Internet Appendix

for

Carbon Tail Risk

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Internet Appendix Part A: Additional Tables

Internet Appendix Table 1
Firms' carbon emissions by industry

Top-20 Industries by Scope 1 firm								
Rank	Industry name	SIC2	Mean	STD	25th	Median	75th	Obs.
1	Petroleum refining & related industries	29	93,403,464	35,699,673	59,279,610	90,068,022	130,000,000	16
2	Primary metal industries	33	43,544,068	1,151,571	42,729,784	43,544,068	44,358,352	2
3	Electric, gas & sanitary services	49	38,065,211	36,047,530	10,112,329	21,708,938	57,000,000	153
4	Transportation by air	45	21,698,358	10,249,014	13,838,695	17,866,753	31,436,892	26
5	Water transportation	44	10,506,412	269,392	10,319,475	10,402,394	10,700,267	6
6	Oil & gas extraction	13	9,799,780	12,297,789	2,856,000	6,065,844	10,450,000	69
7	Motor freight transportation & warehousing	42	8,812,352	5,323,841	1,681,697	11,715,635	12,000,000	11
8	Railroad transportation	40	7,273,642	3,018,934	5,088,315	5,300,099	11,207,344	23
9	Stone, clay, glass, & concrete products	32	4,548,400	471,826	4,529,000	4,703,000	4,805,000	5
10	Paper & allied products	26	3,829,735	3,425,980	222,174	2,611,787	5,669,920	35
11	Metal mining	10	3,715,079	1,730,674	1,590,000	4,110,000	5,358,795	23
12	Nonclassifiable establishments	99	3,065,286	1,393,459	1,970,000	2,598,089	3,988,622	14
13	Chemicals & allied products	28	1,851,756	3,601,290	80,111	324,302	1,176,667	204
14	General merchandise stores	53	1,741,086	2,555,653	104,949	429,980	785,682	33
15	Textile mill products	22	1,602,088		1,602,088	1,602,088	1,602,088	1
16	Food & kindred products	20	1,311,414	3,109,622	127,354	380,118	855,363	133
17	Food stores	54	1,275,677	862,879	374,782	1,619,322	2,010,936	14
18	Lumber & wood products, except furniture	24	865,568	718,040	39,879	1,390,232	1,434,076	11
19	Transportation equipment	37	715,987	726,745	127,564	579,000	955,785	57
20	Rubber & miscellaneous plastic products	30	620,643	607,242	174,981	236,137	1,234,311	20

This table reports firms' Scope 1 carbon emissions (unscaled) by industry. We report figures for the top-20 industries, ranked by the average carbon emissions of firms in an industry. *Scope 1 firm* is a firm's Scope 1 carbon emissions (in metric tons of CO_2) (unscaled). Statistics are reported at the firm-year level across different SIC2 industries. 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.

Internet Appendix Table 2
Carbon intensities within SIC2 industries

Scope 1/MV firm			
	SIC	Mean	Obs.
Electric services	4911	4,609	49
Natural gas transmission & distribution	4923	371	4
Electric & other services combined	4931	2,393	72
Gas & other services combined	4932	2,707	7
Water supply	4941	5	2
Refuse systems	4953	1,026	12
Cogeneration services & small power producers	4991	8,751	7
All	Total	3,216	153

This table illustrates variation in Scope 1 carbon intensities within SIC2 industries. Statistics are reported at the firm-year level for sample firms that operate in the two-digit SIC code "49" (Electric, Gas, & Sanitary Services). *Scope 1/MV firm* is a firm's Scope 1 carbon emissions (in metric tons of CO_2) divided by a firm's equity market value (in million $). The sample includes S&P 500 firms in the specific industry 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 cases falls below eight.

Internet Appendix Table 3
Carbon intensities and option market variables: Right-tail risk

A. Firm-level regression	
Dependent variable:	*SlopeU*
	(1)
log(Scope 1/MV industry)	-0.006***
	(-3.83)
Model	Heckman
Controls	Yes
Year-by-quarter fixed effects	Yes
Level	Firm
Frequency	Monthly
Obs.	18,664
Adj. R^2	n/a

B. Sector-level regression	
Dependent variable:	*SlopeU*
	(1)
log(Scope 1/MV sector)	0.024
	(1.34)
Model	OLS
Sector fixed effects	Yes
Level	Sector
Frequency	Monthly
Obs.	774
Adj. R^2	.138

The regression in panel A is at the firm-month level. *SlopeU* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM call options with 30 days maturity. *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 million $). 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. The regression in panel B is 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) scaled by a sector's equity market value (in million $). The sample includes nine of the eleven 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. *p<.1; **p<.05; ***p<.01.

