflects the expensiveness of protection against left tail events *relative* to the cost of exposure to right tail events. The variance risk premium (*VRP*) allows us to evaluate the cost of protection against general variance risk, and it is computed as the difference between the risk-neutral expected and the realized variances (Carr and Wu 2009; Bollerslev, Tauchen, and Zhou 2009).

We focus on measures constructed from options with 30 days to maturity. Short-term options are traded more frequently and with lower effective transaction costs compared to long-term derivatives. Hence, their prices adjust faster to investors' flow of information as well as to changes in perceived

[3] We follow the literature in using risk-neutral quantities as risk measure proxies. The benefit of option-implied variables compared to equivalents under the physical probability measure is their forward-looking character, while the cost includes a potential bias stemming from the risk premium effect (for discussions of related issues, see, e.g., Chang, Christoffersen, and Jacobs 2013; Cremers, Halling, and Weinbaum 2015; DeMiguel et al. 2013).

uncertainty and risks.[4] Further, we aim to identify the cost of protection against large price drops, and such tail events have the most pronounced pricing effects for short-term options (Cont and Tankov 2004).

Our data on carbon emissions are collected by means of a survey by CDP, formerly known as the Carbon Disclosure Project. We focus on Scope 1 emissions, which originate from the combustion of fossil fuels or from releases during manufacturing. We scale carbon emissions by firms' equity market values to obtain a measure of carbon intensity. We perform this scaling as the impact of the costs of future climate regulation should be considered relative to market values; for a given amount of emissions, firms with high equity market values are likely to suffer less from regulation than firms with low market values. Our main measure is a firm's industry carbon intensity, that is, Scope 1 emissions of all reporting firms in the industry divided by the market value of all reporting firms in the industry. We use this measure as carbon intensities are primarily driven by industry characteristics (as we will show). Recent evidence also indicates that industry characteristics drive the effect of Scope 1 intensities on returns and investor screening (Bolton and Kacperczyk 2020).[5] We use a selection model as firms disclose emissions voluntarily to CDP.

We find strong evidence that climate policy uncertainty is priced in the option market. A one-standard-deviation increase in a firm's log industry carbon intensity increases the implied volatility slope (*SlopeD*) by 0.014, or by 10% of the variable's standard deviation. We confirm our finding for sector exchange-traded fund (ETF) options: the cost of option protection against downside tail risks is higher for the more carbon-intense sectors of the S&P 500. These results are highly robust. For example, they are unaffected if we drop oil and gas firms (our regressions already control for oil betas), and we continue to find effects for option maturities of up to one year. Overall, our estimates suggest that options written on carbon-intense firms are relatively more expensive, especially for the far-left tail region, as they provide protection against downside tail risks associated with climate policy uncertainty.

Evidence for the two other measures is more mixed, but it complements the picture presented by *SlopeD*. While we find some effects for *MFIS* at the sector level, we cannot detect corresponding effects at the firm level. These weaker results reflect that *MFIS*, different from *SlopeD*, does not directly capture left tail risk. Instead, it measures distribution asymmetry by comparing left and right tail risk, with the latter, as we show, also being higher for carbon-intense firms. For *VRP*, we find effects at the firm level, but not at the sector level.

4 For example, Muravyev and Pearson (2020) document that investors trade options on S&P 500 constituents with time to maturity less than 3 months 30% more often (in terms of stock-days) than options with maturities between 3 and 12 months. The bid-ask spreads, adjusted for execution timing based on a high-frequency trade analysis, are on average about 50% higher for longer-term options than for shorter-term ones.

5 Bolton and Kacperczyk (2020) explain their finding with Gennaioli and Shleifer's (2010) local thinking hypothesis, whereby investors use a coarse categorization of firms within a given industry when evaluating carbon risks.

Hence, our results for all three measures combined indicate that higher climate policy uncertainty increases at the firm level the likelihood of left and right tail events, and it has some effect on firm-level uncertainty as measured by *VRP*. On the sector level, however, where firm-specific risks are partially diversified away,[6] we observe that the effect is more systematic and concentrated in the left tail.

In a next step, we investigate whether the effect of carbon intensities on downside tail risk is amplified at times when public attention to climate change is high. Our assumption is that high public attention to global warming increases the probability that pro-climate policies are adopted.[7] Importantly, as the probability of a policy change rises, so does uncertainty about which specific new policies will be selected and what their *impact* on firm profitability will be. While this implies more certainty that a regulatory change occurs, pro-climate policies are characterized by large uncertainties in terms of their impact on firm profitability as such policies represent larger deviations from current practices. The cost of option protection against downside tail risk should therefore be magnified at times when public attention to climate change spikes. To obtain proxies for attention to climate change, we use the negative climate change news index developed by Engle et al. (2020) as well as Google search volume data for the topic "climate change". While we find that the effect of carbon intensities on *SlopeD* is aggravated when there is more negative climate change news, we cannot detect a corresponding effect for Google search data.[8]

Finally, we use the election of President Trump in 2016 as a shock that reduced climate policy uncertainty in the short term. Advantages of the election are that its outcome was unexpected to the market and that it featured two candidates with opposing views on climate regulation. While President Trump signaled in his campaigns that prevailing climate policies would not become stricter, Hillary Clinton, to the contrary, promised pro-climate policies. Hence, President Trump's election meant little change in the status quo of U.S. climate regulation, whereas Clinton's election would have implied the opposite if she were elected.[9] The cost of insurance against downside tail risks

---

6 Full diversification is unlikely for sectors with a low number of constituents and for sectors with a skewed distribution of value weights.

7 In the PV model, the probability of the adoption of new policies increases (a) when the impact of the current policy is harmful to firm profitability and (b) when political costs associated with new policies are low. We are agnostic about which of these components drives our assumption. Public attention on climate change is often increased after natural disasters and climate summits or political events related to climate change. The former likely reveals inadequacy of current climate policies and, thereby, their harmful impact, whereas the latter likely reduces political costs of adopting pro-climate policies.

8 An explanation for the difference in results may be that the Engle et al. (2020) index captures downside aspects associated with climate change more directly, as it focuses on negative news.

9 No or little change in the status quo under President Trump was likely, especially when compared to Clinton's plans, even though he campaigned on withdrawing from the Paris Agreement. However, as the Paris Agreement did not have any in-built enforcement mechanisms and U.S. climate regulation had been lenient prior to his election, the expected uncertainty of the set of potential new policies under a regime of President Trump should still be lower than that under a Clinton regime.

associated with climate policy uncertainty should therefore have declined after President Trump's election, especially for carbon-intense firms. Supporting this prediction, *SlopeD* for highly carbon-intense firms decreased by 0.025 after President Trump's election, relative to less carbon-intense firms, a decline equal to 12% of the variable's standard deviation during the event window. We find similar effects for sector options.

Our findings contribute to two strands of literature. The first strand documents that regulatory or political uncertainty affects asset prices. As mentioned, KPV is most closely related to us as they show that options are more expensive if they provide protection against risks associated with political events. Consistent with their model, PV find that stocks are more volatile and command a higher risk premium when political uncertainty is higher, measured using the Baker, Bloom, and Davis (2016) index. Similar evidence is provided by Brogaard and Detzel (2015). Brogaard et al. (2020) find that higher global political uncertainty is associated with lower equity returns and higher volatilities around the world. Related evidence from the healthcare market comes from Koijen, Philipson, and Uhlig (2016), who show theoretically and empirically that political uncertainty related to medical approval regulation and reimbursement policies affects the profit risk of healthcare firms. As a result, healthcare firms need to compensate investors with a risk premium. Using data on U.S. healthcare firms, they document a 4%–6% annual medical innovation premium, which reflects investor uncertainty about healthcare regulation.

Only a few papers in finance study climate policy uncertainty. Barnett (2019) shows that climate policies that restrict oil use can generate a run on oil, whereby oil firms accelerate extraction. This leads to a decrease in the oil price and the value of oil firms. He also shows that firms with high climate policy risk benefited from President Trump's election. Similarly, Ramelli et al. (2020) show that stock prices of carbon-intensive firms positively reacted to President Trump's election. Delis, de Greiff, and Ongena (2020) find that climate policy uncertainty started to be priced into syndicated loans, especially among fossil fuel firms. Engle et al. (2020) develop a dynamic strategy that hedges news about climate change, and Barnett, Brock, and Hansen (2020) provide a decision theory framework to address how climate uncertainty affects asset prices.

The second strand examines the effects of climate change on asset prices. Hong, Li, and Xu (2019) find that stock prices of food companies do not fully reflect climate risks. Bolton and Kacperczyk (2020) document that firms with higher carbon intensities earn a carbon premium. This finding is similar to Hsu, Li, and Tsou (2020), who find that firms that generate many toxic chemical emissions earn higher returns. Görgen et al. (2020) create a carbon factor to capture firms' sensitivity to the transition to a low-carbon economy. Matsumura, Prakash, and Vera-Munoz (2014) find that higher emissions are associated with lower firm values. Similarly, Berkman, Jona, and Soderstrom (2019) use a firm-specific climate risk measure that they find is negatively related to firm value. Using aggregate market outcomes, De Haas and Popov (2019) show that more equity-funded markets have lower per capita emissions, as stock markets seem to reallocate investment toward more carbon-efficient sectors. Bansal, Kiku, and Ochoa (2017) show that equity portfolios have negative exposure to long-run temperature fluctuations, and Daniel, Litterman, and Wagner (2016) calibrate the price of climate risk. Giglio et al. (2018) study long-term discount rates to evaluate climate change mitigation policies. Although most of these studies concentrate on underlying price effects and risk premiums, we analyze whether the cost of protection against climate policy uncertainty is priced in the option market.

