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ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Carbon Tax Uncertainty

Evidence from the Implied Volatility Surface

Master's Thesis

Submitted in partial fulfilment of the requirements for the degree of Master of Science UZH ETH in Quantitative Finance

Author

Sophia Gläser

Student ID Number: 19-762-046

sophia.glaeser@icloud.com

Supervisor

Prof. Dr. Markus Leippold

Hans Vontobel Professor of Financial Engineering

Department of Banking and Finance

University of Zurich

Co-Supervisor

Dr. Nikola Vasiljevic

Jordy Rillaerts, PhD Candidate

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Abstract

Climate policy uncertainty makes it difficult for investors to assess the impact of future climate regulations. This thesis investigates how uncertainty about carbon taxation is priced in the option market. The results show that the cost of protection against downside and jump risk is higher for firms with high carbon intensity, and firms that do not report carbon emissions. The value of option protection increases when attention to carbon taxation is high.

Keywords: *carbon tax uncertainty, climate change transition, stochastic volatility inspired, downside tail risk, jump risk.*

Task Assignment

The following objectives are assigned to my thesis:

- Replicate essential parts of Ilhan et al. (2021). Deviations from this reference paper should be sufficiently motivated and discussed.
- Explore the effect of transition risk (sensitivity) on different risk components. A motivated selection is made among the proposed variables, including implied moments (volatility, skewness & kurtosis), Variance risk premium (upside and downside), tail risk measures (left tail IV slope, Rare disaster index, VaR & CVaR) and option Greeks.
- Discuss the potential proxies for firms's transition risk sensitivity and motivate the final choice(s).
- Discuss the general research design and assess its suitability for answering the research question.
- Perform comparison with the lead reference paper (Ilhan et al. 2021) and extend the analysis. Potential extension are (depending on time/results):
  - Different firm-level transition risk sensitivity measures
  - Improving on the construction of (implied) volatility surfaces
  - Broaden the set of option Implied measures.
  - Updated dataset
  - Exploring the time (maturity) dimension

Optional - In addition to the above objectives, the following extensions can be considered:

- Explore the impact/information on investor risk-aversion with regard to transition risk.
- Explore the so-called "Brown" factor and especially its relationship with transition downside risk.

The student is invited to adopt some lines of the proceeding by herself.

Executive Summary

Climate change regulation has notable economic and political implications that create uncertainty in financial markets. In this thesis, we investigate how carbon tax uncertainty is reflected in option prices. To do this, we construct an arbitrage-free volatility surface for S&P 500 companies using the stochastic volatility inspired surface during 2007 and 2021. We then compare the shape of the surface across firms with different carbon intensity.

Our analysis suggests that carbon tax uncertainty is priced in the option market. Specifically, the cost of protecting against downside tail and jump risks is higher for firms with high carbon emission consumption relative to their market value and those that do not report emissions. For firms in the upper quartile of carbon intensity, we find a 5% increase in standard deviation of the put-wing implied volatility slope (downside tail risk) and a 7% standard deviation increase in the negative implied volatility skew (jump risk), compared to firms in the lowest quartile. We also find that the value of option protection increases when carbon taxation receives more attention, as measured by the Google Search Volume Index.

When comparing our implied volatility surface to the OptionMetrics Surface File, we find that the latter has a lower ability to capture information for extreme strikes under constant extrapolation. While our key findings remain robust under the Surface File, there are some deviations from the original results.

Since firm carbon emission reporting is voluntary and not standardised, we test for sample selection bias in the cross-section. We do not find evidence that voluntary reporting leads to biased estimates in the model.

Our findings extend the work of Ilhan et al. (2021). They also demonstrate how the forward-looking nature of option contracts helps to disentangle the different aspects of downside, jump, price and variance risk under climate change uncertainty.

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Acronyms

2SLS Two-stage Least Squares.

ATM IV At-the-money Implied Volatility.

Call Slope Implied Volatility Slope for Call Options.

CRSP Center for Research and Security Prices.

ESG Environmental, Social, and Corporate Governance.

GHG Greenhouse Gas.

IV Implied Volatility.

IVS Implied Volatility Surface.

MFIS Model-free Implied Skewness.

OIM Option-implied Measure.

OLS Ordinary Least Squares.

PDE Partial Differential Equation.

Put Slope Implied Volatility Slope for Put Options.

SIC Standard Industry Classification.

Skew Implied Volatility Skew.

SLSQP Sequential Least-Squares Quadratic Programming.

SSVI Surface SVI.

SVI Stochastic Volatility Inspired.

SVI-JW SVI-Jump-Wings.

TIV Total Implied Variance.

VRP Variance Risk Premium.

Chapter 1

Introduction

Climate change and its implications for financial markets have featured prominently in economic research in recent years. While shifts in weather patterns and human contribution to it are scientific consensus (IPCC, 2022), uncertainty remains regarding the trajectory of climate change and its economic consequences. For financial markets the outcomes of climate change are often described in two channels: Physical risk, caused by the destruction of physical assets, and regulatory risk (or transition risk), which captures the mandate of political decision-makers to combat climate change with possibly strong regulatory actions.

Recent approaches in risk management literature have highlighted the advantages of using the forward-looking nature of option data to study uncertainty (e.g., Barone-Adesi et al., 2019; Jiang, 2005). Our objective is to leverage the information content of option contracts to study the impacts of regulatory risk on financial markets. To our knowledge, the seminal paper of Ilhan et al. (2021) is the only approach to address this issue; therefore, many questions remain for this field of research. Following the authors we focus on the impact of carbon taxation, a leading policy tool used in climate change regulation.

We largely follow the approach of Ilhan et al. (2021), with some theoretically and empirically motivated deviations. Among the most important departures we make is how we treat the option data. Ilhan et al. (2021) use the IvyDB OptionMetrics Surface File, interpolate in moneyness with cubic splines and fill implied volatility beyond the observed value on the boundary. However, without imposing certain criteria on the cubic spline interpolation, the result may introduce arbitrage, as shown in Fengler (2009). Moreover, Homescu (2011) highlights that setting implied volatilities to some constant outside the observed moneyness region is flawed, as it introduces unstable behaviour at the boundary between flat and smile volatility. Therefore, we estimate implied volatilities using a binary search algorithm along with Barone-Adesi and Whaley (1987)'s approximation of American option values and fit the implied volatility surface using the arbitrage-free Surface SVI (SSVI) parameterisation from Gatheral and Jacquier (2014). Furthermore, we use an extended time horizon, an intersecting set of option-implied measures, and a different approach (to us more traceable) to account for the possibility of sample selection bias due to voluntary reporting of carbon emissions.

This study makes several contributions to the limited research on the pricing of regulatory risk in the option market. First, we confirm the findings of Ilhan et al. (2021) that carbon-intensive firms have higher costs for options protecting against downside tail risk, under an extended time horizon and an alternative volatility surface calculation. Investigating an extended set of option-implied measures we additionally find that the cost for protection against price jumps increases for firms with carbon-intensive business models. Second, we compare the implied volatility slices from the SSVI to the IvyDB OptionMetrics Surface File, and find that while constant extrapolation of the Surface File underestimates implied volatilities for extreme strikes compared to the SSVI, our results are in essence robust to either implied volatility specification. Finally, we consider the possibility of sample selection bias due to voluntary emission reporting and test for this bias in the cross-section. Our models do not provide evidence for sample selection bias. The results are discussed in terms of both statistical and economic significance.

The work is structured as follows: Chapter 2 theoretically motivates the relevance of carbon tax uncertainty for financial markets. The details of the option data processing are described in Chapter 3. Subsequently, Chapter 4 introduces our empirical research design, including the variable construction and modelling framework. The results are presented in Chapter 5 and discussed in Chapter 6. Chapter 7 concludes the work.

Chapter 2

The Relevance of Carbon Tax Uncertainty to the Option Market

This chapter presents the theoretical motivation for why and how climate policy uncertainty is relevant to the option market. This consists of a literature overview and the general equilibrium model of Pástor and Veronesi (2013). Upfront a note on *uncertainty*: Uncertainty in the strict Knightian sense refers to an *unmeasurable* uncertainty in which neither possible future events nor their probabilities are known (Knight, 1921). We follow the wording of Pástor and Veronesi (2013) who refer to uncertainty as a situation for which the outcome is not known, but as signals can be observed, agents form expectations about possible future states of the world.

2.1 Literature Review

Our work primarily draws from two domains in the financial literature: The study of the effects of climate change regulation on asset prices, and the analysis of uncertainty in financial markets under the risk-neutral probability measure. Close to the presented research question is the work of Ilhan et al. (2021), who, to our knowledge, are the only ones to combine these two research domains to this point. Since our work draws heavily from their research, we provide a review below. The remaining literature is discussed in the following subsection.

2.1.1 Carbon Tail Risk: Results of Ilhan et al. (2021)

Ilhan et al. (2021) show that climate policy uncertainty is priced in the option market, for S&P 500 constituents during 2010 to 2017. In particular, the authors highlight that the cost of downside protection is higher for firms with higher carbon intensity and spikes when public attention to climate change increases. To capture the different effects of uncertainty, Ilhan et al. (2021) construct three Option-implied Measures (OIMs) using daily implied Black-Scholes volatilities from the OptionMetrics IvyDB Surface File:

1. Implied Volatility Slope for Put Options (Put Slope) - Tail Risk.

   The Put Slope slope is the regression coefficient from regressing Implied Volatilitys (IVs) for out-of-the-money put options on moneyness and a constant.

2. Variance Risk Premium (VRP) - Variance Risk.

   The VRP captures the cost of protection against general changes in volatility. It is the difference between the risk-neutral expected variance and realized variance.

3. Model-free Implied Skewness (MFIS) - Asymmetry of the Risk-neutral Distribution.

   MFIS is calculated as the moment coefficient for skewness. A formal definition of how to construct it from the option data is given by Bakshi et al. (2003).

Furthermore, the authors use emission data from the Carbon Disclosure Project[1] and measure firm sensitivity to climate policy uncertainty by carbon intensity (scope 1 carbon emissions/market value). Since the authors observe that the carbon intensity of a firm is primarily determined by industry association at SIC4 level, firm *industry* carbon intensity is their primary variable of interest.

To account for a possible selection bias due to voluntary reporting of carbon emissions, Ilhan et al. (2021) implement a selection model after Heckman (1976) and Wooldridge (2010). The key feature of this model is that the outcome equation is only estimated when a firm discloses carbon

[1] `https://www.cdp.net`

emissions in a given year. They estimate

$$\begin{aligned} OIM_{i,m,t+1} &= \beta_0 + \beta_1 log(Scope1/MVIndustry)_{i,t} + \boldsymbol{x}_{i,t}\boldsymbol{\beta} + u_{i,m,t+1}, \\ CDP\ disclosure_{i,t} &= \gamma_0 + \gamma_1 Industry\ CDP\ disclosure_{i,t} + \boldsymbol{x}_{i,t}\gamma + v_{i,t}, \end{aligned} \tag{2.1}$$

for each firm i, year t and month m, with annual control variables $\boldsymbol{x}$ (given in Appendix B.1), using full-information maximum likelihood. Ilhan et al. (2021) find that a firm's industry carbon intensity has a positive and significant effect on Put Slope and VRP. Since the effect of MFIS is not significant, they conclude that carbon-intense firms also have a larger right tail in the risk-neutral density.