Internet Appendix Table 4
Carbon intensities and option market variables: Robustness checks for firm-level regressions

	Scale by assets	Yearly average of SlopeD	OLS	Firm fixed effects	Exclude oil, gas, coal (SIC 29; 13)	91 days options	182 days options	365 days options	Scope 2
A. Robustness checks for SlopeD									
Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(Scope 1/assets industry)	0.006***								
	(3.43)								
log(Scope 1/MV industry)		0.006***	0.006***	0.019***	0.006***	0.003***	0.002***	0.002***	
		(3.76)	(3.63)	(5.85)	(3.60)	(3.64)	(3.41)	(3.28)	
log(Scope 2/MV industry)									0.002
									(1.00)
B. Robustness checks for MFIS									
Dependent variable:	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(Scope 1/assets industry)	-0.003								
	(-0.97)								
log(Scope 1/MV industry)		-0.004	-0.001	0.007	-0.002	-0.006***	-0.006***	-0.005**	
		(-1.34)	(-0.48)	(0.52)	(-0.76)	(-2.79)	(-2.83)	(-2.39)	
log(Scope 2/MV industry)									0.000
									(0.02)
C. Robustness checks for VRP									
Dependent variable:	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(Scope 1/assets industry)	0.001***								
	(3.82)								
log(Scope 1/MV industry)		0.002***	0.001***	0.001	0.001***	0.001**	0.001**	0.001***	
		(4.12)	(3.60)	(0.19)	(3.27)	(2.12)	(2.02)	(2.78)	
log(Scope 2/MV industry)									0.000
									(0.36)
Model	Heckman	Heckman	OLS	Heckman	Heckman	Heckman	Heckman	Heckman	Heckman
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes	No	No	No	No	No
Level	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Frequency	Monthly	Annual	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
Obs.	18,664	1,771	18,664	18,664	17,744	18,663	18,663	18,663	18,190

Regressions are at the firm-month or firm-year level (indicated accordingly). Each panel reports in each column the results of a different regression. Panel A to C differ in the dependent variable that is used. In panel A, *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 (or longer, indicated accordingly). In panel B, *MFIS* is a measure of the model-free implied skewness. In panel C, *VRP* is a measure of the variance risk premium. *Scope 1/assets 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 assets of all reporting firms in the industry (in million $). *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 million $). *Scope 2/MV industry* is defined accordingly, but for Scope 2 carbon emissions. The regressions control for *log(Assets)*, *Dividends/net income*, *Debt/assets*, *EBIT/assets*, *CapEx/assets*, *Book-to-market*, *Returns*, *Institutional ownership*, *CAPM beta*, *Volatility* (not in panel C), *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. *p<.1; **p<.05; ***p<.01.

Internet Appendix Table 5
Carbon intensities and option market variables: Robustness checks for sector-level regressions

	Scale by assets	Yearly average of SlopeD	Sector-by-quarter fixed effects	Year-by-quarter fixed effects	91 days options	182 days options	365 days options	Scope 2
A. Robustness checks for SlopeD								
Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1/assets sector)	0.045**							
	(2.42)							
log(Scope 1/MV sector)		0.052***	0.039***	0.024*	0.047***	0.046***	0.051***	
		(3.96)	(2.83)	(1.85)	(4.34)	(3.84)	(3.95)	
log(Scope 2/MV sector)								-0.001
								(-0.08)
B. Robustness checks for MFIS								
Dependent Variable:	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1/assets sector)	-0.093**							
	(-2.38)							
log(Scope 1/MV sector)		-0.076**	-0.065*	0.093*	-0.044	-0.055	-0.147***	
		(-2.14)	(-1.83)	(1.88)	(-1.14)	(-1.39)	(-3.26)	
log(Scope 2/MV sector)								-0.018
								(-0.46)
C. Robustness checks for VRP								
Dependent Variable:	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1/assets sector)	0.004							
	(1.26)							
log(Scope 1/MV sector)		0.003	0.004	0.004*	0.006	0.008	0.011*	
		(1.38)	(1.56)	(1.73)	(1.38)	(1.43)	(1.69)	
log(Scope 2/MV sector)								0.000
								(0.04)
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-by-quarter fixed effects	No	No	Yes	No	No	No	No	No
Year-by-quarter fixed effects	No	No	No	Yes	No	No	No	No
Level	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector
Frequency	Monthly	Annual	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
Obs.	774	72	774	774	774	774	774	774