1. Hypotheses Development

Our hypotheses development is guided by PV, who provide a framework to explain why political uncertainty affects asset prices. Asset prices in their model are affected by political shocks, which are due to investors learning about the political costs associated with new policies. As these costs are uncertain, investors are unable to predict which policies will be chosen, and investors change their beliefs once political shocks arise. Hsu, Li, and Tsou (2020) build on PV to analyze how firms with toxic emissions are affected by political uncertainty. In their model, the government learns about the welfare costs of toxic emissions and decides between strong and weak regulatory regimes. Strong regulation has a more negative effect on the profitability of emission-intense firms, and, as a result, these firms face larger risks.

Our hypotheses are related to these papers because global warming generates large climate policy uncertainty for carbon-intense firms. (We consider climate policy uncertainty to be a specific form of political uncertainty.) As global warming is primarily caused by the combustion of fossil fuels, regulation must be aimed at significantly reducing carbon emissions. Importantly, it remains highly uncertain whether, how, and when such regulation would be implemented. How firm profitability would be affected by any new policies is also highly unclear. Climate policy uncertainty matters most for carbon-intense firms, as these firms are the most directly affected by policy instruments that curb emissions, such as emission limits, cap-and-trade schemes, or carbon taxes. These instruments would likely reduce future cash flows of carbon-intense firms and may depress their valuations as a result.

In summary, climate policy uncertainty makes it difficult for investors to quantify the impact of future climate regulation on carbon-intense firms, in terms of both large stock price drops and general increases in return volatility. Hence, the cost of option protection against downside tail and variance risks associated with climate policy uncertainty should be larger for such firms:

Hypothesis 1. *The cost of option protection against downside tail and variance risks associated with climate policy uncertainty is higher at carbon-intense firms.*

High public attention to global warming, which may be the result of climate-related natural disasters or political summits on climate change, should make new pro-climate policies and their adoption more likely. New pro-climate regulations can take many different forms with varying levels of severity (as modelled in PV), and this heterogeneity generates policy uncertainty.[10] As the probability of a policy change rises, so does the political uncertainty about *which* new policies will be adopted and their impact on firm profitability. The cost of protection against downside tail risks associated with climate policy uncertainty therefore should be magnified at such times. This leads to the following hypothesis:

Hypothesis 2. *The cost of option protection against downside tail risks associated with climate policy uncertainty increases at times when public attention to climate change is higher.*

Finally, we exploit President Trump's election in 2016 as a shock that reduced climate policy uncertainty in the short term. The advantage of the 2016 presidential election is that it featured two candidates with opposing views on climate change. While Hillary Clinton supported new pro-climate policies, President Trump signaled that prevailing climate policies were likely to stay. He dubbed climate change "a hoax" and tweeted that "the concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive" (Trump 2012). His stance can be interpreted as a desire to keep the lenient status quo intact, whereas Clinton's position was more radical with a desire to make forward progress in pro-climate regulation. Therefore, the set of climate policies likely to be adopted under President Trump should have a lower variance compared to that under Clinton. Hence, his unexpected election should have reduced uncertainty about which climate policies will be adopted after Election Day.[11] This should reduce the cost of insurance against downside tail risks associated with climate policy uncertainty at carbon-intense firms. This leads to the following hypothesis:

Hypothesis 3. *The cost of option protection against downside tail risks associated with climate policy uncertainty declined after the election of President Trump in 2016 at carbon-intense firms.*

[10] Pastor and Veronesi (2012) formally model impact uncertainty. Pastor and Veronesi (2012) differs from PV's model in a way that has implications for our hypotheses. Pastor and Veronesi (2012) assume that prior beliefs about the impacts of potential policies are identical. In contrast, PV allow the impacts and uncertainties to vary across potential policies. It is these a priori heterogeneous beliefs about potential policies in PV that induce an endogenous increase in political uncertainty as the probability of a policy change rises. In a limiting case in which the probability of policy change goes to zero, there is no political uncertainty since the status quo is sure to remain.

[11] An advantage to the analysis of President Trump's election is that his victory was largely unexpected by the market. On Election Day morning, online gambling company Betfair put the probability of a victory by President Trump at 17% (Wagner, Zeckhauser, and Ziegler 2018). President Trump also lost the popular vote by almost 3 million votes.

2. Data

2.1 Carbon emissions

2.1.1 Data source. We collect data on carbon emissions from CDP, formerly known as the Carbon Disclosure Project. The data are collected by CDP on behalf of institutional investors representing over $87tr in assets under management in 2018.[12] Firms submit their data to CDP at the end of June, covering emissions of the prior calendar year (the deadline was changed to mid-August for 2018 submissions). CDP then releases these data by the end of October. We examine emissions generated between 2009 and 2016. We focus on S&P 500 firms because CDP primarily covers these firms for its U.S. survey. Figure 1 shows that participation in the CDP survey among S&P 500 firms has increased over time, in terms of the number of reporting firms (Figure 1, panel A) and as a fraction of the S&P 500 market capitalization (Figure 1, panel B).

The data include information on three types of emissions. Scope 1 emissions are direct emissions, which originate from the combustion of fossil fuels or from releases during manufacturing. Scope 2 emissions are indirect emissions from the consumption of electricity or steam, and Scope 3 emissions are emissions that occur in the value chain of a firm (both upstream and downstream). CDP translates all greenhouse gases into carbon dioxide (CO_2) equivalents. We focus on Scope 1 emissions because they are directly owned and controlled by firms. (We find no effects for Scope 2 emissions and do not use Scope 3 emissions, because they are not controlled by firms.) Table 1 shows that Scope 1 emissions are highly skewed. While the average S&P 500 firm that reports emissions data produces almost 5 million tons of carbon, the median firm emits only about 118,000 tons.

2.1.2 Variable measurement. We scale firms' Scope 1 emissions by their end-of-year equity market values to obtain a measure of carbon intensity. We divide emissions by equity values because new regulation is likely to be implemented via cap-and-trade mechanisms or carbon taxes, which implies that the amount to be paid by a firm should be considered relative to its market value. Specifically, the stock price of a firm with a large market value is likely to be affected less by, for example, a carbon tax, compared to a firm with the same emissions but a low market value. We show that results are robust if we scale emissions by total assets instead.

We employ a firm's *industry* carbon intensity as the main measure in our regressions. First, Table 2 shows that high carbon intensities cluster within a few industries (and sectors) and are highly skewed. Figure 2 confirms this pattern

---

12 CDP data are reliable. First, many CDP signatories are influential investors in the surveyed firms, so false reporting could have major ramifications. Second, many institutions consider CDP data to be so trustworthy that they use them for their own risk management (Krueger, Sautner, and Starks 2020), and leading ESG data providers use them for rating models (e.g., MSCI ESG Research, Bloomberg, or Sustainalytics).

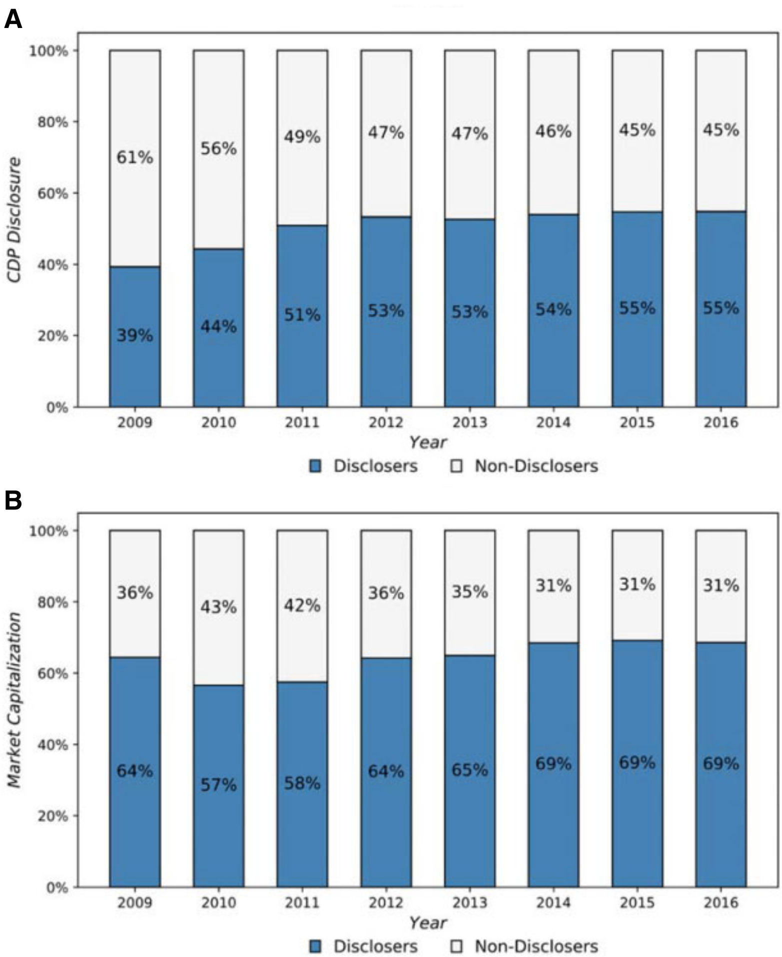

Figure 1
CDP disclosure over time
This figure reports how disclosure of carbon emissions to CDP by S&P 500 firms has evolved over time. Panel A reports the number of S&P 500 firms disclosing (blue) and not disclosing (white) the carbon emissions generated in a given year as a fraction of the number of firms in the S&P 500. Panel B reports the market capitalization of firms disclosing (blue) and not disclosing (white) the carbon emissions generated in a given year as a fraction of the total market capitalization of the S&P 500.

across the sample.[13] Second, Table 3, panel A, documents that firms' carbon intensities are primarily driven by industry characteristics. The panel explains in columns 1 and 2 a firm's carbon intensity, *log(Scope 1/MV firm)*. While column

13 Internet Appendix Table 1 shows that unscaled emissions are similarly skewed. In fact, the top-20 emitting firms alone generate about 60% of all carbon emissions in the S&P 500, and 29% come from just five firms.