2.1.2 Secondary Related Research

Most research on the climate change transition in financial markets addresses pricing in the stock market. Bolton and Kacperczyk (2022) find that stock returns are higher for firms with higher levels and growth rates of carbon emissions in all sectors and most countries, for both direct and indirect emissions. The authors also find that the carbon premium is greater in countries with tighter climate policies. This confirms and extends their earlier result that in the cross-section of US stock returns, investors demand compensation for exposure to carbon risk (Bolton and Kacperczyk, 2021).

Bolton and Kacperczyk (2022) use a firm characteristic-based approach by regressing carbon emissions along with multiple controls against stock returns. In contrast, Görgen et al. (2020) investigate the carbon beta. They find that while brown firms are associated with higher average returns, there is no evidence of a carbon risk premium for a brown-minus-green portfolio as in the Fama-French approach (Fama and French, 1992). Roncalli et al. (2020) extend the results of Görgen et al. (2020) by allowing the carbon risk factor to vary over time and test several specifications of the risk factor. The authors confirm the finding that climate change transition risk is priced at the stock level (higher average returns) but does not constitute a new factor in a factor-based approach. The authors conclude that managing carbon risk is rather a risk management subject than an investment style for a factor investing portfolio.

Other articles study how asset prices react to climate change-related events: Choi et al. (2020) find that the stock prices of carbon-intensive firms underperform the stocks of low carbon emitters when the temperature is abnormally high. Simultaneously, the attention to climate change increases. Similarly, Engle et al. (2020) demonstrate how climate change news series can be used to improve dynamic hedging.

The second domain of related research uses options to study the effects of political uncertainty on the option market. In particular, Kelly et al. (2016) show theoretically and empirically that political uncertainty is priced in the option market as price, tail, and variance risk. Kostakis et al. (2019) investigate option prices around US presidential elections and find that sensitive firms are affected by political uncertainty in firm risk, expected return, trading activity, and dispersion of investor beliefs. Less attention has been given to option pricing of jump risk under political uncertainty. However, Kelly et al. (2016) and Amengual and Xiu (2018) show that the resolution of political uncertainty is associated with jumps in stock prices.

2.2 Theoretical Background

How does uncertainty about future carbon tax regulation affect option prices? Pástor and Veronesi (2013, hereafter PV) provide the theoretical foundation on why political uncertainty affects asset prices. Kelly et al. (2016, hereafter KPV) bridge their result to the option market. We argue that combined these ideas can be applied to carbon tax uncertainty.

2.2.1 The Pastor-Veronesi (PV) Model and its Implications for Options

In the general equilibrium model of PV, firm profitability follows a stochastic process, where the prevailing government policy impacts firm profitability. At each time, the government chooses to retain the old policy or adapt one of N new policies. Each of them again has an unknown impact on firm profitability. When choosing a policy, the government maximises investor welfare but also considers the unknown political cost associated with a new policy. These costs reflect real financial costs but also bundle other aspects of sometimes random or intransparent policy-making, such as redistribution, corruption, or special interests.

Consequently, agents face two sources of uncertainty: Uncertainty about the impact of government policies on firm profitability and uncertainty about the costs of a new policy. Agents observe both firm profitability and political signals, such as news or debates, and hence learn about the impact of a current policy and political costs. The government then chooses a new policy if the effect of the old policy is perceived as unfavourable. A policy is more likely to be adopted the higher and more certain its perceived impact on firm profitability and the lower its political cost.

Concerning the implications for asset prices, PV show that asset prices are driven by fundamental economic shocks and political shocks, which are both affected by political uncertainty: Fundamental economic shocks contain the impact shocks from learning about the prevailing policy and political shocks capture the learning about the costs of new policies. The authors find that both shocks give rise to an equity risk premium while increasing volatility and the correlation of stock returns.

KPV theoretically and empirically analyse the PV model in the option market. In PV, before a new policy is adopted, investors have heterogeneous beliefs about the probabilities of possible future policy choices. Using the option-pricing model of Black and Scholes (1973), KPV show that the price of an option can be rewritten as a probability-weighted average of the expected present values of Black-Scholes option prices under each policy choice.

Additionally, KPV calculate the model-implied values for the at-the-money implied volatility, VRP, and the Put Slope. These measures aim to capture the effect of price, variance, and downside risk, respectively. The authors find that all three measures should be higher in weaker economic conditions and when the uncertainty about the future policy choice is greater. In weaker economic conditions, the current policy is perceived as unfavourable, hence the adoption of a new policy is more likely. Uncertainty about the future policy choice increases the probability that investors assign to an unfavourable policy outcome. The authors also test their models against a panel of options in 20 countries around multiple elections and find empirical support for the model's predictions on all three option-implied measures. In summary, KPV find that when policy changes are more likely and more uncertain, option protection against price, variance, and downside tail risk becomes more valuable.

2.2.2 Interpretation of the Results with Respect to Carbon Tax Regulation

As argued by the Network for Greening the Financial System (NGFS) (2019), climate change is a motivation for structural change in the economy. Since the mandate of financial supervisors comprises price stability and robustness of financial institutions, it falls within their directive to address the adverse consequences of climate change. This motivates our interpretation of the uncertainty of climate change regulation as a special case of political uncertainty of the PV framework.

In the PV and KPV models, stock and option prices are affected through (a), signals indicating that the current policy is harmful to firm profitability, and (b), signals indicating high or uncertain costs of future policies, that is periods of increased political uncertainty.

As observed by Choi et al. (2020), investors' attention to climate change increases and stocks of carbon-intensive firms underperform firms with low carbon emissions during extreme weather events: Natural disasters such as floods, heat waves, or storms and their economic consequences indicate to investors that the current policy pathway harms firm profitability. Hence, they can influence option prices through signals characterised by (a). Furthermore, investors observe the outcome of climate summits, elections, or other political events on climate change. They reveal information about what regulation might or might not be adapted, and hence present signals of sort (b). As KPV find that impact and political shocks affect option prices alike, subsequently, we do not distinguish from what shock the effect on prices originates.

The increase in Greenhouse Gas (GHG) emissions is a dominant cause of global warming (IPCC, 2021). Consequently, carbon pricing is one of the most prominent policy instruments for governments to mitigate climate change (OECD, 2022). Thus, we follow the argument of Ilhan et al. (2021) that regulation of climate change is likely to target the carbon emissions of companies. For easier wording, we understand carbon emissions to refer to all GHG emissions. Overall, we argue that *carbon tax uncertainty* presents a political uncertainty in the interpretation of PV and KPV.

Chapter 3

Option Data Processing

A stock option represents the right to buy or sell an underlying stock at or within a specified period of time at a specified price. Due to the forward-looking nature of option prices, options are often used to study uncertainty and risk in financial markets. Instead of working directly with option prices, to allow for easier comparison across strikes, maturities, and underlyings, it is convenient to map option prices to a real number called Implied Volatility (IV) (Homescu, 2011). We describe how we compute implied volatilities and fit an IV parameterisation to the data.

Throughout this chapter, we work on a filtered probability space $(\Omega, \mathcal{F}, \mathbb{F} = (\mathcal{F}_t)_{t\geq 0}, \mathbb{P})$, satisfying the usual assumptions. In particular, $\mathbb{P}$ denotes the historical probability measure, and the filtration $\mathbb{F}$ describes the flow of information over time. Assuming the absence of arbitrage, we also consider the equivalent martingale measure $\mathbb{Q}$. Let $(S_t)_{t\geq 0}$ be the price of a dividend-paying stock and assume dividends d and interest rates r are constant and proportional. Furthermore, denote $(F_t)_{t\geq 0}$ the forward price process, which under the stated assumptions is related to the stock price by $F_{t,T} = S_t e^{(r-q)(T-t)}$. For a given strike price k and maturity T, C_t^{BS} and P_t^{BS} denote the Black-Scholes price of a call and put option, respectively, with volatility $\sigma > 0$. When needed, the superscripts A and E specify the contract type as American or European.

As the option data processing is one of the main deviations of our paper from Ilhan et al. (2021), the most important results are presented directly. Intermediate theorems, derivations, and poofs can be found in the Appendix A.1 and A.2.

3.1 Estimating Implied Volatilities using the Barone-Adesi Whaley Approximation

Option pricing models, such as the famous model presented by Black and Scholes (1973), relate the price of a stock option to the price of the underlying stock, the volatility of stock returns, and other parameters such as strike price, time to expiration, interest rate and dividend yield. Given that all parameters except volatility of stock returns are observable, the option pricing formula gives a relationship between the option price and the volatility of the underlying stock (Mayhew, 1995). This motivates the following definition.

Definition 3.1. Denote $(V_t^{BS})_{t\geq 0}$ the Black-Scholes price of an option (European or American) on stock S. Then the Black-Scholes *Implied Volatility* is the value $\sigma_{BS}(K,\tau)$ that leads to option model-prices corresponding to those observed on the market V^{Mkt}:

$$V^{BS}(S,K,\tau,r,q,\sigma_{BS}) = V^{Mkt} \tag{3.1}$$

A standard procedure for European options is to invert the Black-Scholes option pricing formula for volatility using observed option prices. However, single stock options are American style, which the holder can exercise before maturity. This early exercise feature commands a premium and introduces a path dependency that has to be accounted for in valuation. Since no closed-form solution is yet available to price American options, implied volatility must be found numerically. We use a binary search algorithm along with the Barone-Adesi and Whaley (1987, hereafter BAW) approximation, which provides the advantage of being both accurate and computationally efficient (Barone-Adesi and Whaley, 1987).

To introduce BAW's modelling framework, we start with the dynamics of the stock price in the Black-Scholes model with dividends, which under $\mathbb{P}$ are specified by

$$\frac{dS_t}{S_t} = (\mu - d)dt + \sigma dW_t, \tag{3.2}$$

where W_t is a $\mathbb{P}$-Brownian motion.

Assuming a risk-less hedge exists between the option and the stock, the price of an option V on that stock can be described with the following partial differential equation.

$$\frac{\partial V_t}{\partial t} + (r-d)S_t\frac{\partial V_t}{\partial S} + \frac{1}{2}\sigma^2 S_t^2\frac{\partial^2 V_t}{\partial S^2} - rV_t = 0. \tag{3.3}$$

Applying the boundary condition of a European call or put option, respectively $max(0, S_T - K)$ and $max(0, K - S_T)$, the value of a European call and put can be derived, which we denote $C_t^{E,BS}(S,T,K)$ and $P_t^{E,BS}(S,T,K)$. For a call option, Merton (1973) shows that this value is

$$C_t^{E,BS} = Se^{-d(T-t)}N(d_1) - Ke^{-rT}N(d_2), \tag{3.4}$$

where $d_1 = \frac{ln(S/K)+(r-d+0.5\sigma^2)T}{\sigma\sqrt{T-t}}$, $d_2 = d_1 - \sigma\sqrt{T-t}$.