Regressions are at the sector-month or sector-year level (indicated accordingly). Each panel reports in each column the results of a different regression. Panel A to C differ in the dependent variable that is used. In panel A, *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM sector put options with 30 days maturity (or longer, indicated accordingly). In panel B, *MFIS* is a measure of the model-free implied skewness. In panel C, *VRP* is a measure of the variance risk premium. *Scope 1/assets sector* is the Scope 1 carbon intensity of a sector. It is defined as a sector's Scope 1 emissions (in metric tons of CO_2) divided by a sector's total assets (in million $). *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 million $). *Scope 2/MV sector* is defined accordingly, but for Scope 2 carbon emissions. The sample includes nine of the eleven sectors of S&P 500. 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 sector and year, are in parentheses. Table A.1 defines all variables in detail. *p<.1; **p<.05; ***p<.01.

Internet Appendix Table 6
Predicted carbon intensities and option market variables

Dependent variable:	*SlopeD*
	(1)
log(Scope 1/MV industry)	-0.000
	(-0.35)
log(Assets)	-0.010***
	(-4.41)
Dividends/net income	0.007
	(1.04)
Debt/assets	0.080***
	(4.53)
EBIT/assets	-0.055
	(-1.13)
CapEx/assets	-0.001
	(-0.02)
Book-to-market	0.037***
	(2.76)
Institutional ownership	-0.077***
	(-4.08)
CAPM beta	-0.008
	(-1.46)
Volatility	0.056
	(0.46)
Oil beta	-0.023*
	(-1.88)
Time trend	0.004***
	(3.39)
Model	OLS
Year-by-quarter fixed effects	Yes
Level	Firm
Frequency	Monthly
Obs.	11,916
Adj. R^2	.120

The regression is 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 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 million $). The sample includes all firms in the S&P 500 with predicted carbon emissions for the period 1995 to 2008. Emissions are backfilled based on a prediction model using emissions data from the years 2009 to 2016. The prediction model is similar to the regression in Column (4) of Table 3, panel A, except that we use industry dummies instead of industry carbon intensities. We estimate the effect of emissions generated between 1995 and 2008 on option market variables measured between November 1996 and December 2008. t-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. Table A.1 defines all variables in detail. *p<.1; **p<.05; ***p<.01.

Internet Appendix Table 7
President Trump's election: Test of parallel trends

	Treatment firm	Control firm	Difference	p-value	Wilcoxon p-value
SlopeD growth (x100)	0.0041	0.0090	-0.005	.9455	.3001

This table compares mean daily growth rates for *SlopeD* between the treatment and control group during the [-1,000;-250] window prior to election of President Trump on November 9, 2016. The analysis follows Lemmon and Roberts (2010). The treatment group consists of high-carbon-emission firms, which are firms that operate in in the top-10 industries based on *Scope 1/MV industry* (see Table 2, panel B). The control groups consists of low-carbon-emission sectors. We present the *p*-value of a difference-in-means test, which tests the hypothesis that mean values of the two groups are the same. We also present the Wilcoxon *p*-value of the two-sample Wilcoxon test, which tests the hypothesis that the two groups are taken from populations with the same median.

Internet Appendix Table 8
Effect of the election of President Trump in 2016: Robustness

A. Alternative event windows				
Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
Event window:	[-300; +300]	[-300; +300], excl. [-50; +50]	[-200; +200]	[-200; +200], excl. [-50; +50]
	(1)	(2)	(3)	(4)
Post Trump election x Scope 1/MV industry high	-0.028**	-0.037***	-0.018	-0.029**
	(-2.53)	(-2.95)	(-1.61)	(-2.13)
Scope 1/MV industry high	0.043*	0.047**	0.037	0.043
	(1.83)	(2.03)	(1.46)	(1.63)
Post Trump election	-0.026***	-0.036***	-0.018***	-0.030***
	(-4.98)	(-6.10)	(-3.11)	(-4.41)
Model	DiD	DiD	DiD	DiD
Controls	Yes	Yes	Yes	Yes
Sector fixed effects	No	No	No	No
Day fixed effects	No	No	No	No
Industry fixed effects	No	No	No	No
Level	Firm	Firm	Firm	Firm
Frequency	Daily	Daily	Daily	Daily
Obs.	234,613	192,757	162,080	120,224
Adj. R^2	.060	.059	.060	.057

Internet Appendix Table 8
(continued)