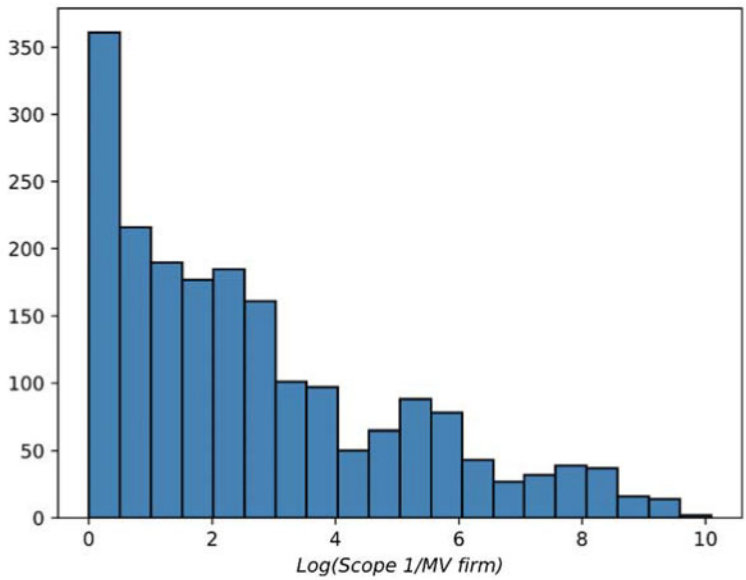

Figure 2
Distribution of carbon intensities across S&P 500 firms
This figure reports a histogram of *log(Scope 1/MV firm)*. *Scope 1/MV firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) divided by the firm's equity market value (in millions $). The sample includes S&P 500 firms with data on carbon emissions disclosed to CDP. The sample covers emissions generated between 2009 and 2016.

1 uses a firm's industry carbon intensity, *log(Scope 1/MV industry)*, as the only explanatory variables, column 2 adds firm characteristics and year fixed effects. In column 1, the adjusted R^2 of the regression is .920, which demonstrates that firm-level variation in carbon intensity is largely subsumed by industry-level variation. In column 2, the adjusted R^2 increases only slightly, which indicates that firm characteristics play only a modest role in explaining firm-level carbon intensities. Columns 3 and 4 estimate the same regressions from columns 1 and 2 but rely on unscaled instead of scaled emissions. We report these two regressions to ensure that our results are not affected by the use of market values on both sides of the equations. Reassuringly, the regressions confirm the pattern that is documented in the first two columns. Third, Bolton and Kacperczyk (2020) show that the effects of Scope 1 intensities on returns and exclusionary screening by investors are driven by industry characteristics.

Therefore, our variable of interest is *Scope 1/MV industry*, defined as total Scope 1 carbon emissions (in metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions $). The measure is calculated at the SIC4 level because emissions can vary substantially within the SIC2 level (Internet Appendix Table 2).

Table 1
Summary statistics

Variable	Mean	STD	25th	Median	75th	Obs.
Scope 1 firm	4,957,597	15,853,469	16,829	117,715	1,078,551	1,963
Scope 1/MV firm	313.82	1,131.91	1.15	6.76	54.46	1,815
Scope 1/MV industry	261.85	757.36	1.61	6.43	48.64	1,903
Scope 2/MV firm	38.20	69.56	5.02	12.70	36.36	1,763
Industry CDP disclosure	0.710	0.238	0.500	0.667	1.000	1,963
SlopeD	0.176	0.136	0.100	0.135	0.207	1,959
MFIS	−0.415	0.271	−0.564	−0.429	−0.284	1,959
VRP	−0.002	0.087	−0.011	0.005	0.021	1,959
Institutional ownership	0.793	0.130	0.711	0.811	0.883	1,916
log(Assets)	10.12	1.33	9.12	9.95	10.88	1,963
Dividends/net income	0.395	0.516	0.165	0.331	0.522	1,949
Debt/assets	0.263	0.157	0.149	0.246	0.362	1,960
EBIT/assets	0.104	0.072	0.053	0.095	0.143	1,963
CapEx/assets	0.039	0.038	0.013	0.028	0.055	1,959
Book-to-market	0.407	0.286	0.202	0.343	0.562	1,815
Returns	0.171	0.270	0.008	0.149	0.307	1,963
CAPM beta	1.065	0.531	0.671	1.021	1.390	1,963
Volatility	0.066	0.028	0.046	0.058	0.079	1,963
Oil beta	−0.018	0.169	−0.115	−0.034	0.057	1,963

Summary statistics are reported at the firm-year level. The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. Table A.1 defines all variables in detail. The sample period covers emissions generated during the years 2009 to 2016 and option market measures from 2010 to 2017.

2.2 Option market measures

2.2.1 Data source. We use option market measures to identify the effects of climate policy uncertainty. Option prices subsume expectations about investment opportunities (Vanden 2008), and option-based variables work well in predicting future assets price dynamics (e.g., Christoffersen, Jacobs, and Chang 2013). Most importantly, options-based measures reflect expectations about all possible future events, even the rarest ones. We use options data from the Surface File of Ivy DB OptionMetrics. For sectors, we use options on State Street Global Advisors' ETFs (SPDR ETFs) as the underlying. The Surface File contains daily Black-Scholes implied volatilities for standard maturities and delta points (for absolute deltas from 0.2 to 0.8, with 0.05 delta increments). The implied volatilities are created from closing options prices through inter- and extrapolation in the time and delta dimensions. Although these implied volatilities do not correspond to traded option contracts and form a standardized volatility surface, they reflect the consensus expectations of market participants priced into the options. We select OTM calls and puts with absolute deltas smaller than 0.5. Return and market capitalization data are from CRSP.[14]

We process the surface data to make them less discrete in the moneyness (defined as strike over spot) dimension. For each underlying, maturity, and day,

14 We obtain the composition of the S&P 500 and its sectors from Compustat and merge these data with data from CRSP through the CCM linking table using GVKEY and IID to link to PERMNO, following the second-best method from Dobelman, Kang, and Park (2014). We match CRSP data with options data through the historical CUSIP link, provided by Ivy DB OptionMetrics.

Table 2
Firms' carbon intensities by industry and sector

A. Ranking of top-10 industries by Scope 1/MV firm

Rank	Industry name	SIC2	Mean	STD	25th	Median	75th	Obs.
1	Primary metal industries	33	12,029	549	11,642	12,029	12,417	2
2	Electric, gas, & sanitary services	49	3,216	3,584	630	2,329	4,119	153
3	Stone, clay, & glass products	32	1,100	356	798	1,022	1,378	5
4	Transportation by air	45	1,091	759	479	937	1,436	26
5	Water transportation	44	334	67	281	314	407	6
6	Petroleum & coal products	29	322	46	285	330	353	16
7	Oil & gas extraction	13	232	151	133	200	306	69
8	Railroad transportation	40	200	50	157	209	244	23
9	Paper & allied products	26	189	244	44	64	421	35
10	Auto repair, services, & parking	75	188	36	163	171	225	7

B. Ranking of S&P 500 sectors by Scope 1/MV sector

Rank	Sector	SPDR ETF	Mean	STD	25th	Median	75th	Obs.
1	Utilities	XLU	2,396	572	1,880	2,602	2,883	8
2	Energy	XLE	324	45	290	314	355	8
3	Materials	XLB	292	59	280	304	327	8
4	Industrials	XLI	54	5	51	53	57	8
5	Consumer staples	XLP	19	3	16	19	21	8
6	Consumer discretionary	XLY	16	12	8	11	21	8
7	Healthcare	XLV	4	2	3	4	6	8
8	Technology	XLK	1.2	0.7	0.6	1.1	1.8	8
9	Financials	XLF	0.8	0.3	0.5	0.8	1.0	8

Panel A reports firms' Scope 1 carbon intensities for the top-10 industries. Statistics are reported at the firm-year level across different SIC2 industries. *Scope 1/MV firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) divided by a firm's equity market value (in millions \$). We rank industries by the average carbon intensity of firms in an industry. The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. The sample period covers emissions generated during the years 2009 to 2016. Not all firms are included in our sample across all years, which explains why the number of observations in some industries falls below eight. Panel B reports Scope 1 carbon intensities of the economic sectors of the S&P 500. Statistics are reported at the sector-year level. *Scope 1/MV sector* are a sector's Scope 1 carbon emissions (in metric tons of CO_2) divided by a sector's equity market value (in millions \$). We rank sectors by the average sector carbon intensity. The sample includes 9 of the 11 sectors of the S&P 500. The sample period covers emissions generated during the years 2009 to 2016.

we interpolate the observed implied volatilities as a function of moneyness within the available data range using monotonic cubic splines (piecewise cubic Hermite interpolating polynomials). We then fill in the implied volatilities beyond the observed moneyness bounds with the volatilities on the bounds. For OTM puts, we use the leftmost available data point (corresponding to a Black-Scholes delta of -0.2), and for OTM calls, we use the rightmost available data point (corresponding to a delta of 0.2). In this way, we produce 1,001 data points over the moneyness range from 1/3 to 3 (corresponding to equally spaced points from a log-moneyness of -log 3 to log 3). Each of these data points contains an implied volatility for a particular moneyness level and, hence, for an option delta level.