As mentioned, American option valuation is complicated by the fact that the possibility of early exercise has to be accounted for. Denoting the early exercise premium $\varepsilon_C(S,T,K)$, we can write the American call value $C^{A,BS}$ as

$$C^{A,BS}(S,T,K) = C^{E,BS}(S,T,K) + \varepsilon_C(S,T,K). \tag{3.5}$$

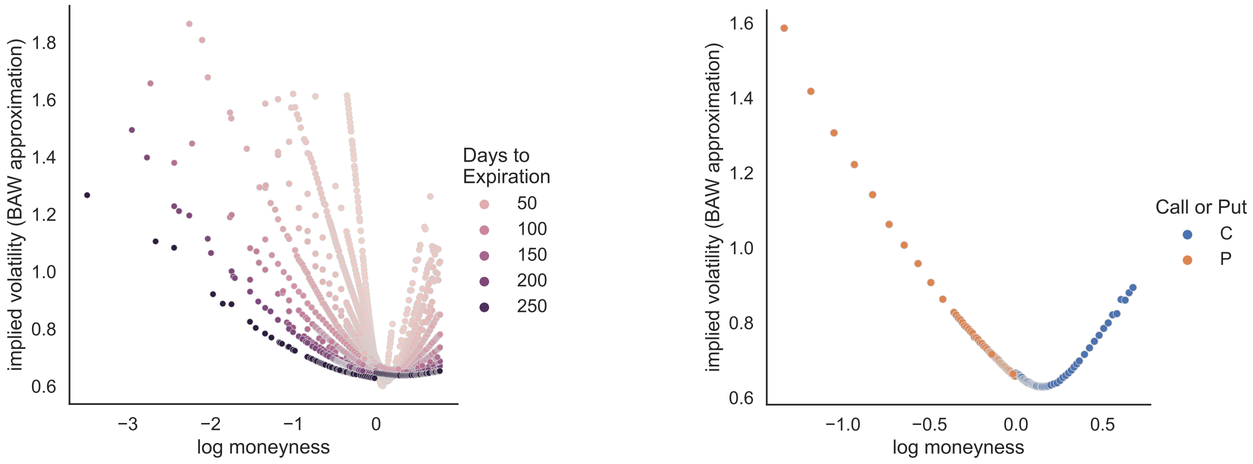
The approximation derived by Barone-Adesi and Whaley (1987) is

$$C^{A,BS}(S,\tau,K) = C^{P,BS}(S,\tau,K) + A_2(S/S^*)^{q_2}, \qquad \text{when } S < S^*\text{, and} \tag{3.6}$$

$$C^{A,BS}(S,\tau,K) = S - K, \qquad \text{when } S \geq S^*, \tag{3.7}$$

where $\tau = T - t$ denotes the time to maturity, $A_2 = (S^*/q_2)\left\{1 - e^{-d\tau}N[d_1(S^*)]\right\}$ and $q_2 = [-(N - 1) + \sqrt{(N-1)^2 + 4M/L}]/2$, with $M = 2r/\sigma^2$, and $N = 2(r-q)/\sigma^2$, $L = 1 - e^{-r\tau}$, is the positive root of $[q^2 + (N-1)q - M/L] = 0$, which is used to find the solution to the approximated Partial Differential Equation (PDE) for the early exercise premium. S^* denotes the critical stock price above which the call is exercised, which must be found iteratively.

Similar results hold for an American put option. The approximation of the American put value, as well as derivations and the iteration formulas are in Appendix A.1.



(a) IV approximation for all expirations

(b) IV approximation for one month to expiration

Figure 3.1 – Implied Volatility Approximation Example for American Options. The example is taken on 30 November 2021 for Tesla Inc. Subfigure (a) shows the estimated implied volatilities for all observed maturities. Subfigure (b) uses 31 days to expiration, which is closest to our desired 30 days to expiration, and highlights which estimates are generated from calls or puts. The implied volatilities are calculated using a binary-search algorithm along with Barone-Adesi and Whaley (1987)'s approximation for American option values. The example is chosen for a liquid company (1.535 contracts traded that day in total).

Barone-Adesi and Whaley (1987) conduct a sensitivity analysis to compare the values of American options for a range of simulated parameters and find that the results of the quadratic approximation are very close to the finite-difference method.

Using BAW's approximation, we need to find the implied volatility that comes closest to satisfying Equation 3.1. We use a binary search algorithm, which has been shown to correctly calculate implied volatilities in a wide range of circumstances (Berry and Zuo, 2009). The binary search is applied to the interval $[10^{-3}, 10]$ with a maximum acceptable error of 10^{-10}. If no value for implied volatility could be found (after a maximum number of $1,000$ iterations), the respective observation is discarded.

An exemplary result of the approximation is visualized in Figure 3.1. Firstly, we observe that clearly the slices violate the Black-Scholes assumption of constant volatility and show the well-documented smile or skew shape (e.g., Mayhew, 1995). Secondly, we observe that though by the law of one price IV slices should match between call and put options[2], there is an at-the-money jump where the call and put slices meet. We assume this does not present true arbitrage opportunities

[2] For European options we can use put-call parity to show that IV should be the same for call and put options. Though put-call parity does not hold for American options, σ characterises the volatility of the underlying stock price, which should not change, notwithstanding what option contract is written on the stock.

but is introduced due to data processing. In particular, since we use mid-prices, our IV slices do not correspond directly to prices from traded options. As shown in Figure 3.1, this behaviour is particularly pronounced for longer (and less frequently) traded maturities, and less so for the one month to maturity that we use in our analysis.

3.2 Fitting the Implied Volatility Surface: The SVI Model Family

To compare implied volatilities across options with different strikes and maturities, we need to calculate IVs beyond those observed in the market. The required mapping of IV for moneyness across maturities is called Implied Volatility Surface (IVS). Unfortunately, a simple interpolation and extrapolation would not serve to construct the slices or the surface, as this could introduce arbitrage.

Various approaches have been proposed to construct an arbitrage-free IVS for a discrete set of market data. We need a methodology that can robustly fit a surface to sometimes few data points available for single-stock options while being not overly complicated to implement. As argued by Öhman (2019), the parametric Stochastic Volatility Inspired (SVI) model family presents a good fit for that purpose.

We introduce the following additional notation: We specify moneyness as forward log-moneyness $k = ln(K/F_{t,T})$. Furthermore, denote the implied variance by $v(k,\tau) = \sigma^2_{BS}(k,\tau)$, and the Total Implied Variance (TIV) by $w(k,\tau) = \sigma^2_{BS}(k,\tau)\tau$. The two-dimensional map $(k,\tau) \mapsto w(k,\tau)$ denotes the implied volatility surface, and for a fixed $\tau > 0$, $k \mapsto w(k,\tau)$ is a volatility slice.

In the next sections, no-arbitrage is defined and it is explained why it is crucial that our surface satisfies no-arbitrage. Then the SVI parameterisations employed are spelt out, and the conditions that follow for the parameters from the concept of no-arbitrage are given. Finally, an algorithm is presented that can fit the parameterisation to the market data under the given constraints.

3.2.1 No-Arbitrage in the Implied Volatility Surface

The concept of no-arbitrage formalises the idea of *no free lunch*: In an efficient financial market, market participants cannot enter a cost-free strategy that has zero probability of losing money but a positive probability of making money. A market is said to be *arbitrage-free* if no such opportunity exists. Furthermore, since the volatility surface is defined at a given time, we are concerned with *static* arbitrage opportunities, which refer to strategies set up at some time and kept unchanged over the life of the investment.

Consequently, to obtain realistic values for our option-implied measures we need to ensure that the constructed implied volatility surface does not violate the concept of no-arbitrage. Formally, Roper (2010) find that an IVS is free of static arbitrage if there exists a model under which the discounted stock price process is a non-negative martingale, and European call prices are given by the expectation of their pay-offs at maturity[3]. To obtain a more traceable framework from which sufficient conditions on an arbitrage-free surface can be derived, Gatheral and Jacquier (2014) introduce the following definition.

Definition 3.2 (Definition 2.3 from Gatheral and Jacquier (2014))**.** An Implied Volatility Surface (IVS) is free of static arbitrage if and only if the following conditions are satisfied:

(i) it is free of calendar spread arbitrage,

(ii) each time slice is free of butterfly arbitrage.

In particular, the first condition ensures the existence of (non-negative) probability density, whereas the second condition implies that option prices are a monotonic function with respect to maturity (Carr and Madan, 2005). Gatheral and Jacquier (2014) translate these conditions to numeric constraints on the total implied variance with Lemmas A.1 and A.2 (see Appendix A.2).

[3] More precisely, these are the conditions Roper (2010) give for a call price surface to be free of static arbitrage, but they state that the IVS is free of arbitrage if the call price surface is free of static arbitrage. In addition, the expectation is taken as conditional on filtration $\mathbb{F}$. This is similar to Definition 4.1. from Cox and Hobson (2005), except for Roper (2010) insisting on a true instead of a local martingale.

3.2.2 The (S)SVI Specifications

The SVI parameterisation was originally developed at Merrill Lynch in 1999 and made public by Gatheral (2004). After Roper (2010) showed that the original presented SVI is not generally free from arbitrage, Gatheral and Jacquier (2014) introduced a new parameterisation, called Surface SVI, introducing an at-the-money dependence. Intuitionally, this is sensible, as these options have been found to be the most liquid and therefore the most reliable data (Öhman, 2019). This work uses the SVI-Jump-Wings (SVI-JW) and SSVI parameterisation.

The Surface SVI (SSVI)

The SSVI is given by the following definition:

Definition 3.3 (The Surface SVI (SSVI), Definition 4.1. from Gatheral and Jacquier (2014))**.** Let φ be a smooth function from $\mathbb{R}_+^*$ to $\mathbb{R}_+^*$ such that the limit $\lim_{\tau\to 0}\theta_\tau\varphi(\theta_\tau)$ exists in $\mathbb{R}$. We refer to the SSVI as the surface defined by

$$w(k,\theta_\tau) = \frac{\theta_\tau}{2}\left\{1+\rho\varphi(\theta_\tau)k+\sqrt{(\varphi(\theta_\tau)k+\rho)^2+(1-\rho^2)}\right\}. \tag{3.8}$$

Thereby we have that $\mathbb{R}_+^* = \{x\in\mathbb{R}|x>0\}$ and θ_τ is the at-the-money implied total variance, hence $\theta_\tau := \sigma_{BS}^2(0,\tau)\tau$. As this will be useful later, we will state a result of Gatheral and Jacquier (2014) that relates the SSVI specification to the SVI-JW parameterisation.

Lemma 3.1 (Lemma 4.1. from Gatheral and Jacquier (2014))**.** *The SVI-JW parameters associated with the SSVI surface from Definition 3.3 are:* $v_\tau = \theta_\tau/\tau$, $\psi_\tau = \frac{1}{2}\rho\sqrt{\theta_\tau}\varphi(\theta_\tau)$, $p_\tau = \frac{1}{2}\sqrt{\theta_\tau}\varphi(\theta_\tau)(1-\rho)$, $c_\tau = \frac{1}{2}\sqrt{\theta_\tau}\varphi(\theta_\tau)(1+\rho)$, $\tilde{v}_\tau = \frac{\theta_\tau}{\tau}(1-\rho^2)$.

To ensure no arbitrage, we need to find the conditions under which Lemma A.1 for no calendar spread arbitrage and Lemma A.2 for no butterfly arbitrage hold in the SSVI. Gatheral and Jacquier (2014) summarise the general parameter constraints in Theorems A.1 and A.2, which can be found in the Appendix A.2. Since the conditions in Theorems A.1 and A.2 depend on $\varphi(\theta)$, we must specify the dependence on at-the-money variance. Although theoretically any smooth function that satisfies the requirements of Definition 3.3 is possible, Gatheral and Jacquier (2014) propose two specifications:

the *Heston-like* parameterisation and the *Power-law* parameterisation. Following Öhman (2019) we implement the power-law parameterisation. A possibility is the general power-law specification, given by $\varphi(\theta) = \eta\theta^{-\gamma}$, with $\eta > 0$ and $0 < \gamma < 1$. To ensure, however, that the entire surface is free of static arbitrage Gatheral and Jacquier (2014) propose the modification $\varphi(\theta) = \frac{\eta}{\theta^{\gamma}(1+\theta)^{1-\gamma}}$. The authors claim that this choice leads to a surface free of static arbitrage when choosing $\gamma = 1/2$ and ensuring that $\eta(1 + |\rho|) \leq 2$.