B. Placebo event windows							
Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
Placebo year	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2017*
Event window:	[-250; +250]	[-250; +250]	[-250; +250]	[-250; +250]	[-250; +250]	[-250; +250]	[-250; +250]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post November 9 x Scope 1/MV industry high	0.007	0.010	0.005	0.010	-0.001	-0.010	0.006
	(0.75)	(0.81)	(0.53)	(0.76)	(-0.04)	(-0.70)	(0.54)
High Scope 1/MV industry	0.020**	0.025	0.030**	0.037**	0.040*	0.049**	0.014
	(2.15)	(1.58)	(1.97)	(2.07)	(1.68)	(2.29)	(0.75)
Post November 9	0.016***	0.002	-0.043***	0.013*	0.049***	0.021***	-0.001
	(3.10)	(0.31)	(-7.06)	(1.96)	(8.33)	(4.14)	(-0.08)
Model	DiD	DiD	DiD	DiD	DiD	DiD	DiD
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	No	No	No	No	No	No	No
Firm fixed effects	No	No	No	No	No	No	No
Industry fixed effects	No	No	No	No	No	No	No
Level	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Frequency	Daily	Daily	Daily	Daily	Daily	Daily	Daily
Obs.	170,436	186,032	187,810	190,812	193,358	195,199	113,581
Adj. R^2	.025	.035	.080	.091	.106	.073	.039

Internet Appendix Table 8
(continued)

C. Sector-level regressions					
Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
Event window:	[-100; +100]	[-100; +100]	[-100; +100]	[-100; +100]	[-100; +100], excl. [-50; +50]
	(1)	(2)	(3)	(4)	(5)
Post Trump election x Scope 1/MV sector high	-0.025**	-0.025***	-0.024**	-0.024**	-0.033**
	(-3.26)	(-3.56)	(-2.72)	(-2.88)	(-2.46)
Scope 1/MV sector high	-0.070*	-0.069*			-0.057*
	(-2.10)	(-2.10)			(-2.16)
Post Trump election	0.002		0.002		0.003
	(0.30)		(0.22)		(0.29)
Model	DiD	DiD	DiD	DiD	DiD
Day fixed effects	No	Yes	No	Yes	No
Sector fixed effects	No	No	Yes	Yes	No
Level	Sector	Sector	Sector	Sector	Sector
Frequency	Daily	Daily	Daily	Daily	Daily
Obs.	1,790	1,790	1,790	1,790	882
Adj. R^2.	.053	.042	.332	.355	.062

Regressions in panel A are at the firm-day level. We report results from difference-in-differences regressions around the date of the 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 sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. t-statistics, based on standard errors double clustered by firm and day, are in parentheses. Regressions in panel B are at the firm-day level. We report results from different placebo difference-in-differences regressions around the date of November 9 of placebo years between 2010 and 2017. t-statistics, based on standard errors double clustered by firm and day, are in parentheses. The regressions in panel C are at the sector-day level. *Scope 1/MV sector* high equals for the two sector with the highest mean values of *Scope 1/MV sector* (Utilities and Energy), and zero otherwise. The sample includes nine of the eleven sectors of the S&P 500. t-statistics, based on standard errors double clustered by sector and day, are in parentheses. Table A.1 defines all variables in detail. *p<.1; **p<.05; ***p<.01.

Internet Appendix Part B: Illustration and Relationship of Option Market Measures

This internet appendix illustrates the information content of the three option market measures. The panels below depict volatility smiles for four different hypothetical firms, with the x-axis reporting option deltas. Options with deltas to the left of -0.5 are OTM puts (deeper OTM as we move to the left), while options to the right of 0.5 are OTM calls (deeper OTM as we move to the right). All three panels contain the implied volatility smile IV(0) for benchmark firm (firm 0). We then display in each panel a smile for a different firm (firm 1, 2, and 3), each representing a particular deviation of the volatility smile from IV(0). Panel A illustrates a parallel upward shift from IV(0) to IV(1), that is, all options are more expensive (in volatility terms). In panel B, deep OTM puts are relatively more expensive, and deep OTM calls are relatively less expensive, leading to a shift from IV(0) to get IV(2). Panel C displays the same left-tail transformation as in panel B, but additionally makes OTM puts and OTM calls more expensive the further away they are from the ATM level. This leads to a shift from IV(0) to IV(3).