2.2.2 Variable measurement.

2.2.2.1 Primary measure: Implied volatility slope. The implied volatility slope (*SlopeD*), borrowed from KPV, is a function relating the left-tail

Table 3
Determinants of carbon intensities, carbon emissions, and carbon disclosure to CDP

	A. Determinants of carbon intensities or carbon emissions				*B. Disclosure decision*
Dependent variable:	*log(Scope 1/ MV firm)*		*log(Scope 1 firm)*		*CDP disclosure*
	(1)	(2)	(3)	(4)	(5)
log(Scope 1/MV industry)	0.969***	0.940***			
	(180.20)	(87.06)			
log(Scope 1 industry)			1.015***	0.927***	
			(148.91)	(50.36)	
Industry CDP disclosure					0.926***
					(113.84)
log(Assets)		0.015		0.342***	0.076***
		(0.89)		(8.77)	(11.69)
Dividends/net income		0.056*		0.125**	0.019
		(1.78)		(2.44)	(1.35)
Debt/assets		0.561***		1.123***	−0.067*
		(3.80)		(4.19)	(−1.75)
EBIT/assets		0.073		2.334***	0.202**
		(0.23)		(3.85)	(1.99)
CapEx/assets		1.807**		5.812***	−0.121
		(2.27)		(3.98)	(−0.88)
Book-to-market		0.365***		0.142	−0.104***
		(3.82)		(0.93)	(−2.85)
Returns		0.013		0.059	−0.051*
		(0.16)		(0.33)	(−1.89)
Institutional ownership		0.212		0.022	−0.084
		(1.26)		(0.09)	(−1.35)
CAPM beta		0.093***		0.168**	0.042***
		(2.98)		(2.57)	(3.16)
Volatility		−2.444***		−8.362***	−0.530*
		(−3.05)		(−4.45)	(−1.70)
Oil beta		−0.096		−0.341*	0.041
		(−1.13)		(−1.86)	(1.23)
Time trend		−0.006		−0.029	−0.006**
		(−0.70)		(−1.37)	(−1.97)
Model	OLS	OLS	OLS	OLS	OLS
Year fixed effects	No	Yes	No	Yes	Yes
Level	Firm	Firm	Firm	Firm	Firm
Frequency	Annual	Annual	Annual	Annual	Annual
Obs.	1,815	1,772	1,963	1,772	3,206
Adj. R^2	.920	.922	.827	.850	.461

Regressions in panel A are estimated at the firm-year level. *Scope 1/MV firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) divided by the firm's equity market value (in millions \$). *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions \$). *Scope 1 firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) (unscaled). *Scope 1 industry* are the Scope 1 carbon emissions (in metric tons of CO_2) of all firms in the same industry (SIC4) and year (unscaled). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. The sample period covers emissions generated during the years 2009 to 2016. Regressions in panel B are estimated at the firm-year level. *CDP disclosure* equals one for a given firm-year if a firm discloses data on the carbon emissions released during the year, and zero otherwise. *Industry CDP disclosure* is the fraction of firms in the same SIC4 industry and year that discloses data on the carbon emissions released during the year. The sample includes all firms in the S&P 500. The sample period is the same as in the first panel. Table A.1 defines all variables in detail. t-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

implied volatility to moneyness, measured using the Black-Scholes delta. Specifically, *SlopeD* is the slope coefficient from regressing implied volatilities of OTM puts (deltas between -0.5 and -0.1) on the corresponding deltas and a constant. Because far OTM puts (with smaller absolute deltas) are typically more expensive, *SlopeD* usually takes positive values. A more positive value of *SlopeD* indicates that deeper OTM puts are relatively more expensive, suggesting a relatively higher cost of protection against downside tail risks. Because *SlopeD* is defined as a regression slope, it measures relative expensiveness and does not depend on the average level of the implied volatility. This feature allows us to compare the measure across firms with different levels of general risk. *SlopeD* is our preferred measure as it most directly captures the relative cost of protection against downside tail risk. Intuitively, it quantifies the cost of protection against extreme downside tail events relative to the cost of protection for less extreme downside events. We derive our results from options with 1-month maturities and provide results for maturities of up to 12 months for robustness. (Internet Appendix B illustrates the information content of this and the two other measures.)

2.2.2.2 Additional measures: Model-free implied skewness and variance risk premium. *MFIS* is constructed following Bakshi, Kapadia, and Madan (2003, BKM hereafter) and quantifies the asymmetry of the risk-neutral distribution. It is computed using the standard formula for the skewness coefficient, that is, as the third central moment of the risk-neutral distribution, normalized by the risk-neutral variance (raised to the power of 3/2). By being normalized, *MFIS* also provides information about the expensiveness of protection against left tail events, though now relative to right tail events. As changes in the distribution asymmetry are driven by the probability mass in the downside relative to the upside region, *MFIS* is affected by both tails. In terms of interpretation, more negative values of *MFIS* indicate a relocation of probability mass under the risk-neutral measure (i.e., after adjusting for preferences toward risk) from the right to the left tail. Like in BKM, *MFIS* at time t for period τ is given by

$$MFIS(t,\tau)=\frac{e^{r\tau}W(t,\tau)-3\mu(t,\tau)e^{r\tau}V(t,\tau)+2\mu(t,\tau)^3}{[e^{r\tau}V(t,\tau)-\mu(t,\tau)^2]^{3/2}}$$

where $V(t,\tau)$ and $W(t,\tau)$ are prices of variance and cubic contracts, respectively; r is the prevailing risk-free rate; and $\mu(t,\tau)$ is the risk-neutral expectation of the underlying log return over the period τ. All unknown ingredients (variance, cubic contracts, and expected log return) in the formula are computed by integration of some functions of options prices over the continuum of strikes for a given maturity (see BKM for details). We approximate these integrals with finite sums using the interpolated volatility surface (see above). As *MFIS* captures the distribution of the probability mass in the left versus the right tail of the risk-neutral distribution, it can be interpreted as the cost of protection against left tail events relative to the cost of gaining positive realizations on the left tail.

VRP is computed as the difference between the risk-neutral expected and the realized variance (Carr and Wu 2009; Bollerslev, Tauchen, and Zhou 2009). As a proxy for the risk-neutral expected variance, we use the model-free implied variance ($MFIV_{t,t+M}$) computed on day t for maturity M following Britten-Jones and Neuberger (2000) by again approximating the respective integrals with finite sums using the interpolated volatility surface observed on day t for maturity M. The realized variance ($RV_{t,t+M}$) is computed from daily log returns over a future window from t to $t+M$, that is, with a length corresponding to the maturity of the options used for the risk-neutral variance. The variance risk premium ($VRP_{t,t+M}$) for maturity M is computed in the ex post version on each day t as $MFIV_{t,t+M} - RV_{t,t+M}$, and expressed in annual terms.[15]

VRP captures the cost of protection against general uncertainty-related volatility changes in down and up directions, whereas our other measures capture the relative cost of protection against left tail risk (relative to "normal" risks, *SlopeD*, or relative to the right tail, *MFIS*).

3. Empirical Model

3.1 Selection model and truncation rule

We estimate a selection model to mitigate the concern that our estimates are biased because firms voluntarily disclose their carbon emissions to CDP. The need for a selection model arises because firms only disclose their emissions if the (unobservable) net benefit of disclosing is positive. As a result, we only observe the emissions generated by firm i during year t if the firm discloses this information to CDP (i.e., if $CDP\ disclosure_{i,t} = 1$). In all other cases, data on carbon emissions is missing (i.e., if $CDP\ disclosure_{i,t} = 0$). We therefore jointly estimate the following model:

$$OMM_{i,m,t+1} = \beta_0 + \beta_1 Log(Scope1/MV\ industry)_{i,t} + \boldsymbol{x_{i,t}\beta} + u_{i,m,t+1}, \quad (1)$$

$$CDP\ disclosure_{i,t} = \gamma_0 + \gamma_1 Industry\ CDP\ disclosure_{i,t} + \boldsymbol{x_{i,t}\gamma} + v_{i,t}, \quad (2)$$

whereby Equation (1) constitutes the outcome equation and Equation (2) the selection equation. As explained, Equation (1) is only observed if $CDP\ disclosure_{i,t} = 1$. We relate a firm's carbon intensity in year t to option market measures ($OMM_{i,m,t+1}$) in year $t+1$ as emissions of year t are only made public

---

[15] We follow KPV to compute the ex post *VRP* as opposed to an ex ante *VRP* (which is used by, e.g., Bollerslev, Tauchen, and Zhou 2009). The reason for selecting the ex post version is that, by construction, it reflects all the information flow from the observation date to the option maturity and can capture the reaction of traders to particular events, while the ex ante version is based only on expectations formed before and on the observation date, which implies that it can miss important information. We thank a referee for pointing out this potential problem. Note that our results are robust to using either version of *VRP*.

by CDP in year $t+1$ (at the end of October). Consequently, information about emissions generated in year t is only available to investors in the 12-month period starting from November of year $t+1$. For our sample period, this implies that we estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. Note that we employ a firm-level selection model even though carbon intensities are at the industry level. The reason is that, for some industries, no firms within the S&P 500 disclose any emissions data. This makes industry carbon intensities unobserved for some firms and may bias ordinary least squares (OLS) estimates.

We estimate our model using full-information maximum likelihood (FIML) with the assumptions that $(u_{i,m,t+1}, v_{i,t})$ is bivariate normal with zero means and nonzero variances; $u_{i,m,t+1}$ is uncorrelated over m within a given firm-year; and $Cov(u_{i,m,t+1}, v_{i,t})$ is nonzero. Joint normality of the error terms is more restrictive than the assumptions required by the Heckman (1979) two-step procedure. However, the FIML estimator has the advantage that it is more efficient (Wooldridge 2010) and that it produces standard errors that can be used directly. Our setting differs from a standard selection model in that Equations (1) and (2) operate at different observation levels. While the decision to disclose carbon emissions is at the firm-year level (i.e., (i,t)), the option market measures are the firm-month-year level (i.e., $(i,m,t+1)$). Internet Appendix C discusses how this affects the FIML estimator. A similar FIML model with data from different observation levels is also estimated in Brav et al. (2019).

3.2 Outcome equation: Option market variables and carbon intensities

For firm i in month m and year $t+1$, each option market measure is calculated as the average across daily values. We estimate regressions at the firm-month level to increase power, to exploit that the options measures are available throughout the year, and because emissions are relatively persistent within the firm-year. Importantly, some of our tests also explore how the effect of emissions varies when climate attention fluctuates *within* the year (monthly).