We summarise the no-arbitrage results in the following:

Corollary 3.1 (No arbitrage in the SSVI with Power-law φ)**.** *If we specify the SSVI as in definition 3.3 and use the power-law specification for φ given by $\varphi(\theta) = \frac{\eta}{\theta^{\gamma}(1+\theta)1-\gamma}$ with $\eta > 0$, then the SSVI is free of static arbitrage if we choose*

i) $\gamma = \dfrac{1}{2}$, *and*

ii) $\eta\,(1 + |\rho|) < 2$.

The SVI-Jump-Wings (SVI-JW) Parameterisation

The SVI-JW parameterisation is not specified directly but in terms of the raw SVI parameterisation. The *raw SVI parameterisation* of the Total Implied Variance for the parameter set $\mathcal{X}_R = \{a, b, \rho, m, \sigma\}$ is given by $w(k; \mathcal{X}_R) = a + b\left\{\rho(k - m) + \sqrt{(k - m)^2 + \sigma^2}\right\}$, where $a \in \mathbb{R},\ b \geq 0,\ |\rho| < 1,\ m \in \mathbb{R},\ \sigma > 0$ and to ensure $w(k; \mathcal{X}_R) > 0\ \forall\ k \in \mathbb{R}$: $a + b\sigma\sqrt{1 - \rho^2} \geq 0$. Then for the parameter set $\mathcal{X}_J = \{v_\tau, \psi_\tau, p_\tau, c_\tau\tilde{v}_\tau\}$ the *SVI-JW* parameterisation is defined in terms of the raw SVI parameters as follows

$$
\begin{aligned}
v_\tau &= \frac{a + b\{-\rho m + \sqrt{m^2 + \sigma^2}\}}{\tau}, \\
\psi_\tau &= \frac{1}{\sqrt{w_\tau}} \frac{b}{2} \left(-\frac{m}{\sqrt{m^2 + \sigma^2}} + \rho \right), \\
p_\tau &= \frac{1}{\sqrt{w_\tau}} b(1 - \rho), \\
c_\tau &= \frac{1}{\sqrt{w_\tau}} b(1 + \rho), \\
\tilde{v}_\tau &= \frac{1}{\tau} \left(a + b\sigma\sqrt{1 - \rho^2} \right),
\end{aligned}
\tag{3.9}
$$

and $w_\tau := v_\tau \tau$. Compared to the raw SVI, the SVI-JW parameterisation allows for dependence on the time to maturity τ. Moreover, the SVI-JW parameterisation has the convenient feature that the parameters can be interpreted for the shape of the IV slice as follows: v_τ gives the at-the-money variance, ψ_τ gives the at-the-money skew, p_τ controls the slope of the left IV wing (from put options), c_τ controls the slope of the right IV wing (from call options), $\tilde{v}_\tau$ is the minimum implied variance.

As for the SSVI, we need to find the conditions under which the no-arbitrage conditions from Lemmas A.1 and A.2 hold in the SVI-JW. For calendar arbitrage, we rely on a result of Fengler (2009), which shows that the definition of no calendar arbitrage implies that the total variance must be an increasing function of maturity. Therefore, we can guarantee that there is no calendar arbitrage in the SVI-JW by ensuring that the TIV slices do not intersect:

Corollary 3.2 (No calendar spread arbitrage in the SVI-JW)**.** *The SVI-JW parameterisation is free of calendar arbitrage, if for $\tau_1 < \tau_2 < \tau_3$ we have $w_1 < w_2 < w_3$.*

Gatheral and Jacquier (2014) state that unfortunately, it is impossible to find general conditions on the raw and jump-wing parameters that ensure the absence of butterfly arbitrage as after A.2 this depends on a highly non-linear function g. Therefore they use the fact that the SSVI can be defined free of butterfly arbitrage given three observables and that the SVI-JW and SSVI parameterisations are related by Lemma 3.1.

Lemma 3.2 (No butterfly arbitrage in the SVI-JW Gatheral and Jacquier (2014))**.** *Suppose that we choose to fix the SVI-JW parameters v_τ, ψ_τ, p_τ for a given SVI smile, we may guarantee a smile without butterfly arbitrage by choosing the remaining parameters c'_τ and $\tilde{v}'_\tau$ as*

$$c'_\tau = p_\tau + 2\psi_\tau, \qquad \textit{and} \qquad \tilde{v}'_\tau = v_\tau \frac{4 p_\tau c'_\tau}{(p_\tau + c'_\tau)^2}.$$

3.2.3 Calibrating the Volatility Surface to Market Data

We describe how the SSVI can be calibrated to market data. These results are based on the work of Gatheral and Jacquier (2014), along with extensions provided by Ferhati (2020) and Öhman (2019). In particular, the calibration follows essentially the *xSSVI* procedure from Öhman (2019). The following steps are applied to fit the volatility surface for each day and each option contract.

1. Compute the TIV from mid-IV data.
2. Pick the at-the-money value of TIV if available; if not, compute it using linear interpolation as a function of log-moneyness.
3. Initial fit: Create an initial global fit using the SSVI specification by solving the optimisation of Equation 3.10 given below. This returns for each day and security the parameters $[\rho, \eta]$.
4. Convert the initial fit to SVI-JW parameters using Lemma 3.1.
5. Second fit: Iterate through each slice forward in maturity and improve the fit by solving the optimisation of Equation 3.11 below. This returns for each day, security, and maturity the parameters $[v_\tau, \psi_\tau, p_\tau, c_\tau, \tilde{v}_\tau]$.
6. With the parameters from the previous step, we could compute the TIVs using the SVI-JW parameterisation 3.9. Since we require option contracts with 30 days to expiration, we first interpolate in maturity as described in the end of the section.

The optimisation problem for the global SSVI fit from Step 3 is given by

$$\begin{aligned} &\min_{\rho,\eta} \sum_{s=1}^{S} \sum_{i=1}^{n} \left(w(k, \theta_\tau; \rho, \eta, \gamma = \frac{1}{2}) - \hat{w}_{s,i} \right)^2, \\ &\text{such that } \eta \left(1 + |\rho|\right) < 2, \end{aligned} \tag{3.10}$$

where S is the number of maturities, n the number of data points per maturity, $\hat{w}_{s,i}$ the market data and $w_{s,i}(k, \theta_\tau)$ the parameterisation. To solve this problem, a non-linear optimisation procedure is required. We follow Ferhati (2020) who propose the Sequential Least-Squares Quadratic Programming (SLSQP) algorithm for constraint nonlinear gradient-based optimisation. This method is particularly well suited, as it allows us to solve a non-linear optimisation problem with any combination of bounds and non-linear constraints (Ferhati, 2020).

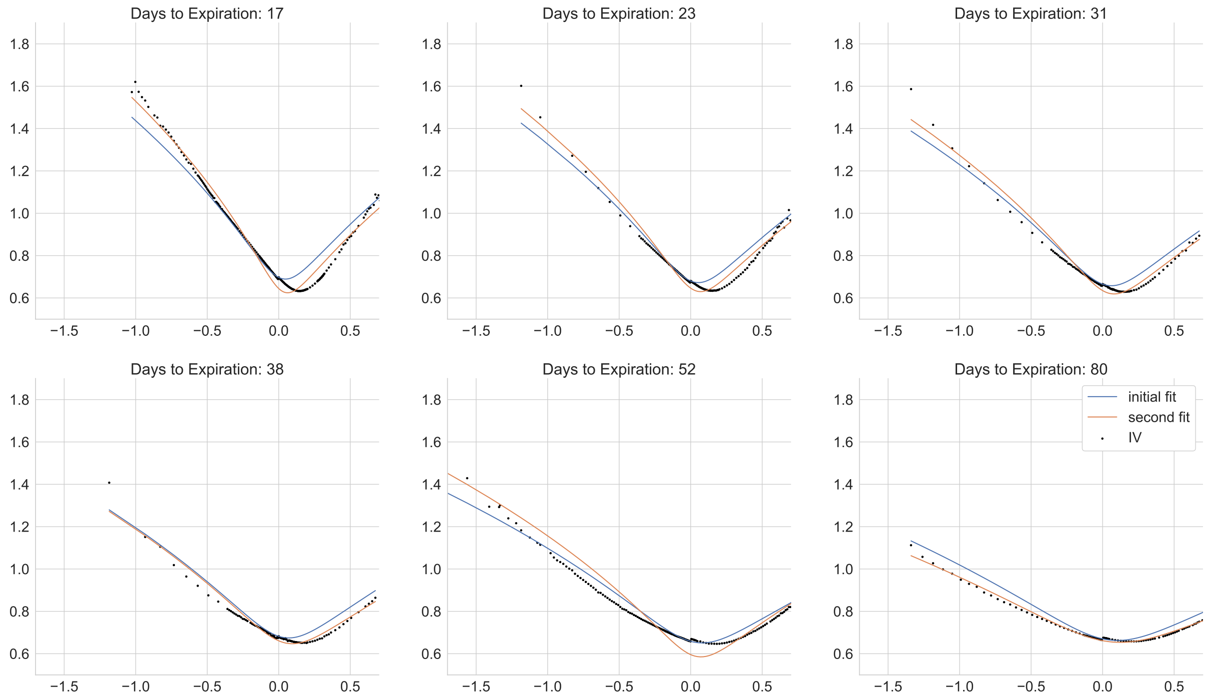


Figure 3.2 – An exemplary fit of the Stochastic Volatility Inspired Surface to market observed implied volatilities on 30 November 2021 for Tesla Inc. Each subfigure shows the implied volatility slice for a maturity traded that day, for maturities between two weeks and three months. The implied volatilities estimated from market prices are plotted in black dots and the dark (blue) line shows the first global fit of the SSVI. The light (orange) line plots the second fit improved for each maturity using the SVI-JW parameterisation. The example is chosen for a liquid company (1.535 contracts traded that day in total).

For the second fit of Step 5, we again apply the SLSQP algorithm to solve for each maturity.

$$\begin{gathered}\min_{v_\tau,\psi_\tau,p_\tau,c_\tau,\tilde{v}_\tau} \sum_{i=1}^{n} \left(w_i(v_\tau,\psi_\tau,p_\tau,c_\tau,\tilde{v}_\tau) - \tilde{w}_i\right)^2, \\ \text{such that } g(x) \geq 0 \\ \text{and such that for } \tau_{i-1} < \tau_i < \tau_{i+1}, \text{we have } w_{i-1} < w_i < w_{i+1}. \end{gathered} \tag{3.11}$$

As mentioned above, it is difficult to apply the constraint $g(x) \geq 0$, which is why, to ensure no butterfly arbitrage, we optimise over v_τ, ψ_τ, p_τ, and then set c_τ, $\tilde{v}_\tau$ according to the arbitrage constraints from Lemma 3.2. The constraint on the maturities is the condition for no calendar arbitrage. Since this concerns the relation of slices, it is not a constraint to the SLSQP optimisation for each slice, and we set a penalty for each slice that violates these constraints.

An exemplary fit of the SSVI to market data is shown in Figure 3.2. We observe that while the initial fit presents a decent global fit, deviations from the market data can be reduced by adjusting the fit for each maturity.