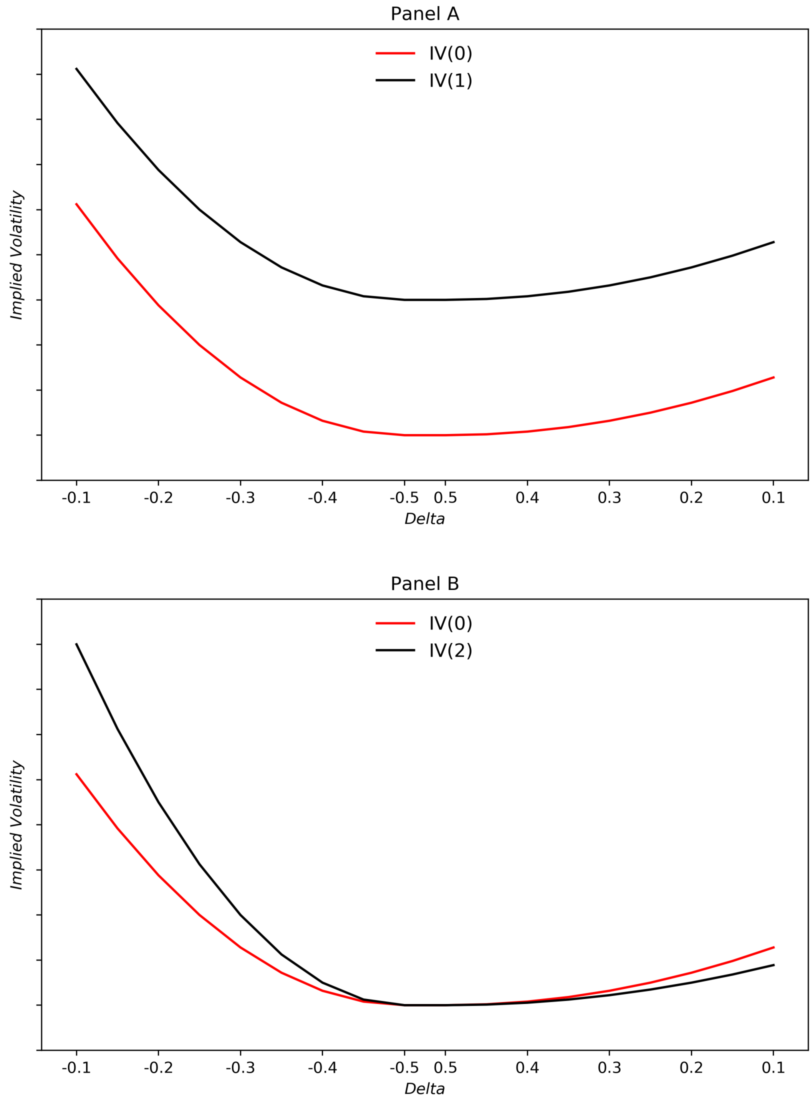
What are the implications of these changes in IV smiles for our measures? In panel A, *SlopeD* remains unchanged because the shift from IV(0) to IV(1) is parallel. *MFIS* also remains unaffected as the symmetry properties of the risk-neutral probability distribution are unchanged. The effect on *VRP* is unclear: while the model-free variance based on IV(1) is higher than the one based on IV(0), the *VRP* difference depends on the realized variances for both firms. Thus, if the realized variance for firm 1 is much higher than the one for firm 0, it can overcompensate the difference in the model-free implied variances, and make *VRP* for firm 1 smaller than that for firm 0.

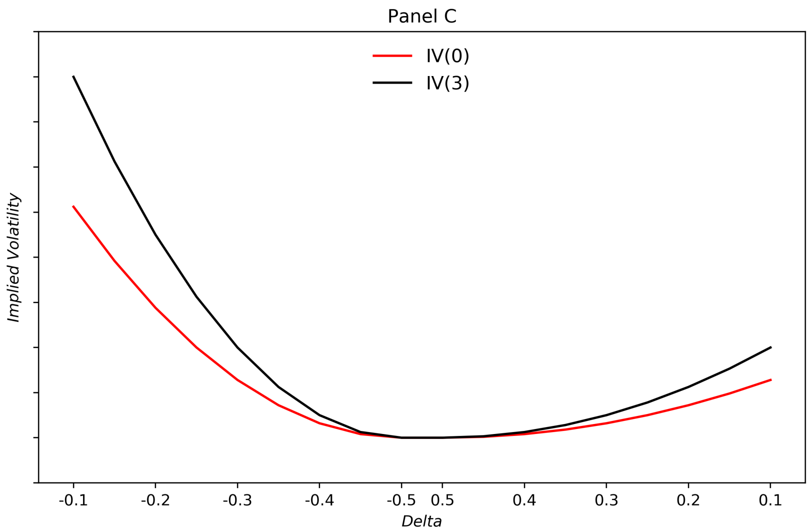
Turning to panel B, one can see that *SlopeD* for IV(2) is steeper than for IV(0), indicating a higher cost of downside protection (note that, as the x-axis gets larger once we move to the left, the regression slope from regressing implied volatility on delta is positive). *MFIS* is also more negative for IV(2) compared to IV(0), because downside protection gets more expensive, while it is now cheaper to get upside potential. The effect on *VRP* is again unclear: though one can expect that the expected risk-neutral variance increases (due to the fact that, computationally, OTM puts have a stronger effect on the model-free implied variance), the *VRP* difference again reveals the price of uncertainty about the realized variance, and it cannot be determined from option prices alone.