Scope 1/MV industry$_{i,t}$ is the Scope 1 industry carbon intensity of firm i during year t. We use (one plus) the variable's natural logarithm because emission intensities are highly skewed. Results are unaffected by within-year changes in equity market values (the denominator of the emissions variable) as we scale emissions by end-of-year market capitalizations.

We control for firm characteristics that prior work identified as determinants of firm risk, notably *log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, Returns, CAPM beta*, and *Volatility* (unless we explain the *VRP*). We also control for *Institutional ownership, Oil beta*, and a time trend. Control variables are measured at year t.

3.3 Selection equation: CDP disclosure decision

CDP disclosure$_{it}$ equals one if firm i discloses data to CDP on the carbon emissions released during year t and zero otherwise. Equation (2) includes the same control variables as the outcome regression, but additionally controls for the disclosure level in firm i's industry in year t (*Industry CDP disclosure*$_{it}$). We include this variable to capture the effects of peer pressure on the decision to disclose emissions. As more firms within an industry disclose their emissions, nondisclosers likely feel greater pressure to disclose their CO_2 footprints too. Like with Matsumura, Prakash, and Vera-Munoz (2014), for our purposes, this variable constitutes the excluded instrument in Equation (2), so it is omitted in Equation (1). Internet Appendix D discusses potential violations of the exclusion restriction.

Table 3, panel B, reports the selection regression. The estimates show that the propensity for a firm to report emissions significantly increases if other firms in the same industry disclose their data as well. In column 5, a one-standard-deviation shock in *Industry CDP disclosure* (0.32) increases the probability to disclose emissions by 30%, a large number relative to the unconditional mean of 51%. The estimates in Table 3, panel B, confirm the importance of accounting for selection bias. Firms that disclose emissions are larger, have lower leverage, higher earnings, lower book-to-market ratios, higher betas, and lower volatility.

4. Empirical Results

4.1 Carbon intensity and downward option protection: Cross-sectional results

4.1.1 Firm- and sector-level evidence: Main results. Table 4, panel A, tests Hypothesis 1 and reports firm-level regressions of the effects of *log(Scope 1/MV industry)* on option market measures. Column 1 shows that a firm's industry carbon intensity has a positive and significant effect on *SlopeD*. A one-standard-deviation increase in a firm's log industry carbon intensity (2.28) increases *SlopeD* by 0.014, which equals 10% of the variable's standard deviation. In comparison, a one-standard-deviation decrease in a firm's profitability (*EBIT/assets*) increases *SlopeD* by 0.013 or 10% of the variable's standard deviation. *SlopeD* is generally lower for firms that are larger, that are more profitable, invest less, and have lower volatility. It is higher for firms with higher leverage and with higher book-to-market ratios.

Column 2 shows that we cannot detect that a higher carbon intensity is associated with a more negatively skewed risk-neutral distribution of a firm's stock return (*MFIS*). The weaker results for *MFIS* may reflect that this measure does not directly capture left tail risk. Instead, *MFIS* captures the cost of protection against left tail events relative to right tail events. In fact, Internet Appendix Table 3 shows that carbon-intense firms also have higher right tail risk (as reflected in the negative coefficient on *SlopeU*), which may explain why we do not find effects for *MFIS*. In column 3, we find that carbon-intense firms exhibit a higher variance risk premium (*VRP*): a one-standard-deviation increase in log industry emissions increases the *VRP* by 0.002, or 3% of the standard deviation.

Table 4
Carbon intensities and option market variables: Main results

A. Firm-level regressions

Dependent variable:	*SlopeD* (1)	*MFIS* (2)	*VRP* (3)
log(Scope 1/MV industry)	0.006***	−0.002	0.001***
	(3.85)	(−0.70)	(3.79)
log(Assets)	−0.029***	−0.043***	−0.005***
	(−9.22)	(−8.04)	(−7.10)
Dividends/net income	0.009	−0.014	−0.000
	(1.54)	(−1.26)	(−0.00)
Debt/assets	0.038**	0.062**	0.003
	(2.28)	(2.00)	(0.71)
EBIT/assets	−0.187***	−0.078	−0.018
	(−4.59)	(−1.02)	(−1.60)
CapEx/assets	−0.374***	0.216*	−0.060**
	(−5.13)	(1.75)	(−2.35)
Book-to-market	0.077***	0.122***	0.016***
	(8.10)	(5.21)	(4.30)
Returns	−0.018**	−0.054***	−0.010*
	(−2.13)	(−2.95)	(−1.93)
Institutional ownership	−0.045*	−0.085	−0.008
	(−1.75)	(−1.59)	(−1.20)
CAPM beta	0.010	−0.033***	−0.001
	(1.42)	(−3.18)	(−0.44)
Volatility	−0.687***	1.926***	
	(−6.48)	(8.27)	
Oil beta	−0.008	−0.003	−0.020***
	(−0.50)	(−0.10)	(−2.73)
Time trend	−0.000	0.033***	−0.001*
	(−0.29)	(9.93)	(−1.67)
Model	Heckman	Heckman	Heckman
Year-by-quarter fixed effects	Yes	Yes	Yes
Level	Firm	Firm	Firm
Frequency	Monthly	Monthly	Monthly
Obs.	18,664	18,664	18,664
Adj. R^2	n/a	n/a	n/a

(*Continued*)

If industry characteristics largely capture investors' perceptions of firms' carbon intensities, then we should be able to also identify effects at the sector level. We next use option measures directly derived from S&P 500 sector ETF options. To calculate a sector's carbon intensity, *Scope 1/MV sector*, we aggregate emissions of all CDP-disclosing S&P 500 firms in a sector and divide them by the respective firms' equity market values. To do this, we first identify the sectors to which each disclosing firm belongs. As sector weights vary with stock market performance, we then construct monthly sector weights (averages of daily weights) for each firm. Subsequently, we multiply these weights by the emissions of each sector constituent, using only disclosing firms. We use the resultant weighted average emissions as a proxy for sector-level emissions.[16]

[16] The sector-level analysis does not allow us to estimate a selection model. However, bias from selective disclosure could be plausibly less of a concern in this analysis, as there are only a few S&P 500 sectors.

Table 4
(Continued)

B. Sector-level regressions

Dependent variable:	*SlopeD* (1)	*MFIS* (2)	*VRP* (3)
log(Scope 1/MV sector)	0.037***	−0.067*	0.003
	(2.80)	(−1.92)	(1.46)
Model	OLS	OLS	OLS
Sector fixed effects	Yes	Yes	Yes
Level	Sector	Sector	Sector
Frequency	Monthly	Monthly	Monthly
Obs.	774	774	774
Adj. R^2	.138	.366	.005

Regressions in panel A are estimated at the firm-month level. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity. *MFIS* is a measure of the model-free implied skewness. *VRP* is a measure of the variance risk premium. *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions $). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. We estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. t-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. Regressions in panel B are at the sector-month level. The option variables are calculated for S&P 500 sector options. *Scope 1/MV sector* is the Scope 1 carbon intensity of a sector. It is defined as a sector's Scope 1 carbon emissions (in metric tons of CO_2) divided by a sector's equity market value (in millions $). The sample includes 9 of the 11 sectors of the S&P 500. The sample period is the same as in the first panel. t-statistics, based on standard errors clustered by sector and year, are in parentheses. Table A.1 defines all variables in detail. n/a, not applicable. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

A similar procedure is used to compute the equity market values of each sector, using again only disclosing firms. Our sample includes 9 of the 11 sectors of the S&P 500. Sector intensities are largest in the Utilities and Energy sector, as displayed in Table 2, panel B.

Table 4, panel B, documents in column 1 that sector carbon intensities remain positively and statistically related to *SlopeD*. A one-standard-deviation increase in a sector's log carbon intensity (2.35) increases *SlopeD* by 0.09, almost 1.4 times the risk variable's standard deviation. Results are again weaker for the other two measures. While we now find a weakly significant effect for *MFIS* in column 2, the effect for *VRP* in column 3 is insignificant with a t-stat of 1.46.

Taken together, the results indicate that higher climate policy uncertainty increases the firm-level likelihood of left and right tail events, and it has some effect on firm-level *VRP*. On the sector level, where firm-specific risks are diversified away, we observe an effect that is more systematic and concentrated in the left tail. (One other reason sector-level results may differ from those at the firm level is that sector carbon intensities are noisier as we do not have carbon emissions for all firms in a given sector; this may introduce measurement error.)

4.1.2 Firm versus industry carbon intensities: Relative importance. The firm-level analysis raises the question of whether firms with carbon intensities that are lower (higher) than those of their industry peers exhibit

Table 5
Firm versus industry carbon intensities: Relative importance

Dependent variable:	*SlopeD* (1)	*SlopeD* (2)	*SlopeD* (3)
log(Scope 1/MV firm)	0.006***		
	(3.39)		
Residual log(Scope 1/MV firm)		0.003	0.005
		(0.81)	(1.06)
log(Scope 1/MV industry)			0.006***
			(3.76)
Model	Heckman	Heckman	Heckman
Controls	Yes	Yes	Yes
Year-by-quarter fixed effects	Yes	Yes	Yes
Level	Firm	Firm	Firm
Frequency	Monthly	Monthly	Monthly
Obs.	18,664	18,664	18,664
Adj. R^2	n/a	n/a	n/a

Regressions are estimated at the firm-month level. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity. *Scope 1/MV firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) divided by the firm's equity market value (in millions \$). *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions \$). *Residual log(Scope 1 MV/firm)* is the residual of an OLS regression with *log(Scope 1/MV firm)* as the dependent variable and *log(Scope 1/MV industry)* as the independent variable. The regressions in the table control for *log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, Returns, Institutional ownership, CAPM beta, Volatility, Oil beta,* and a time trend (not reported). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. We estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. t-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. Table A.1 defines all variables in detail. n/a, not applicable. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

less (more) downside tail risk once we account for industry effects. To this end, Table 5 evaluates the relative importance of firm- versus industry-level carbon intensities. As a starting point, column 1 documents that firm-level carbon intensities, *log(Scope 1/MV firm)*, are also positively and significantly related to *SlopeD*. The economic magnitudes of the effects are also similar. Nevertheless, to what extent this finding reflects firm, rather than industry, effects is unclear. We therefore evaluate in the next two columns whether there is information in firm-level carbon intensities *beyond* what is captured in industry-level variation. We first estimate a regression in which we calculate for each firm-year the part of firm-level carbon intensities that is unexplained by industry-level intensities. By construction, the estimated regression residual is positive (negative) for firm-years where firm-level carbon intensities are above (below) those of the industry peers. Columns 2 and 3 of Table 5 replace *log(Scope 1/MV firm)* with this regression residual. The estimates show that firm-level *residual* carbon intensities are unrelated to *SlopeD*, when we both do and do not control for industry-level emissions. Importantly, *log(Scope 1/MV industry)* remains positively and significantly related to *SlopeD*, even after accounting for the firm-level residual. This confirms that the market's perception of a firm's exposure to climate policy uncertainty is driven by its industry affiliation.