We aim to construct OIMs from options with 30 days to maturity. Since such contracts are not traded for every day and for every security, we interpolate the IV slices. Gatheral and Jacquier (2014) suggest interpolating by computing Black-Scholes option prices from the fitted volatility, linearly interpolating in the option prices, and obtaining interpolated IVs by inversion of the Black-Scholes formula. We deviate from this approach since a closed-form solution for American option prices is unavailable. While a possible alternative could be to calculate option prices using BAW's approximation from Section 3.1, we concluded that another numerical search would be computationally expensive, and we did not want to introduce another modelling layer. Instead, we follow the interpolation employed by Lucescu (2020), who also constructs a IVS using single stock American options. The procedure to obtain the τ_{30} corresponding to 30 days to expiration is:

1. If a IV slice with τ_{30} is available, use this.
2. Otherwise, interpolate:
   (a) Select the slices closest to 30 days to maturity, that is, such that $\tau_j < \tau_{30} < \tau_{j+1}$. Since we want to exclude extrapolation, we discard slices where such slices are not available.
   (b) Using the SVI-JW parameters calibrated in Step 5 calculate $w_i^{\tau_j} = w(k_i, \mathcal{X}_J^{\tau_j})$ and $w_i^{\tau_{j+1}} = w(k_i, \mathcal{X}_J^{\tau_{j+1}})$ for 500 equally spaced log-moneyness values between -0.5 and 0.5.
   (c) Linearly interpolate according to the distance in log-moneyness of j and $j+1$:
   $$w_i^{\tau_{30}} = \frac{\tau_{30} - \tau_j}{\tau_{j+1} - \tau_j} w_i^{\tau_j} + \frac{\tau_{j+1} - \tau_{30}}{\tau_{j+1} - \tau_j} w_i^{\tau_{j+1}}. \tag{3.12}$$
   (d) Refit the SSVI on $w_i^{\tau_j}$, $w_i^{\tau_{30}}$ and $w_i^{\tau_{j+1}}$ as described in Step 2-3 of Section 3.2.3 to ensure that there is no arbitrage in the interpolated slice.
   (e) Extract the SVI-JW parameters using Lemma 3.1, calculate TIVs using Equation 3.9 and IVs with $\sigma(k_i, \tau_{30}) = \sqrt{w(k_i, \tau_{30})/\tau}$.

An example of a thus constructed IVS is shown in Figure A.1.

Chapter 4

Empirical Framework: Variable Construction and Modelling Approach

This chapter outlines the empirical methodology used in our study, including the steps to clean and prepare the data, the process of constructing relevant variables, and the models estimated. We also provide details on the sample selection and the assumptions made in the analysis.

4.1 Data Processing and Variable Construction

We analyse options on constituents of the S&P 500 from 2007 to 2021. The construction of the dataset aims to address four challenges. The first is to obtain S&P 500 constituents for each month, as choosing today's index constitution might introduce survivor bias. The second is constructing the panel dataset congruously, as security keys are not consistent across databases. Moreover, we need to find a sensible time aggregation since variables are obtained at different frequencies, and it is unclear when emission data is publicised to investors. Finally, missing values and possible outliers in the data need to be addressed.

We obtain S&P 500 constituents for each month from the Center for Research and Security Prices (CRSP)[4] and map all other links to CRSP's primary key (called `permno`). For Compustat[5],

[4] CRSP (2021)
[5] S&P Global Market Intelligence (2021)

and OptionMetrics[6] dated link tables are available, thus for each month, we merge the databases using the last best available link. For Refinitiv Eikon[7], we match the data via a security `CUSIPs`. As `CUSIPs` can change over time, it is not our preferred method when a dated linking table is available.

Since reporting carbon emissions is voluntary and not standardised, we do not know when a firm's carbon emissions are available to investors. We assume that firms publish their emissions along with their annual reports, which under the 10-K form are due within 90 days after the fiscal year-end (SEC, 2021), which for most firms matches calendar-year end. Therefore, we date carbon emissions and annual report data to 31^{th} March of the subsequent year. We show in Section 5.2 that our results are robust to using an alternative assumption on emission publication dates.

4.1.1 Carbon Emissions

Carbon emissions are sampled from Refinitiv Eikon, which collects emissions from publicly available sources annually. Though Refinitiv substitutes some missing emissions with an estimate, we focus on company-reported variables available to all investors. As Figure 4.1 shows since 2010 more than 50% of firms report GHG emissions each year, increasing to 84% of firms with reported emissions in 2021.

The data cover direct and indirect emissions across scopes 1-3. Scope 1 includes direct emissions from sources owned or controlled by the company, scope 2 comprises indirect emissions from purchased electricity, and all other indirect emissions from company activity are included in scope 3 (Ranganathan et al., 2004). We focus on scope 1 emissions, as they are directly controlled and owned by the company. We do not interpolate the emissions since non-reporting can also present a signal to investors and may not be random.

We scale carbon emissions by the firm's end-of-year market value to measure firm carbon intensity (= firm scope 1 GHG emissions/firm market value). Ilhan et al. (2021) use firm *industry* carbon intensity as their main explanatory variable. As in our sample, the authors observe that the emissions cluster within a few industries and sectors and are highly skewed (see Table 4.1 for summary statistics, as well as Figure B.1 for emissions composition per industry and sector). Moreover, the

[6] OptionMetrics (2021)
[7] Refinitiv (2021)

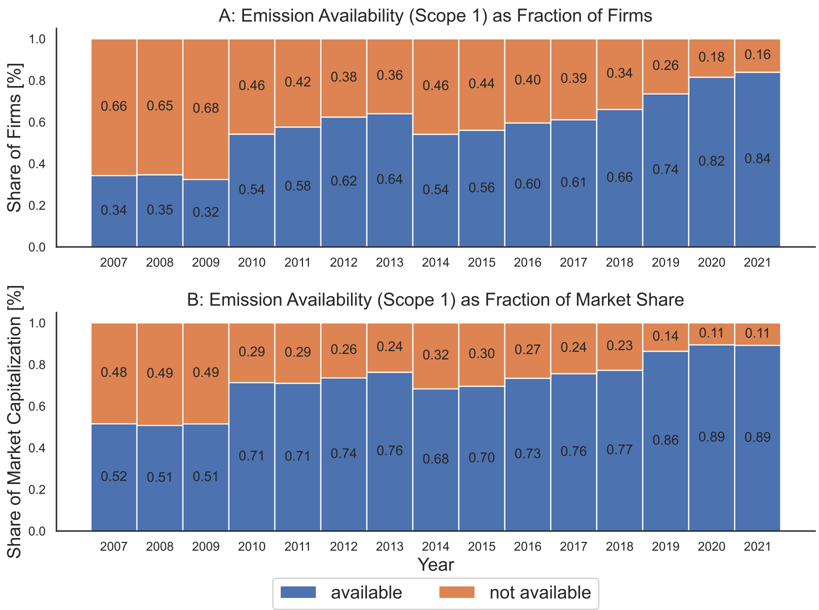


Figure 4.1 – Availability of scope 1 GHG emissions over time relative to firm count and market capitalisation. The dark (blue) bars indicate the fraction of available emissions, the light (orange) bars show the fraction on non-available emissions. The figure is based on end-of-year values of self-reported company emissions generated between 2007 and 2021 for S&P 500 constituents with sufficient data availability to construct implied volatility surfaces. This corresponds to 517 out of 818 companies and a total of 4,988 observations.

authors regress firm intensity on industry intensity as the only explanatory variable and add firm characteristics and year-fixed effects in a subsequent step. They find that a firm's carbon intensities are driven mainly by industry characteristics since the first regression's adjusted R^2 is 0.920 and increases only slightly when adding firm controls. We can only partly confirm this conclusion. We observe a similar pattern when the regression is estimated without intercept, but under inclusion of an intercept, the adjusted R^2 of the industry-only regression is only 0.626. The full results are summarised in Tables B.3 and B.2. The findings are similar when using sector instead of industry intensity (Tables B.5 and B.4). If the intercept is missing, most regression packages compute an uncentered R-squared R_0^2. As Wooldridge (2010) note, R_0^2 is rarely suitable as a goodness-of-fit measure and is usually much larger than R^2. We do not know whether Ilhan et al. (2021) estimate with a constant. Since we cannot confirm that firm carbon intensity is almost perfectly explained by industry carbon intensity, we use *firm* carbon intensity as our main explanatory variable and add sector-fixed effects to account for sector clustering of emissions. The model with industry intensity is estimated as a robustness test.

Table 4.1 – Summary Statistics

	mean	std	25%	50%	75%	count
Put Slope	0.520	0.275	0.411	0.568	0.696	55888
ATM IV	0.495	0.270	0.319	0.426	0.591	55888
VRP	0.304	0.462	0.097	0.174	0.336	55888
Skew	-0.218	0.253	-0.336	-0.203	-0.100	55888
Scope 1/MV Firm	0.221	0.945	0.001	0.007	0.097	33016
Scope 1/MV Industry	0.123	0.308	0.001	0.008	0.098	48033
Log(Assets)	9.886	1.308	8.937	9.759	10.668	55888
Div. payout ratio	0.387	0.824	0.011	0.264	0.479	55888
Debt/Assets	0.276	0.188	0.140	0.251	0.388	55888
Ebit/Assets	0.110	0.080	0.055	0.098	0.152	55888
CapEx/Assets	0.043	0.044	0.013	0.030	0.059	55888
Book-to-Market	0.383	0.298	0.181	0.321	0.519	55888
Log(Return)	0.045	0.330	-0.105	0.086	0.242	55888
Inst. Own.	0.810	0.144	0.731	0.821	0.893	55888
CAPM beta	1.122	0.683	0.692	1.077	1.446	55888
Oil beta	0.018	0.259	-0.119	-0.007	0.118	55888
Volatility	0.086	0.056	0.054	0.073	0.100	55888
ESG Score	0.534	0.190	0.396	0.551	0.686	55888
Trends CO2 Tax	0.213	0.114	0.140	0.180	0.250	55888

Note: Summary statistics are reported at the firm-year level. The figure is based on end-of-year values of self-reported company emissions generated between 2007 and 2021 for S&P 500 constituents with sufficient data availability to construct implied volatility surfaces. Carbon Emissions are reported in kt of CO2 equivalents, firm fundamentals in M $.

4.1.2 Option-Implied Measures

Option Data Cleaning

As motivated in Section 2.2.2 we use options to study carbon tax uncertainty. Option data are obtained from the OptionMetrics IvyDB US price file, which contains daily data on American-style individual stock options. We query option prices for the last business day of each month. Single stock options are less frequently traded than their index counterparts. Therefore, we impose a set of reliability criteria.

To avoid using illiquid contracts, we exclude in-the-money options as proposed by Aït-Sahalia and Lo (1998). Additionally, we require positive volume, positive open interest, and a maximum of three days of no trading in the contract. To minimise recording errors, we discard options for which the bid price is zero, the ask price is lower than the bid price, or the bid-ask spread is lower than the minimum tick (which is \$0.05 for options trading below \$3 and \$0.10 else, after Goyal and Saretto (2009)). For comparability between contracts, we eliminate all options with special settlement criteria. Finally, in our model, we use options with 30 days to maturity, but since the calibration of the SSVI requires options across multiple maturities, we keep contracts between one day and 365 days to expiration. After filtering, we are left with around 40% of the raw data. To obtain one price per contract, we work with mid prices (i.e. averages of bid-ask prices). We query zero coupon interest rate data from the zero curve file from OptionMetrics IvyDB, and add the interest with the corresponding maturity to each contract. If no such interest rate is available, we linearly interpolate within the range of observed interest. The dividend yield is more difficult to obtain since for most stocks, only past discrete dividend payments are available. As in Aït-Sahalia and Lo (1998), we infer the dividend yield from futures prices using the relation already found in Chapter 3: $F_{t,T} = S_t e^{(r_{t,T} - d_{t,T})(T-t)}$.