In panel C, IV(3) will have the same value as IV(2) for *SlopeD*, because the measure is based on OTM puts only. Hence, whether *SlopeD* becomes larger relative to IV(0) does not depend on the OTM call pricing. *MFIS* can change either way, depending on both the put and call price changes. However, even if it gets more negative by moving from IV(0) to IV(3), the effect is smaller than in panel B, where it moves from IV(0) to IV(2). The reason is that both OTM option types are getting more expensive and, thus, the probability mass is relocated from the central region to the tail region on both sides. The effect for *VRP* effect is again unclear. As in panel A, we can assert that the risk-neutral variance gets higher by moving from IV(0) to IV(3).

The final change in *VRP* will depend on the realized counterparts.

Thus, *SlopeD* quantifies the expensiveness of protection against extreme price drops relative to cost of protection for less extreme (downside) events. Somewhat differently, *MFIS* captures the expensiveness of left-tail protection relative to the right tail, that is, the cost of protection against losses relative to the cost of gaining positive realizations. *VRP* rather captures price of uncertainty about the variance, that is, it quantifies how much investors are willing to pay for hedging the risk of (mostly) increasing variance, which is typically generated by tail-risk realizations or increasing uncertainty about the future prospects of a firm.




Panel C
IV(0)
IV(3)
Implied Volatility
-0.1
-0.2
-0.3
-0.4
-0.5
0.5
0.4
0.3
0.2
0.1
Delta

Internet Appendix Part C: Full-Information Maximum Likelihood Estimator

In this appendix, we derive the Full-Information Maximum Likelihood (FIML) for our empirical model. The derivations build on Wooldridge (2010). Our basic model set-up is as follows:

$$OMM_{i,m,t+1} = \beta_1\, Scope\, 1_{i,t} + \boldsymbol{x_{i,t}\beta} + u_{i,m,t+1} \tag{A1}$$

$$CDP\, disclosure_{i,t} = 1[\boldsymbol{z_{i,t}}\gamma + v_{i,t} > 0] \tag{A2}$$

The sample selection nature of our estimation arises since the emissions generated by firm i in year t, $Scope\,1_{i,t}$, are only observed when $CDP\,disclosure_{i,t} = 1$.[1] Our derivation differs from the standard case as the outcome and selection equations are estimated at different levels. Notably, while the option market variable $OMM_{i,m,t+1}$ in Equation (A1) is measured at the firm-month level (i.e., $(i, m, t+1)$), the decision to disclose carbon emissions $CDP\,disclosure_{i,t}$ in Equation (A2) is at the firm-year level (i.e., (i,t)). As a result, our empirical model merges observations of the (i,t)-level into the $(i,m,t+1)$-level. The approach of estimating a FIML selection model with data from different observation levels is similar to the estimation problem in Brav et al. (2019).

To derive the log likelihood function, we make the following assumptions:

(1) $\boldsymbol{x_{i,t}}$ is a strict subset of $\boldsymbol{z_{i,t}}$ and there exists at least one variable in $\boldsymbol{z_{i,t}}$ that is excluded from $\boldsymbol{x_{i,t}}$.

(2) $(u_{i,m,t+1}, v_{i,t})$ is bivariate normal with zero means, $\text{Var}(u_{i,m,t+1}) = \sigma^2$, and $\text{Var}(v_{i,t}) = \alpha^2 < 1$.[2]

(3) $(u_{i,m,t+1}, v_{i,t})$ is independent of $\boldsymbol{z_{i,t}}$ and $u_{i,m,t+1}$ is uncorrelated over m within a given firm-year.