4.1.3 Firm- and sector-level evidence: Robustness. Internet Appendix Tables 4 and 5 address different concerns with our analysis. Internet Appendix Table 4, panel A, shows that our firm-level results for *SlopeD* are highly robust. In column 1, results are unchanged if we scale emissions by total assets instead of equity values. In column 2, results are unaffected when we estimate a regression at the firm-year level using annual values of *SlopeD*. Column 3 shows that results are similar for OLS regressions. In column 4, the magnitude of the effects increases with firm fixed effects. In column 5, results hold after dropping oil and gas firms, indicating that results are not driven by the decline in oil prices between 2014 and 2016. In columns 6 to 8, we continue to find effects if we calculate *SlopeD* from options with 3- to 12-month maturities. Column 9 shows that Scope 2 intensities are unrelated to *SlopeD*. In panel B, we continue to find mostly insignificant effects for *MFIS* when using 30-day options (the point estimates for most specifications remain negative). Interestingly, we do however observe significant coefficients for longer maturities. Thus, the cost of left tail protection relative to right tail gains seems to be growing with an option's horizon. Short-term options instead seem to be used mostly to take firm-specific (volatility) bets in both directions. In panel C, the firm-level results for *VRP* remain largely robust.

Internet Appendix Table 5, panel A, shows that the sector results for *SlopeD* remain highly robust. Apart from scaling by assets and using annual values, the robustness tests include a variety of alternative fixed effects as well as option maturities of up to one year. Panel B confirms the sector-level evidence for *MFIS* from the main analysis: the point estimates are negative in almost all cases, though highly significant coefficients appear rarely. In panel C, results continue to be mostly insignificant for *VRP*, as in the main analysis.

Our emissions data from CDP are only available for the years between 2009 and 2016, but options data exist for much longer. To analyze results for the more distant past, we use a prediction model and backfill *Scope 1/MV firm* for the years 1995 to 2008. Using predicted carbon intensities, we observe a statistically insignificant effect of carbon intensities on *SlopeD* (see Internet Appendix Table 6). This suggests that climate policy uncertainty was priced to a lower extent in the more distant past, assuming that our prediction model delivers reasonable emission estimates.

4.2 Carbon intensity, downward option protection, and attention to climate change

To test Hypothesis 2, we allow the effect of carbon intensities to vary with two proxies for public attention to climate change. To create the first proxy, we use an index developed by Engle et al. (2020) which captures the share of news articles in outlays, such as *Wall Street Journal, The New York Times*, or *Yahoo News*, that are about "climate change" and have been assigned to a "negative sentiment" category. We capture the time-series effects of climate attention by creating *Negative climate change news high*, which equals one if the Engle et al. (2020) index is above the median, and zero otherwise.

To create the second proxy, we use Google's search volume index (SVI) for the search topic "climate change." The index takes values between 0 and 100, with 100 corresponding to the month with the highest number of searches on climate change topics during our sample period. We use monthly U.S. search data. We then create the dummy variable *Climate change SVI high*, which equals one if the search index is above the median, and zero otherwise. Search activity on Google plausibly proxies for attention by investors, as shown by Da, Engelberg, and Gao (2011). Choi, Gao, and Jiang (2020) show that search volume on climate change topics surges when investors experience abnormally high temperatures.

The regressions in Table 6 then interact each of these two variables with *log(Scope 1/MV industry)*. Column 1 provides the results for the Engle et al. (2020) index, and column 2 those for Google's SVI. The estimates in column 1 show that *log(Scope 1/MV industry)* has a positive and significant effect on *SlopeD* during low-attention times (i.e., when *Negative climate change news high* is zero). Importantly, the coefficient estimate on the interaction term, which is positive (0.002) and significant (t-stat of 1.67), reveals that the effect of carbon intensities on *SlopeD* increases by 40% during high-attention times. During such times, the total effect of *log(Scope 1/MV industry)* on *SlopeD* equals $0.007(=0.002+0.005)$, which is also statistically significant. In column 2, using Google's SVI as the proxy for attention, we continue to find a positive effect of *log(Scope 1/MV industry)* on *SlopeD* during periods of low and high climate change attention. However, the interaction term that reflects the difference between these two states of the world is statistically insignificant (though it has the predicted positive sign). Overall, the results in Table 6 therefore provide only weak evidence in support of Hypothesis 2.

4.3 Effect of the 2016 election of President Trump: Event study results

To test Hypothesis 3, we use President Trump's election in 2016 as an event that reduced climate policy uncertainty in the short term. President Trump's election was unexpected and, unlike his opponent Hillary Clinton, his positions on climate policies were mostly about preserving the status quo, which was characterized by a lack of strict climate regulation. His election on November 9, 2016, therefore, should have lowered the cost of option protection for carbon-intense firms. To quantify the effect of President Trump's election, we estimate a difference-in-differences (DiD) model, using daily option data around Election

Table 6
Carbon intensities and option market variables: Effects of public attention to climate change

Dependent variable:	*SlopeD* (1)	*SlopeD* (2)
log(Scope 1/MV industry) x Negative climate change news high	0.002*	
	(1.67)	
log(Scope 1/MV industry) x Climate change SVI high		0.001
		(0.45)
log(Scope 1/MV industry)	0.005***	0.006***
	(3.47)	(3.61)
Negative climate change news high	−0.003	
	(−0.82)	
Climate change SVI high		−0.005
		(−1.01)
Estimated slope if *Negative climate change news high* = 1	0.007***	
Estimated slope if *Climate change SVI high* = 1		0.007***
Model	Heckman	Heckman
Controls	Yes	Yes
Year-by-quarter fixed effects	Yes	Yes
Level	Firm	Firm
Frequency	Monthly	Monthly
Obs.	18,664	18,664
Adj. R^2	n/a	n/a

Regressions are estimated at the firm-month level. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity. In column 1, we measure attention to climate change using *Negative climate change news high,* which is a dummy variable based the CH Negative Climate Change News Index developed in Engle et al. (2020) (as in their paper, we use monthly averaged AR(1) innovation of the index). *Negative climate change news high* equals one if the index is above the median, and zero otherwise. In column 2, we measure attention to climate change using monthly values of Google's SVI for the search topic "climate change." SVI is a relative index and takes values between 0 and 100. The highest number of searches in a month takes the value of 100 and values for other months are relative to this number. *Climate change SVI high* equals one if Google's SVI is above the median, and zero otherwise. *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions \$). The regressions control for *log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, Returns, Institutional ownership, CAPM beta, Volatility, Oil beta,* and a time trend (not reported). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. We estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. t-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. Table A.1 defines all variables in detail. n/a, not applicable. *$p<.1$; **$p<.05$; ***$p<.01$.

Day 2016. We estimate the following model for firm i at day t:

$$\begin{aligned} OMM_{i,t} = &\gamma_0 + \gamma_1 Post\ Trump\ election_t \times Scope\ 1/MV\ industry\ high_i \\ &+ \gamma_2 Scope\ 1/MV\ industry\ high_i + \gamma_3 Post\ Trump\ election_t \\ &+ \boldsymbol{x_{i,t-1}}\boldsymbol{\gamma} + \epsilon_{i,t} \end{aligned} \tag{3}$$

In this regression, *Post-Trump election* equals one for all firm-day observations after Election Day on November 9, 2016, and zero for all firm-day observations before. To identify treatment firms for which climate policy uncertainty likely declined the most after President Trump's election, we create *Scope 1/MV industry high*, which equals one for the ten industries with the highest carbon intensities, and zero otherwise (see Table 2, panel A). We use

SlopeD as the proxy for *OMM* and employ a relatively wide event window of [−250; +250] days as daily option measures for single names tend to be noisy and driven by idiosyncratic effects. For robustness, we exclude in some tests the [−50; +50] days around Election Day.[17] We report results with different sets of fixed effects.

Our test relies on the sharp climate policy differences between President Trump and Hillary Clinton. Other policy differences may confound our results if they are correlated with the treatment status. Two such important differences are tax and healthcare policies. With respect to tax policies, Clinton supported an increase in taxes on high-income earners, whereas President Trump campaigned on large corporate tax cuts.[18] To ensure that expected tax changes do not contaminate our results, we control for firms' effective tax rates (interacted with the post-election dummy). With respect to healthcare policies, President Trump campaigned on repealing Obamacare, whereas Clinton did not announce any plans to do so. To verify that results are not driven by an increase in *SlopeD* among healthcare firms (which have low emissions and are part of the control group), we exclude such firms in a robustness test.