Having thus obtained a dataset of sufficiently reliable option prices, we process the data as described in Chapter 3 to obtain implied volatility slices for 30 days to maturity, each firm and day. During the implied volatility computations, we furthermore discard options for which only a single strike per maturity or fewer than three different maturities are available to avoid interpolating with too little information, as well as options with the smallest maturity above or the largest maturity below 30 days to avoid extrapolation in maturity.

After option data cleaning and IV computation, surface construction and interpolation we obtain IV slices for 63,939 out of the possible 87,580 observations (73%).[8] If we were to drop all firms with missing values, we would be left with 50 out of the possible 818 firms (6%), which is too small that we decided to work with an unbalanced panel. In the unbalanced panel, we keep all companies for which not more than 40% of the implied volatility slices are missing. This corresponds to 55,888 observations (64%) from 571 companies (70%).

[8] 87,580 is smaller than 500 firms × 12 months × 15 years = 90,000 observations since we match S&P 500 constituents by months. Therefore, if a firm drops out of the index between April and March, we stop observing monthly values after the dropout, but obtain new annual values for the replacement firm only the next 31^{th} March.

Construction of the Option-implied Measures

To capture different characteristics of the IV slices, we compute four Option-implied Measures (OIMs): Put Slope, At-the-money Implied Volatility (ATM IV), VRP, and Implied Volatility Skew (Skew). Put Slope, ATM IV and VRP are found to be relevant to political uncertainty by KPV. We add the Skew to capture the curvature of the implied volatility slice. All OIMs are estimated for options with 30 days to maturity, hence, we drop the subscript τ.

Put Slope - Downside Tail Risk. The Put Slope is inspired from KPV to capture tail risk. It measures the steepness of the left IV slope by regressing IVs from out-of-the-money put options on the negative of log moneyness and a constant.

$$\sigma_{BS,t}(k) = \beta_0 + \mathit{Put\ Slope}_t \times -k \qquad \text{for } k \in [-0.5, -0.001]. \tag{4.1}$$

The higher the Put Slope the more expensive deep out-of-the-money put options are relative to at-the-money put options. Since deep out-of-the-money put options provide better protection against large price declines, a higher value of Put Slope indicates a higher cost of protection against downside tail risk.

At-the-money Implied Volatility (ATM IV) - Price Risk. ATM IV is computed as the average volatility from at-the-money options, that is, from implied volatilities for the log-moneyness left and right of zero in our discrete log-moneyness grid.

$$\text{ATM IV}_t = \frac{\sigma_{BS,t}(-0.001) + \sigma_{BS,t}(0.001)}{2} \tag{4.2}$$

A larger value of ATM IV indicates a higher cost of protection against stock price drops (price risk) (Kelly et al., 2016; Kostakis et al., 2019). If the ATM IV is higher, the whole IV slice is shifted upwards. Hence option protection against price moves in the underlying becomes more valuable.

Variance Risk Premium (VRP) - Variance Risk. The VRP is the difference between the conditional risk-neutral expected total return variation and realised variation (e.g. Bollerslev et al., 2009; Carr and Wu, 2009):

$$VRP_t = IV_t^2 - RV_t^2, \tag{4.3}$$

where we calculate IV_t^2 = ATM IV_t^2 and $RV_t^2 = \sum_{i=1}^{30} r_{t-30+i}^2$, $r_t = ln(p_t - p_{t-1})$ for p_t price on day t.[9] Carr and Wu (2009) show that under no-arbitrage $IV_t^2 = \mathbb{E}^{\mathbb{Q}}[RV_{t,t+30}]$, which is the amount investors pay to enter a 30-day variance swap that pays out $RV_{t,t+30}$ at maturity. In that way, a higher VRP captures a higher cost of protection against return variation.

Implied Volatility Skew (Skew) - Jump Risk. As observed in Section 3.1, in contrast to the Black-Scholes assumption of constant volatility, the implied volatility slices follow a smile or skew pattern: For a given expiration and underlying, IV increases the farther away the stock price is from the strike (smile). This increase can be stronger for stock prices lower than the strike (skew). The Skew captures to what extent the IV slice bends away from a flat line. Following Mixon (2011) we define Skew as:

$$Skew\ _t = \frac{\sigma_{BS,t}(-0.125) + \sigma_{BS,t}(0.125)}{ATM\ IV_t}. \tag{4.4}$$

The skew in the implied volatility is often traced back to a jump premium (e.g. Bakshi et al., 1997; Pan, 2002). Therefore, a more negative Skew indicates an increased demand for protection against downward price jumps. In contrast to Put Slope which captures the protection of downside tail risks relative to 'normal' risks, the Skew is measured relative to the right tail of the implied volatility slice.

In that way, we broaden the set of option-implied measures compared to Ilhan et al. (2021), although their MFIS is the skewness coefficient of the risk-neutral density, while Skew measures the skewness of the IV slices. From the results of Ilhan et al. (2021) and KPV we would expect that the cost of option protection against downside tail, price, variance, and jump risk is higher for firms more sensitive to carbon tax uncertainty. Thus for firms with more carbon-intensive business models, Put Slope, ATM IV, and VRP should be higher, while Skew should be lower.

9 Three notes on the VRP: 1) We differ from Ilhan et al. (2021), who calculate an ex-post version with RV_t^2 over $[t, t+30]$. As this information is not available at t, we compute the ex-ante version of VRP as, for example, in Bollerslev et al. (2009). 2) Our measure of IV^2 is not model-free as the one proposed by Bollerslev et al. (2009); Carr and Wu (2009). KPV measure IV^2 as we do and test for robustness using a model-free version. While their results are unchanged, the model-free measure is much noisier as it requires option contracts across various strikes and hence reduces sample size. 3) The measure for realised variation is based on Andersen et al. (2010). They use high-frequency returns for construction, which is more accurate than our use of daily returns.

4.1.3 Control Variables

We utilise the same control variables as in Ilhan et al. (2021) that have been identified in previous work to determine firm risk. These include *log(Assets), Dividends/Net income, Debt/Assets, EBIT/Assets, CapEx/Assets, Book-to-market, log(Returns), Institutional Ownership* and a *Time Trend* at an annual frequency. *CAPM beta, Oil beta, Volatility* are estimated as monthly averages from daily price data. Moreover, we control for a proxy of public attention to carbon tax with the monthly *Google Trends Search Volume Index for the topic "CO2 tax"*. The index takes values between zero and one, scaled to the search period. In addition to Ilhan et al. (2021) we include a control for a company's *Environmental, Social, and Corporate Governance (ESG) rating.* Missing values are interpolated using k-nearest neighbours and annual control variables are winsorised at the 1% level. Summary statistics are presented in Table 4.1. A detailed overview of all variables employed, including their data source and computation, is found in Table B.1.

4.2 Model

We aim to investigate whether the OIMs described in the previous section vary with a firm's carbon intensity while accounting for missing emission data due to voluntary disclosure.

In the first model, we compute a categorical variable for firm carbon intensity indicating either the quartile of the intensity or non-reporting (see Equation 4.6). Consequently, we assume that the reason why emissions are not reported does not depend on unobserved factors. We estimate our first model using Ordinary Least Squares (OLS):

$$\begin{aligned} OIM_{i,t+1,m+1} = \beta_0 + \beta_1 [\mathit{QI{=}2}]_{i,t} + \beta_1 [\mathit{QI{=}3}]_{i,t} + \beta_1 [\mathit{QI{=}4}]_{i,t} + \beta_1 [\mathit{QI{=}5}]_{i,t} + \\ \boldsymbol{x}^a_{i,t}\boldsymbol{\beta}^a + \boldsymbol{x}^m_{i,t+1,m}\boldsymbol{\beta}^m + u_{i,t+1,m+1}, \end{aligned} \tag{4.5}$$

where

$$QI_{i,t} = \begin{cases} i & \text{if } \textit{Scope 1/MV Firm} \text{ in quartile } i, \text{ year } t, i = 1,2,3,4, \\ 5 & \text{if firm } i \text{ does not report emissions in year } t \end{cases} \tag{4.6}$$

for quartiles defined each year, $\boldsymbol{x}^a$ denoting annual controls, and $\boldsymbol{x}^m$ monthly controls as described in Section 4.1. We observe all explanatory variables in March of the following year (see Section 4.1), except for the monthly controls that we observe each month, starting in March. The OIMs are included in April-March of the subsequent year. In this way, they are always observed with a lag of $1-12$ months with respect to the annual controls and a lag of one month with respect to the monthly controls. The model is estimated using the covariance matrix estimator *HC3* proposed by MacKinnon and White (1985), to account for the possible presence of heteroscedasticity. HC3 also produces reliable estimators in the case of no-heteroscedasticity (MacKinnon and White, 1985).

The advantage of this approach is that we employ all data as well as the potential information conveyed by not disclosing emissions. This comes however with the downside that we force carbon intensity into a categorical variable, and do not allow emission disclosure to depend on unobserved factors. Simply dropping all firms that do not report emissions is not a helpful alternative, as this could lead to biased and inconsistent estimators, particularly if the data is not missing at random (Wooldridge, 2010). Therefore, we account for a possible sample selection bias in a second model. The advantage of this approach is that we allow emission reporting to depend on unobserved factors, such as the firms' benefit from disclosing emissions and that we can treat carbon intensity as a continuous variable. As a drawback, this model is applicable only in the cross-section.[10]

For implementation, we follow Wooldridge (2010)'s extension of Heckman (1976). The main feature of this model is that the Outcome Equation 4.7 is only estimated for companies that report emissions, including the estimated 'probability of reporting'. Estimation is performed using Two-stage Least Squares (2SLS) in the selected subsample, and the results of the Probit Selection Equation 4.8 enter through $\hat{\lambda}$. The two-step estimation of our second model reads:

$$OIM_{i,t+1} = \beta_0 + \beta_1 \mathit{log(Scope1/MV\ Firm)}_{i,t} + \beta_2 \hat{\lambda}_{i,t} + \boldsymbol{x}_{i,t}\boldsymbol{\beta} + u_{i,t+1} \tag{4.7}$$

$$\mathit{Firm\ Dis}_{i,t} = \left[\alpha_0 + \alpha_1 \mathit{Ind\ Dis}_{i,t} + \alpha_2 \mathit{log(Scope1/MV\ Sector)}_{i,t} + \boldsymbol{x}_{i,t}\boldsymbol{\alpha} + e_{i,t} > 0\right], \tag{4.8}$$

where [.] denotes the indicator function using Iverson brackets, that is, for a statement P, $[P] = 1$ if P is true and zero else. $\boldsymbol{x}$ contains the same control variables as $\boldsymbol{x}^a$ and $\boldsymbol{x}^m$ in Equation 4.5, with annual averages for monthly controls over April-March (denoted year t) and excluding the time

[10] An extension of sample correction in the case of endogeneous explanatory variables for panel data is provided by Semykina and Wooldridge (2010). We propose this implementation as a possible avenue for future research.

trend. The OIMs are averaged over April-March of the subsequent year to guarantee a time lag with respect to the explanatory variables. $\textit{Firm Dis}_{i,t}$ is a binary variable that is one if the firm i discloses emissions in year t and zero else; *Ind Dis* is the average disclosure for the firms' industry (SIC4 level). We use the natural logarithm of carbon intensity since the variable is highly skewed.