(4) $\text{Cov}(u_{i,m,t+1}, v_{i,t}) = \sigma_{12}$, so that the correlation coefficient $\rho = \sigma_{12}/\sigma\alpha$.

Under these assumptions, FIML estimation can be used to estimate Equations (A1) and (A2). For brevity, let us denote the disclosure decision of firm i in year t with $s_{i,t}$. Because emissions are only observed when $s_{i,t} = 1$, we first use the density $f(OMM_{i,m,t+1}|s_{i,t}, \boldsymbol{z_{i,t}})$ when $s_{i,t} = 1$. To find $f(OMM_{i,m,t+1}|s_{i,t}, \boldsymbol{z_{i,t}})$ at $s_{i,t} = 1$, we use Bayes' rule and write:

$$f(OMM_{i,m,t+1}|s_{i,t}, \boldsymbol{z_{i,t}}) = \frac{f(s_{i,t}|OMM_{i,m,t+1}, \boldsymbol{z_{i,t}})f(OMM_{i,m,t+1}|\boldsymbol{z_{i,t}})}{f(s_{i,t}|\boldsymbol{z_{i,t}})}$$

[1] For brevity, we use $Scope\,1_{i,t}$ in Equation (A1) while our actual estimation uses $Log(Scope\,1/MV\,industry)_{i,t}$. In Equation (A2), $\boldsymbol{z_{i,t}}$ includes $Industry\,CDP\,disclosure_{i,t}$ and $\boldsymbol{x_{i,t}}$.

[2] A typical assumption in the standard FIML model for the error term v is to assume that it follows the standard normal distribution (Wooldridge 2010). However, our procedure to merge observations of the (i,t)-level into the $(i,t+1)$-level implies that the same values are replicated twelve times. In the actual estimations, this should reduce the variance of the error term v. Therefore, this reduction is reflected in the additional assumption that $\text{Var}(v_{i,t}) = \alpha^2 < 1$.

Therefore,

$$f(OMM_{i,m,t+1}|s_{i,t}=1,\boldsymbol{z_{i,t}}) = \frac{P(s_{i,t}=1|OMM_{i,m,t+1},\boldsymbol{z_{i,t}})f(OMM_{i,m,t+1}|\boldsymbol{z_{i,t}})}{P(s_{i,t}=1|\boldsymbol{z_{i,t}})}$$

Because we consider the case when emissions are observed (i.e., $s_{i,t}=1$), the denominator equals $P(s_{i,t}=1|\boldsymbol{z_{i,t}})=1$, and the right-hand side in the expression reduces to only the numerator. Note that $OMM_{i,m,t+1}|\boldsymbol{z_{i,t}} \sim N(\beta_1 Scope\,1_{i,t} + \boldsymbol{x_{i,t}\beta}, \sigma^2)$ and furthermore that:[3]

$$s_{i,t} = 1\left[\boldsymbol{z_{i,t}}\gamma + \frac{\sigma_{12}}{\sigma\alpha}\frac{\alpha}{\sigma}(OMM_{i,m,t+1} - \beta_1 Scope\,1_{i,t} - \boldsymbol{x_{i,t}\beta}) + e_{i,t} > 0\right],$$

where $e_{i,t}$ is independent of $(\boldsymbol{z_{i,t}}, OMM_{i,m,t+1})$ and $e_{i,t} \sim N(0,(1-\rho^2)\alpha^2)$ (this follows from standard conditional distribution results for joint normal random variables). Therefore,

$$P(s_{i,t}=1|OMM_{i,m,t+1},\boldsymbol{x_{i,t}}) = \Phi\left\{\frac{\boldsymbol{z_{i,t}}\gamma + \sigma_{12}\sigma^{-2}(OMM_{i,m,t+1} - \beta_1 Scope\,1_{i,t} - \boldsymbol{x_{i,t}\beta})}{\sqrt{\mathrm{Var}(e_{i,t})}}\right\} \quad \text{(A3)}$$

For the case where emissions are not observed (i.e., $s_{i,t}=0$), we can write the following term:

$$(1-s_{i,t})\log\left(1-\Phi(\boldsymbol{z_{i,t}}\gamma)\right)$$

and for the case where emissions are observed (i.e., $s_{i,t}=1$):

$$s_{i,t}\left(\log\Phi\left\{\frac{\boldsymbol{z_{i,t}}\gamma + \sigma_{12}\sigma^{-2}(OMM_{i,m,t+1} - \beta_1 Scope\,1_{i,t} - \boldsymbol{x_{i,t}\beta})}{\sqrt{\mathrm{Var}(e_{i,t})}}\right\}\right.$$
$$\left. + \log(\phi[(OMM_{i,m,t+1} - \beta_1 Scope\,1_{i,t} - \boldsymbol{x_{i,t}\beta})/\sigma]) - \log(\sigma)\right)$$