Table 7 shows that γ_1 in Equation (3), the DiD estimator, is negative and statistically significant across all specifications. This indicates that the cost of downward protection at highly carbon-intense firms significantly decreased after President Trump's election, relative to less carbon-intense firms. In economic terms, column 1 implies that *SlopeD* of firms in carbon-intense industries decreased by 0.025 after the election, relative to firms in industries with low carbon intensities. This decline equals 12% of the variable's standard deviation during the event window. Results are similar in Columns 2 to 4, which add different sets of fixed effects to the model. The point estimate of the DiD effect is largest in Column 5, in which we exclude the narrow window directly surrounding the election. Results are unaffected if we drop healthcare firms in column 6. The estimates further indicate that tail risk generally declined after President Trump's election (negative coefficients on *Post-Trump election*), which may reflect that policies are more business friendly under a Republican government.

We perform several further robustness tests. Internet Appendix Table 7 shows that *SlopeD* exhibits parallel trends for high- and low-emission firms prior to the election. Internet Appendix Table 8, panel A, shows that results are similar for longer and shorter event windows. However, the statistical significance gets weaker once we move to a shorter window. Internet Appendix Table 8, panel B, verifies that our results do not reflect a seasonal pattern in early November. To this end, we generate a series of placebo dates with the same day and month

[17] We want to exclude potentially confounding effects related to the generally higher uncertainty around elections, which are reflected in options spanning those days (see KPV).

[18] Wagner, Zeckhauser, and Ziegler (2018) find that firms with high effective tax rates and large deferred tax liabilities benefitted from President Trump's election.

Table 7
Effect of the election of President Trump in 2016 on option market variables

Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
Event window:	[−250; +250]	[−250; +250]	[−250; +250]	[−250; +250]	[−250; +250], excl. [−50; +50]	[−250; +250], excl. [−50; +50], excl. Healthcare
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Trump election x Scope 1/MV industry high	−0.025**	−0.029**	−0.025***	−0.020**	−0.037***	−0.035**
	(−2.18)	(−2.43)	(−2.88)	(−2.20)	(−2.63)	(−2.45)
Scope 1/MV industry high	0.041*	0.043*			0.046*	0.043*
	(1.67)	(1.77)			(1.88)	(1.72)
Post-Trump election	−0.025***			−0.022***	−0.036***	−0.041***
	(−4.63)			(−4.33)	(−5.97)	(−6.13)
Model	DiD	DiD	DiD	DiD	DiD	DiD
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	No	Yes	Yes	No	No	No
Firm fixed effects	No	No	Yes	No	No	No
Industry fixed effects	No	No	No	Yes	No	Yes
Level	Firm	Firm	Firm	Firm	Firm	Firm
Frequency	Daily	Daily	Daily	Daily	Daily	Daily
Obs.	200,897	200,897	200,897	200,897	159,041	139,635
Adj. R^2	.062	.091	.294	.184	.061	.060

Regressions are estimated at the firm-day level. We report results from difference-in-differences regressions around the date of President Trump's election on November 9, 2016. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity. *Post-Trump election* equals one for all days after President Trump's election, and zero for all days before the election. *Scope 1/MV industry high* equals one for firms that operate in the top-10 industries based on *Scope 1/MV industry*, and zero otherwise (see Table 2, panel A). The regressions control for *Effective tax rate, Effective tax rate* × *Post-Trump election, log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, Returns, Institutional ownership, CAPM beta, Volatility*, and *Oil beta* (not reported). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. Column 6 excludes firms in the healthcare industry (SIC4 codes 2834, 3841, 6324, 3826, 3842, 2836, 5122, 3845, 8062, 8071, 5912, 2835, 3851, 3844, 3843, and 5047). t-statistics, based on standard errors double clustered by firm and day, are in parentheses. Table A.1 defines all variables in detail. *$p < .1$; **$p < .05$; ***$p < .01$.

as the election date, but from all other sample years. These seven pseudo-DiD estimators are all statistically insignificant. Internet Appendix Table 8, panel C, uses regressions at the sector level. At the sector level, we are able to use a shorter event window of $[-100, +100]$ days as daily sector options are less noisy. To identify treatment sectors, we create *Scope 1/MV sector high,* which equals one for the two sectors with the highest sector carbon intensities (Utilities and Energy), and zero otherwise (see Table 2, panel B). The results are consistent with those in Table 7: *SlopeD* of the highly carbon-intense sectors decreased after President Trump's election, relative to less carbon-intense sectors.[19]

[19] The noninteracted effect of *Scope 1/MV sector high* is negative, which is surprising, though it is only weakly significant (while *Scope 1/MV industry high* has the expected positive direct effect in Table 7). A reason for the differences may be that the number of observations (sectors) we are identifying the effects off is smaller at the sector level (two vs. seven sectors). Moreover, sector intensities may be noisier, since not all sector constituents disclose their emissions.

5. Conclusion

Strong regulatory actions are needed to avoid the potentially catastrophic consequences of climate change. As climate change is mostly caused by the combustion of fossil fuels, new regulation will have to aim at significantly curbing firms' carbon emissions. Whether, how, and when regulatory climate policies will be implemented is highly uncertain, and firms with carbon-intense business models will be most affected by this uncertainty.

We show that climate policy uncertainty is priced in the option market. Specifically, the cost of option protection against downside tail risk is larger for more carbon-intense firms. A one-standard-deviation increase in a firm's log industry carbon intensity increases the implied volatility slope, which captures protection against downside tail risk, by 10% of the variable's standard deviation. We confirm our results using sector options. The cost of downward option protection is magnified when public attention to climate change spikes. Moreover, it significantly decreased at highly carbon-intense firms after President Trump's election in 2016, relative to other firms.

Appendix

Table A.1
Variable definitions

Variable	Definition	Source
SlopeD	Steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with a 30-day maturity. It is constructed as the slope coefficient from regressing implied volatilities of OTM puts (deltas between -0.5 and -0.1) on the corresponding deltas and a constant. Because far OTM puts (with smaller absolute deltas) are typically more expensive, the variable usually takes positive values. We also construct similar measures using 91-, 182-, and 365-day maturities. To construct the variable, we follow Kelly, Pastor, and Veronesi (2016). The variable is constructed at the monthly level (average of daily values) or the daily level (indicated accordingly).	OptionMetrics
MFIS	Model-free implied skewness for options with a 30-day maturity. It is computed as the third central moment of the risk-neutral distribution, normalized by the risk-neutral variance (raised to the power of 3/2). To construct the variable, we follow Bakshi, Kapadia, and Madan (2003). The variable is constructed at the monthly level (average of daily values).	OptionMetrics
VRP	Ex post variance risk premium for options with a 30-day maturity. It is computed for each day t as the difference between the risk-neutral expected variance for the period from t to t+30 calendar days and the realized variance measured from daily log returns for the same period [t, t+30] (Carr and Wu 2009; Bollerslev, Tauchen, and Zhou 2009). As a proxy for the risk-neutral variance, we use the model-free implied variance computed like in Britten-Jones and Neuberger (2000). The variable is constructed at the monthly level (average of daily values).	OptionMetrics
Scope 1/MV industry	Annual Scope 1 carbon intensity of all carbon-disclosing firms in the same industry (SIC4) and year. It is computed as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions $).	CDP, Compustat
Scope 1/MV industry high	Dummy variable that equals one for firms that operate in the top-10 industries based on *Scope 1/MV industry*, and zero otherwise. The industries are listed in Table 2, panel A.	
Scope 1/MV firm	Annual Scope 1 carbon intensity of the firm itself. It is computed as a firm's total Scope 1 carbon emissions (metric tons of CO_2) divided by the firm's equity market value (in millions $) at the end of the year.	CDP, Compustat
Scope 1/MV sector	Annual Scope 1 carbon intensity of a sector. It is computed as a sector's total Scope 1 carbon emissions (in metric tons of CO_2) divided by a sector's equity market value (in millions $) at the end of the year.	CDP, Compustat
Scope 1/MV sector high	Dummy variable that equals one for the two sectors in the S&P 500 with the highest mean values of *Scope 1/MV sector*, and zero otherwise. The sectors are listed in Table 2, panel B.	CDP, Compustat
Scope 2/MV industry	Defined as *Scope 1/MV industry* but for Scope 2 carbon emissions instead of Scope 1 carbon emissions.	CDP, Compustat
CDP disclosure	Dummy variable that equals one for a given firm-year if a firm discloses to CDP data on the carbon emissions released during the year, and zero otherwise.	CDP
Industry CDP disclosure	Fraction of firms in the same SIC4 industry and year that discloses data to CDP on the carbon emissions released during the year.	CDP
Negative climate change news high	Dummy variable that equals one if the CH Negative Climate Change News Index is above the median, and zero otherwise. CH Negative Climate Change News Index is developed in Engle et al. (2020) and captures the share of all news articles that are about "climate change" and have been assigned to a "negative sentiment" category. As in their paper, we use monthly averaged AR(1) innovation of the index.	Engle et al. (2020)

(*Continued*)

Table A.1
(Continued)