$\hat{\lambda}$ is the estimate for the Inverse Mills ratio obtained from the Probit model for the Selection Equation 4.8. We estimate using all observations:

$$\mathbb{P}[\textit{Firm Dis}_{i,t} = 1 | \boldsymbol{z}_{i,t}] = \Phi(\boldsymbol{z}_{i,t}\boldsymbol{\gamma}) \tag{4.9}$$

for $\boldsymbol{z}$ including $\boldsymbol{x}$, *Ind Dis* and *log(Scope1/MV Sector)*. *Ind Dis* is included to have at least one variable that affects selection but does not appear in the reduced form of the 2SLS model to avoid multicollinearity in the reduced form. The estimated Inverse Mills ratio is then $\hat{\lambda}_{i,t} = \phi(\boldsymbol{z}_{i,t}\hat{\boldsymbol{\gamma}})/\Phi(\boldsymbol{z}_{i,t}\hat{\boldsymbol{\gamma}})$.

In the second step, we estimate the Outcome Equation 4.7 on the selected subsample and include $\hat{\lambda}$ as an explanatory variable. In fact, if we were now to estimate Equation 4.7 simply with *log(Scope1/MV Firm)*, $\hat{\lambda}$ and $\boldsymbol{x}$ as explanatory variables using OLS this would be the approach suggested by Heckman (1976). However, since we have (possibly) non-random missing observations depending on *log(Scope1/MV Firm)*, this renders *log(Scope1/MV Firm)* endogenous in the selected subsample, even if it might be exogenous in the population. Thus, we need to include an instrument for *log(Scope1/MV Firm)* to estimate Equation 4.7 using 2SLS. We know from Section 4.1 (in particular Tables B.2 and B.4) that industry and sector intensity are good predictors for firm carbon intensity. As industry intensity is not always observed, we use *log(Scope1/MV Sector)* as an instrument. Consequently, the reduced-form equation is given by the linear projection

$$\textit{log(Scope1/MV Firm)}_{i,t} = \delta_0 + \delta_1 \textit{log(Scope1/MV Sector)}_{i,t} + \delta_2 \hat{\lambda}_{i,t} + \boldsymbol{x}_{i,t}\boldsymbol{\delta} + v_i. \tag{4.10}$$

We estimate the model for the last full year in our dataset (that is $t = 2019$, April 2019-March 2020, and $t + 1 = 2020$, April 2020-March 2021) and run a robustness test for previous years.

Statistics were done using Python (van Rossum, 1995, v. 3.9.7), using the statsmodels (Seabold and Perktold, 2010, v. 0.13.2) and scipy (Virtanen et al., 2020, v. 1.1.1) packages.

Chapter 5

Results

In this chapter, we summarise the empirical results of this thesis. This covers the main findings of our analysis as well as a series of robustness checks to ensure the reliability of our results.

5.1 Main Model Results

The key findings of the panel model are summarised in Table 5.1. The results show that high carbon intensity and undisclosed emissions increase the Put Slope, at-the-money implied volatility, VRP, and the negative implied volatility Skew. The findings are most pronounced for the downside risk measures Put Slope and Skew. In particular, not reporting emissions increases the Put Slope on average by 0.018, and the negative Skew by 0.017, compared to firms in the first carbon intensity quantile, ceteris paribus. Both changes are equivalent to 7% of the respective option-implied measure standard deviation. The effect for emissions in the upper quantile is of similar magnitude (5% and 7% standard deviation increase in each OIM). For ATM IV and VRP, the effect is only significant for firms in the third intensity quartile. When attention to climate change is high, the value of option protection increases for all option-implied measures: A one standard deviation increase in Google Search Volume increases the standard deviation of the Put Slope by 1%, of ATM IV by 5%, of VRP by 4%, and of the Skew by 2%.

The results for the cross-sectional model are shown in Table 5.2. Column 4 highlights that, similar to the panel model, firms with higher carbon intensity have a more negatively skewed implied volatility. A 1% increase in carbon intensity increases the negative implied volatility Skew by 3% of its standard deviation. Estimates for Put Slope, ATM IV, and VRP are no longer significant, and neither is the Google Search Volume. We can not find evidence for sample selection bias since the Inverse Mills ratio is not significantly different from zero in all models.

5.2 Robustness Tests

During data processing and modelling we mostly follow the assumptions made by Ilhan et al. (2021). One important deviations is that we construct the SVI using the SSVI parameterisation for implied volatilities calculated with a bisection algorithm, instead of from the Surface File from IvyDB. We compare the key features and model results of the two surfaces.[11]

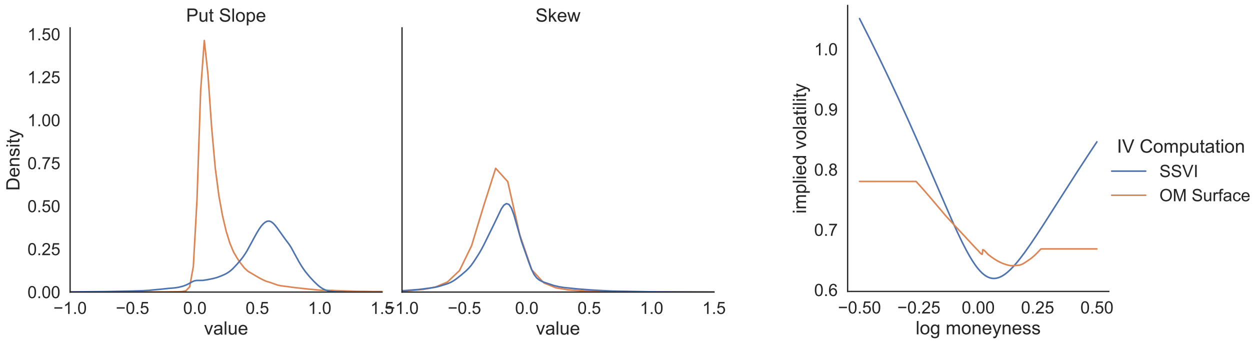
The Surface File contains implied volatility slices for standard maturities with Black-Scholes volatility computed based on a binomial-tree model, for standard maturities and moneyness. The surface is constructed using a kernel smoothing technique (OptionMetrics, 2021). Following Ilhan et al. (2021), we select slices with 30 days to maturity based on out-of-the-money put and call options. We interpolate in log moneyness using monotonic cubic splines (piecewise cubic Hermite interpolating polynomials) and fill implied volatilities beyond the observed moneyness with the value from the boundary. The option-implied measures are calculated as described in Section 4.1.2.

A comparison of the SSVI and OptionMetric Surface is displayed in Figure 5.1. We find that the SSVI has a more pronounced skew, and steeper right-and left-tail wing. Consequently, the values for Put Slope are on average lower in the Surface File. This is consistent with the lower volatilities for large strikes due to constant extrapolation.

Similar to the SSVI surface, Put Slope, ATM IV, VRP and the negative Skew are larger for firms with high carbon intensity and non-reporters. The results for the Put Slope and Skew are however weaker than in the SSVI surface, as they are not significant across all quartiles. The findings for investor attention (Google Trends Search Volumen Index) confirm our main finding except for the Put Slope, where increased investor attention decreases the slope of the implied volatility. Overall,

[11] A detailed comparison of modelling choices can be found in Table D.1.

the option-implied measures of the Surface File show a more consistent pattern across the control parameters: The cost of protection against downside tail, price, and variance risk is higher for smaller firms with high leverage and volatility, as well as for firms with lower returns and lower ESG scores. The full result is shown in Table C.3.



(a) Comparison of key option-implied measures: Put Slope and Skew.

(b) Exemplary IV slice.

Figure 5.1 – Comparison of the Surface SVI and the OptionMetrics Surface. The dark (blue) line represents the SSVI and the light (orange) line shows the OptionMetrics Surface with monotonic cubic spline interpolation and constant extrapolation. Figure (a) shows the density for our key option-implied measures. Figure (b) displays an example implied volatility slice from each surface. The example slice is chosen from a liquid company (Tesla Inc., 1.535 contracts traded that day in total), for 30th November 2021 and plotted for 30 days to maturity.

We conduct a series of additional robustness tests and find that the results for carbon intensity quartiles and non-reporting of our panel model are robust to a variety of model specifications. However, the effect of increased investor attention is less robust. Findings for carbon intensity are unchanged when we date emission publication to September, which was the publication date for firms reporting to the Carbon Disclosure Project.[12] Similarly, estimates for carbon intensity remain significant for starting the panel in 2010, where after Figure 4.1 carbon emission data were available for more than half of the firms in the sample. We can confirm our findings for both carbon intensity and increased investor attention by using industry instead of firm carbon intensity as a main explanatory variable. Full results can be found in Appendix C.2.

In the cross-section, the results for the IV Skew are robust going back to 2014. Most years do not show evidence of sample selection bias based on the Inverse Mills ratio. The results are included in Appendix C.3 . Similarly, Ilhan et al. (2021) find that their model with sample selection correction produces similar results to estimation with OLS, that is, without correcting for sampling bias.

[12] `https://www.cdp.net`

Table 5.1 – Results for the First Model: Panel Model

	Put Slope	ATM IV	VRP	Skew
	(1)	(2)	(3)	(4)
Intercept	0.113***	0.774***	0.562***	0.184***
	(0.019)	(0.020)	(0.036)	(0.016)
Scope 1/MV Firm Q2	0.019***	-0.002	0.007	-0.030***
	(0.004)	(0.004)	(0.006)	(0.004)
Scope 1/MV Firm Q3	0.014***	0.008*	0.012*	-0.023***
	(0.005)	(0.004)	(0.007)	(0.004)
Scope 1/MV Firm Q4	0.014**	0.001	0.001	-0.017***
	(0.005)	(0.005)	(0.008)	(0.005)
Scope 1 not reported	0.018***	-0.002	0.010	-0.017***
	(0.004)	(0.003)	(0.006)	(0.003)
Trends CO2 Tax	0.031***	0.126***	0.178***	-0.040***
	(0.010)	(0.008)	(0.015)	(0.009)
Model	OLS	OLS	OLS	OLS
Additional Variables	Controls	Controls	Controls	Controls
Fixed Effects	Sector	Sector	Sector	Sector
Frequency	Monthly	Monthly	Monthly	Monthly
Observations	55,888	55,888	55,888	55,888
R^2	0.077	0.292	0.182	0.112
Adjusted R^2	0.076	0.291	0.182	0.111
Residual Std. Error	0.264	0.227	0.418	0.239
F Statistic	175.814***	443.321***	168.856***	283.806***

Note: Regressions are estimated at firm-month level using OLS for S&P 500 constituents during 2007-2021 with sufficient data availability to construct implied volatility surfaces. *Scope 1/MV Firm Q1-Q4* is each a binary variable indicating the quartile of a firm's carbon intensity relative to all other firms in the same year. A firm's carbon intensity is defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Scope 1 not reported* equals one if a firm's carbon emissions are not available in a given year, and zero else. Hence the intercept of the reference group (*Scope 1/MV Firm Q1*) is the intercept for the entire model. We assume emission data is published in March each year. *Put Slope, ATM IV, VRP* and *Skew* are calculated from the Implied Volatility Surface and measure downside tail risk, price risk, variance risk, and jump risk respectively. The dependent variables are lagged by one to twelve months with respect to the independent variables. Standard errors are calculated using the heteroscedasticity robust HC3 covariance estimator from MacKinnon and White (1985). Additional control variables are *log(Assets), Dividends/Net income, Debt/Assets, EBIT/Assets, CapEx/Assets, Book-to-market, log(Returns), Institutional Ownership, a Time Trend, CAPM beta, Oil beta*, and *Volatility.* Full results are included in Table C.1. t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 5.2 – Results for the Second Model: Cross-sectional Model with Sample Correction