Noting $\rho = \frac{\mathrm{Cov}(u_{i,m,t+1},v_{i,t})}{\sqrt{\mathrm{Var}(u_{i,m,t+1})\mathrm{Var}(v_{i,t})}} = \frac{\sigma_{12}}{\sigma\alpha}$ and putting all of these ingredients together, we get:

$$\begin{aligned} l_{i,m,t+1} = {} & (1-s_{i,t})\log\left[1-\Phi\left(\boldsymbol{z_{i,t}}\gamma\right)\right] \\ & + s_{i,t}\log\Phi\left\{\frac{\boldsymbol{z_{i,t}}\gamma + \rho\alpha/\sigma(OMM_{i,m,t+1} - \beta_1 Scope\,1_{i,t} - \boldsymbol{x_{i,t}\beta})}{\sqrt{1-\rho^2}\cdot\alpha}\right\} \\ & + s_{i,t}\log\left(\phi\left[\left(OMM_{i,m,t+1} - \beta_1 Scope\,1_{i,t} - \boldsymbol{x_{i,t}\beta}\right)/\sigma\right] - s_{i,t}\log(\sigma)\right) \end{aligned} \quad \text{(A4)}$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ refer to the standard normal cumulative distribution function (CDF)

[3]For two jointly normal variables $X \sim N(0,\sigma_X^2)$ and $Y \sim N(0,\sigma_Y^2)$, conditional expectation of X given Y can be written as $E(X|Y) = E(X) + \rho\sigma_X/\sigma_Y[Y - E(Y)]$. Moreover, the estimation error $\tilde{X}$ has a normal distribution $\tilde{X} \sim N(0,\sigma_{\tilde{X}}^2)$ where $\sigma_{\tilde{X}}^2 = (1-\rho^2)\sigma_X^2$ with $\mathrm{Corr}(X,Y) = \rho$.

and the probability density function (PDF), respectively. The log likelihood is obtained by summing $l_{i,m,t+1}$ across all observations.

Internet Appendix Part D: Discussion of the Exclusion Restriction

Our analysis assumes that *Industry CDP disclosure* does not directly affect our option market measures. A concern could be that, if emissions data are widely disclosed at the industry level, disclosure may make aggregate emissions and their effects for climate change more salient. As a result, a high level of disclosure by an industry may increase the likelihood of future regulatory changes, and such regulation may target those industries that most disclosed. Highly carbon-intense firms could be affected more strongly by such regulation, and this could increase the cost of downside option protection at these firms. This channel could violate the exclusion restriction, as it implies a direct effect of industry disclosure on the option market measures.

We perform several tests to mitigate this concern. First, we exploit monthly time-series changes in public climate attention as an additional layer of variation to identify the effects of carbon intensities. The benefit of this analysis is that it allows us to study how the cost of option protection shifts *within the year* as climate attention varies, holding fixed firms' industry carbon intensities. Importantly, climate attention is largely unrelated to contemporaneous industry disclosure rates ($\rho < 10\%$), and disclosure rates do not vary within the year. Therefore, the sensitivity of the option measures to changes in climate attention should be unaffected by a potentially confounding direct effect of *Industry CDP disclosure*. Second, Lennox, Francis, and Wang (2012) point out that multicollinearity issues can arise in a selection model if a weak exclusion restriction is imposed. Thus, we verify, using variance inflation factors, that our outcome equation does not suffer from such problems. Third, we report OLS regressions for robustness, which are unaffected by a potential violation of the exclusion restriction. This also follows Lennox, Francis, and Wang (2012), who recommend testing for robustness using alternative model specifications. Fourth, we continue to find significant effects of carbon intensities if we examine an alternative instrument (unreported) that exploits that firms that generate more foreign earnings have a higher propensity to report to CDP (Stanny and Ely 2008). At the same time, the fraction of foreign income is unlikely to have a direct effect on the cost of option protection against climate policy uncertainty. The economic effects in the outcome equation are somewhat smaller with this instrument. The reason is that information on foreign income is missing for most firms in the utilities industry. However, these firms belong to the most carbon-intense firms and excluding them biases effects downwards. Fifth, we use President Trump's election as an exogenous shock to climate policy uncertainty to mitigate concerns about the exclusion restriction.