Variable	Definition	Source
Climate change SVI high	Dummy variable that equals one if Google's search volume index (SVI) for the search topic "Climate change" is above the median, and zero otherwise. We use monthly values of the index during our sample period. The index is a relative index and takes values between 0 and 100. The highest number of searches in a month takes the value of 100, and values for other months are relative to this number.	Google Trends
Assets	Total assets (Compustat data item AT) at the end of the year. Winsorized at the 1% level.	Compustat
Dividends/net income	Dividends (Compustat data item DVT) at the end of the year divided by net income at the end of the year (Compustat data item NI). Winsorized at the 1% level.	Compustat
Debt/assets	Sum of the book value of long-term debt (Compustat data item DLTT) and the book value of current liabilities (DLC) at the end of the year divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level.	Compustat
EBIT/assets	Earnings before interest and taxes (Compustat data item EBIT) at the end of the year divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level.	Compustat
CapEx/assets	Capital expenditures at the end of the year (Compustat data item CAPX) divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level.	Compustat
Book-to-market	Difference between common equity (Compustat data item CEQ) and preferred stock capital (PSTK) at the end of the year divided by the equity market value (MKVALT) at the end of the year. Winsorized at the 1% level.	Compustat, CRSP
Returns	Stock price at the end of the year (Compustat data item PRCC_F) divided by the stock price at the end of the previous year, minus 1. Winsorized at the 1% level.	CRSP
Institutional ownership	Fraction of outstanding shares owned by institutional investors at the end of the year. Winsorized at the 1% level.	Thomson-Reuters
CAPM beta	Sensitivity of monthly stock returns to monthly S&P 500 returns. The variable is computed for each month with a rolling window of 60 months. For each firm i, the variable corresponds to the β_1 coefficient in the regression $Returns_{it} = constant + \beta_1 Market\ Returns_t$. We use averaged values over the year. Winsorized at the 1% level.	Kenneth French's data library
Oil beta	Sensitivity of monthly stock returns to monthly WTI oil returns after controlling for monthly market returns. The variable is computed for each month with a rolling window of 60 months. For each firm i, the variable corresponds to the β_2 coefficient in the regression $Returns_{it} = Constant + \beta_1 Market\ returns_t + \beta_2 Oil\ returns_t$. We use averaged values over the year. Winsorized at the 1% level.	U.S. Energy Information Administration, Kenneth French's data library
Volatility	Standard deviation of monthly stock returns, computed for each month with a rolling window of 12 months. We use averaged values over the year. Winsorized at the 1% level.	CRSP
Time trend	Linearly increasing variable that takes different integer values for each year in the sample, starting with zero.	Self-constructed
Effective tax rate	Cash taxes paid (Compustat data item TXPD) divided by current year pretax income (Compustat data items PI). Pretax income is adjusted for special items (Compustat data items SPI).	Compustat
Post-Trump election	Dummy variable that equals one for all days after President Trump's election on November 9, 2016, and zero for all days before the election.	Self-constructed

References

Baker, S., N. Bloom, and S. J. Davis. 2016. Measuring economic policy uncertainty. *Quarterly Journal of Economics* 131:1593–36.

Bakshi, G., N. Kapadia, and D. B. Madan. 2003. Stock return characteristics, skew laws, and differential pricing of individual equity options. *Review of Financial Studies* 16:101–43.

Bali, T., and H. Zhou. 2016. Risk, uncertainty, and expected returns. *Journal of Financial and Quantitative Analysis* 51:707–35.

Bansal, R., D. Kiku, and M. Ochoa. 2017. Price of long-run temperature shifts in capital markets. Working Paper, Duke University.

Barnett, M. 2019. A run on oil: Climate policy, stranded assets, and asset prices. Working Paper, Arizona State University.

Barnett, M., W. A. Brock, and L. P. Hansen. 2020. Pricing uncertainty induced by climate change. *Review of Financial Studies* 33:1024–66.

Berkman, H., J. Jona, and N. S. Soderstrom. 2019. Measurement and market valuation of climate risk. Working Paper, University of Auckland.

Bolton, P., and M. T. Kacperczyk. 2020. Do investors care about carbon risk? Working Paper, Imperial College.

Bollerslev, T., G. Tauchen, and H. Zhou. 2009. Expected stock returns and variance risk premia. *Review of Financial Studies* 22:4463–92.

Bollerslev, T., and V. Todorov. 2011. Tails, fears, and risk premia. *Journal of Finance* 66:2165–211.

Bollerslev, T., V. Todorov, and L. Xu. 2015. Tail risk premia and return predictability. *Journal of Financial Economics* 118:113–34.

Brav, A., W. Jiang, T. Li, and J. Pinnington, 2019. Picking friends before picking (proxy) fights: How mutual fund voting shapes proxy contests. Working Paper, Duke University.

Britten-Jones, M., and A. Neuberger. 2000. Option prices, implied price processes, and stochastic volatility. *Journal of Finance* 55:839–66.

Brogaard, J. A. and A. Detzel. 2015. The asset pricing implications of government economic policy uncertainty. *Management Science* 61:3–18.

Brogaard, J. A., L. Dai, P. Ngo, and B. Zhang. 2020. Global political uncertainty and asset prices. *Review of Financial Studies* 33:1737–80.

Carr, P. and L. Wu. 2009. Variance risk premiums. *Review of Financial Studies* 22:1311–41.

Chang, B. Y., P. Christoffersen, and K. Jacobs. 2013. Market skewness risk and the cross section of stock returns. *Journal of Financial Economics* 107:46–68.

Cremers, M., M. Halling, and D. Weinbaum. 2015. Aggregate jump and volatility risk in the cross-section of stock returns. *Journal of Finance* 70:577–614.

Christoffersen, P., K. Jacobs, and B. Y. Chang. 2013. Forecasting with option-implied Information. In *Handbook of economic forecasting*, eds. G. Elliott, C. Granger, and A. Timmermann. North Holland, the Netherlands: Elsevier.

Choi, D., Z. Gao, and W. Jiang. 2020. Attention to global warming. *Review of Financial Studies* 33:1112–45.

Cont, R., and P. Tankov. 2004. *Financial modelling with jumps*. New York: Chapman & Hall.

Da, Z., J. Engelberg, and P. Gao. 2011. In search of attention. *Journal of Finance* 66:1461–99.

Daniel, K. D., R. B. Litterman, and G. Wagner. 2016. Applying asset pricing theory to calibrate the price of climate risk. Working Paper, Columbia Business School.

De Haas, R., and A. Popov. 2019. Finance and carbon emissions. Working Paper, Tilburg University.

Delis, M. D., K. de Greiff, and S. R. Ongena. 2020. Being stranded on fossil reserves? Climate policy risk and the pricing of bank loans. Working Paper, University of Zurich.

DeMiguel, V., Y. Plyakha, R. Uppal, and G. Vilkov. 2013. Improving portfolio selection using option-implied volatility and skewness. *Journal of Financial and Quantitative Analysis* 48:1813–45.

Dobelman, J., H. B. Kang, and S. W. Park. 2014. WRDS index data extraction methodology. Technical Report, Rice University.

Engle, R., S. Giglio, H. Lee, B. Kelly, and J. Stroebel. 2020. Hedging climate change news. *Review of Financial Studies* 33:1184–216.

Financial Times. 2019. Carbon pricing: Heavy weather. June 11. https://www.ft.com/content/322c5de2-8c58-11e9-a24d-b42f641eca37.

Gennaioli, N., and A. Shleifer. 2010. What comes to mind. *Quarterly Journal of Economics* 125:1399–433.

Giglio, S., M. Maggiori, K. Rao, J. Stroebel, and A. Weber. 2018. Climate change and long-run discount rates: Evidence from real estate. Working Paper, New York University and Yale University.

Görgen, M., A. Jacob, M. Nerlinger, R. Riordan, M. Rohleder, and M. Wilkens. 2020. Carbon risk. Working Paper, University of Augsburg.

Heckman, J. 1979. Sample selection bias as specification error. *Econometrica* 47:153–61.

Hong, H. G., F. W. Li, and J. Xu. 2019. Climate risks and market efficiency. *Journal of Econometrics* 208:265–81.

Hsu, P.-H., K. Li, and C.-Y. Tsou. 2020. The pollution premium. Working Paper, HKUST.

IPCC. 2018. Intergovernmental Panel on Climate Change, Special report: Global warming of 1.5° C. IPCC, Geneva, Switzerland.

Kelly, B., L. Pastor, and P. Veronesi. 2016. The price of political uncertainty: Theory and evidence from the option market. *Journal of Finance* 71:2417–80.

Koijen, R. S., T. J. Philipson, and H. Uhlig. 2016. Financial health economics. *Econometrica* 84:195–242.

Krueger, P., Z. Sautner, and L. T. Starks. 2020. The importance of climate risks for institutional investors. *Review of Financial Studies* 33:1067–111.

Lemmon, M., and M. R. Roberts. 2010. The response of corporate financing and investment to changes in the supply of credit. *Journal of Financial and Quantitative Analysis* 45:556–87.

Lennox, C. S., J. R. Francis, and Z. Wang. 2012. Selection models in accounting research. *Accounting Review* 87:589–616.

Litterman, B. 2016. *Climate risk: Tail risk and the price of carbon emissions—Answers to the risk management puzzle*. Hoboken, NJ: John Wiley & Sons.

Matsumura, E. M., R. Prakash, and S. C. Vera-Munoz. 2014. Firm-value effects of carbon emissions and carbon disclosures. *Accounting Review* 89:695–724.

Muravyev, D., and N. D. Pearson. 2020. Option trading costs are lower than you think. *Review of Financial Studies*. Advance Access published February 10, 2020, 10.1093/rfs/hhaa010.

Pastor, L., and P. Veronesi. 2012. Uncertainty about government policy and stock prices. *Journal of Finance* 67:1219–64.

———. 2013. Political uncertainty and risk premia. *Journal of Financial Economics* 110:520–45.

Ramelli, S., A. F. Wagner, R. J. Zeckhauser, and A. Ziegler. 2020. Stock price rewards to climate saints and sinners: Evidence from the Trump Election. Working Paper, University of Zurich.

Stanny, E., and K. Ely. 2008. Corporate environmental disclosures about the effects of climate change. *Corporate Social Responsibility and Environmental Management* 15:338–48.

Trump, D. J. 2012. The concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive [Tweet], posted on November 6, 2012.

Vanden, J. M. 2008. Information quality and options. *Review of Financial Studies* 21:2635–76.

Wagner, A. F., R. J. Zeckhauser, and A. Ziegler. 2018. Company stock price reactions to the 2016 election shock: Trump, taxes, and trade. *Journal of Financial Economics* 130:428–51.

Wooldridge, J. M. 2010. *Econometric analysis of cross section and panel data*. Cambridge: MIT Press.