	Put Slope	ATM IV	VRP	Skew
	(1)	(2)	(3)	(4)
Intercept	0.353	0.720	0.775	0.119
	(0.374)	(0.491)	(0.820)	(0.311)
Log(Scope 1/MV Firm)	0.001	-0.006	-0.009	-0.010***
	(0.004)	(0.005)	(0.008)	(0.003)
Trends CO2 Tax	1.173	1.339	1.374	-1.440
	(1.978)	(2.597)	(4.334)	(1.642)
Inverse Mills	0.013	-0.038	-0.063	0.001
	(0.027)	(0.035)	(0.058)	(0.022)
Model	IV2SLS	IV2SLS	IV2SLS	IV2SLS
Additional Variables	Controls	Controls	Controls	Controls
Fixed Effects	None	None	None	None
Year (t)	2019	2019	2019	2019
Observations	316	316	316	316
R^2	0.174	0.565	0.501	0.397
Adjusted R^2	0.133	0.543	0.476	0.367
Residual Std. Error	0.104	0.136	0.227	0.086
F Statistic	4.216***	26.172***	20.186***	13.981***

Note: Regressions are estimated at firm-year level using 2SLS for S&P 500 constituents during during 2019-2021 with sufficient data availability to construct implied volatility surfaces. *Log(Scope 1/MV Firm)* is a firm's carbon intensity, defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The Inverse Mills ratio is the conditional estimate of firm disclosure from a Probit model on all firms to control for a possible sample selection bias. The independent variables are calculated from April 2019 to March 2020, the dependent variables are observed from April 2020 to March 2021. Additional control variables are *log(Assets), Dividends/Net income, Debt/Assets, EBIT/Assets, CapEx/Assets, Book-to-market, log(Returns), institutional ownership, CAPM beta, Oil beta, and Volatility.* Full results are included in Table C.2. t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Chapter 6

Discussion

In this chapter, we discuss the implications of our findings. This includes an evaluation of the empirical framework, as well as a review of the model results. For that purpose, we compare our findings to the discussed literature, and evaluate the economic significance of our estimates.

6.1 Discussion of the Empirical Framework

Our empirical framework is subject to a number of assumptions that may impact the interpretation of our results. We discuss the main limitations of the data set construction and modelling choice, and how this may impact the generalisability of our findings.

We had to make a number of simplifying assumptions during option data treatment. Firstly, we fit the implied volatility surface to mid-price implied volatilities. Though industry-standard, mid prices do not correspond to traded option contracts. Improvements might be achieved by fitting a volatility surface to bid and ask prices separately and average the resulting implied volatility. This comes however at the trade-off of higher computational effort. Since the construction of the implied volatility surface was nevertheless computationally expensive, we had to limit our study to using option contracts at the last business day of each month, instead of using monthly averages of daily measures (cf. Ilhan et al., 2021). This can render our option-implied measures noisier. Finally, we are aware that the construction of the SSVI can be improved in many ways. This includes adding weights to the optimisation to account for varying reliability of the raw data, or considering a wider range in forward log-moneyness. More detailed suggestions are included in Appendix B.2.

Additionally, computing implied volatility with BAW's approximation relies on the Black-Scholes model assumptions. In particular, this involves assuming constant volatility in the underlying. As we saw in Figure 3.1 this assumption is clearly violated. Consequently, we use implied volatility under Black-Scholes assumptions as a *useful language* in which to express an option price that allows for easier comparability across contracts. This does not entail the belief that volatility is actually a constant (Lee, 2005). Hence, when we say "priced" we mean that the cost for option protection against a particular risk is higher. This is different to the wording used to imply that investors are compensated for exposure to risk with an expected return.

As mentioned in Section 4.1, due to non-standardised reporting it is unknown when the data used in our models were actually made available to investors, and emissions may be back-filled by data vendors. While we try to mitigate this issue in two robustness tests, these measures might not fully address the impact of this limitation on our results. Additional assumptions on measuring firm sensitivity to climate change uncertainty and their implications are outlined in Appendix B.2.

Finally, our main panel model treats carbon intensity as a categorical variable. This allows us to integrate the possible effect of not reporting emissions. However, we can only compare all carbon-related estimates to the base group, that is firms in the lowest quartile of emission intensity. Also, we assume that the carbon emission reporting does not depend on unobserved factors in the error term. Additionally, since we do not control for interaction effects between investor attention and carbon intensity, we can only interpret the effect of increased political uncertainty unconditionally on a firm's carbon intensity.

6.2 Discussion of Empirical Results

We compare the cost of option protection depending on a firm's scope 1 GHG emission consumption in relation to market value. In particular, we investigate the cost of option protection against price, variance, downside tail, and jump risk; measured through at-the-money implied volatility, variance risk premium, the steepness of the downside volatility slope, and the implied volatility Skew respectively. To capture periods of increased uncertainty, we control for investor attention with Google Search Volume for "CO2 tax".

The main results from our panel model show that the cost of protection against downward jump and tail risk is higher for firms with carbon-intensive business models. On average, the Put Slope and Skew increase by 5-7% of their respective standard deviation for firms with high or unreported carbon intensity, compared to firms with low carbon intensity, holding the control variables constant. In comparison, a one-standard-deviation increase in volatility increases the Put Slope by 2% and the Skew by 9% of their standard deviation. As explained in Section 4.1, we interpret the Put Slope as a measure for downside tail risk, since deep out-of-the-money put option provide protections against large price drops in the stock price. Our estimates indicate, that on average, this strategy of downside protection is 0.007 vol points more expensive for carbon-intensive firms.[13] The significance of the Put Slope and Skew is robust to all alternative panel model specifications, though, for some robustness tests significance does not hold across all emission intensity quartiles. To abstract, our conclusions may hold up under a variety of assumptions and conditions.

The evidence for protection against price and variance risk is not significant across all carbon intensity levels. Both ATM IV and VRP depend on at-the-money implied volatility. Thus, they capture the general "risk" of stock price movements but do not consider whether the stock price rises or drops. As shown by the variance risk premium decomposition of Feunou et al. (2018), on average the VRP is positive when computed with realised volatilities following negative returns ("bad uncertainty"), and negative conditional on positive return realised volatility ("good uncertainty"). Hence investors are willing to pay a premium to avoid exposure to bad uncertainty, while seeking exposure to good uncertainty. We infer that our measures for price and variance risk could amalgamate two types of uncertainty that investors perceive differently.

During periods of increased investor attention, the magnitude of all option-implied measures increases. Hence, when uncertainty about carbon taxation is high, protection against downside tail, price, variance, and jump risk is more expensive – unconditional on a firms carbon-intensity. Although the findings are robust to some alternative model specifications, they deviate in other robustness tests. This suggests that whether the value of option protection increases during periods

[13] We calculate this from $(\beta_4 = 0.014) \times (|k_{out-of-the-money-put}| = 0.05) = 0.007$.

of increased political uncertainty may be sensitive to certain assumptions, such as the choice of proxies for political uncertainty and investor attention.

The availability of carbon emission data is limited due to voluntary disclosure by firms. To address the potential of sample selection bias, we estimate a second model for the cross-section of 2019 in which we allow carbon emission reporting to depend on unobserved factors and control for possible sample selection bias. Surprisingly, we do not find evidence that estimates are biased due to voluntary reporting. This finding is robust to estimating the model in the cross-sections of earlier years. However, we can not extend this conclusion from the cross-section to the panel model, as changes in variables over the years and variation within-units is not accounted for.

Our main robustness test is based on an alternative construction for the implied volatility surface. Our estimation of implied volatilities uses a binary search and fit the arbitrage-free stochastic volatility implied surface, as described in Section 3.2. In the robustness test, we follow Ilhan et al. (2021). They interpolate the OptionMetrics Surface File using monotonic cubic splines and fill implied volatilities outside the observed log-moneyness with the value from the boundary. We conclude that the most important difference between these two methods can be found for volatilities at extreme strikes as the constant extrapolation used in the robustness test creates narrower tails. While our findings for downside tail risk in the surface confirm those of Ilhan et al. (2021), the results for jump risk are weaker. The Skew captures the cost of protection against left-tail events *relative* to right-tail events. To gain more insight, we estimate the steepness of the Call slope of the implied volatility[14] and find that under the SSVI surface it decreases for higher carbon intensity, but it increases in the robustness test. We conclude that our findings can be sensitive to the assumptions made during option data treatment, though our key findings remain robust under the alternative surface construction.

Our findings on the increased cost of protection against downside tail risk confirm previous research on the pricing of policy uncertainty in the option market (e.g., Ilhan et al., 2021; Kelly et al., 2016; Kostakis et al., 2019). To this point, the role of jumps has rarely been addressed. As mentioned in Section 2.1.2, Kelly et al. (2016) and Amengual and Xiu (2018) show that the resolution of political uncertainty is associated with jumps in stock prices. Our findings indicate that this risk is priced ahead of policy resolution in the option market.

[14] More details of the construction are provided in Table B.1.

Chapter 7

Conclusion

Political uncertainty surrounding carbon taxation can make it difficult for investors to assess the financial impact of such policies. To better understand how carbon tax uncertainty affects the option market, we replicate and extend the work of Ilhan et al. (2021).

Our findings show that firms with high carbon intensity and unreported emissions demand higher costs for protection against downside tail and jump risk, as measured by the Put Slope and Skew of the implied volatility. On average, these measures increase by 5-7% of their respective standard deviation for firms with high or unreported carbon intensity. The value of option protection increases for all firms when political uncertainty is high. The key findings are robust to most but not all alternative model specifications and, thus, should be treated with some remaining caution.

Given that carbon emission reporting is voluntary, we also consider the possibility of sample selection bias in the cross-section. While we did not find evidence of sample selection, we suggest that future research incorporate control for sample selection bias in the panel model, using methods such as those proposed by Semykina and Wooldridge (2010).

Overall, our study contributes to the existing literature on the economic consequences of climate change regulation. In line with Ilhan et al. (2021), our findings suggest that carbon tax uncertainty is priced in the option market.

Appendices

Appendix A

Additional Notes on Formulas and Derivations

A.1 Notes on the Quadratic Approximation for American Options

This section presents the Barone-Adesi and Whaley (1987) approximation from Section 3.1. The derivation of the approximation is outlined to introduce assumptions and variable definitions. The details can be found in Barone-Adesi and Whaley (1987). Subsequently, we give details on the formulas used to iteratively find the value of the American Call and Put options.

Outline of the Approximation for the American Call Value

We recall the value of the early exercise premium defined as

$$\varepsilon_C(S,T,K) = C^{A,BS}(S,T,K) - C^{E,BS}(S,T,K). \tag{A.1}$$

The key insight of the quadratic approximation used by Barone-Adesi and Whaley (1987) is that the PDE defined in equation 3.3 governing the movement of American and European Options through time also applies to the early exercise premium. Denoting partial derivatives $\frac{\partial f}{\partial x} = f_x$ the PDE for $\varepsilon(S,T,K)$ is then

$$\varepsilon_t + (r-d)S\varepsilon_S + \frac{1}{2}\sigma^2 S^S \varepsilon_{SS} - r\varepsilon = 0. \tag{A.2}$$

The derivation of the American Call value approximation can be separated into the following steps:

1. Simplify notation[15].

   In particular, denote $\tau = T - t$ the time to maturity, such that $\varepsilon_\tau = -\varepsilon_t$, introduce $M = 2r/\sigma^2$ and $N = 2(r-d)/\sigma^2$, and define $\varepsilon_C(S, L) = L(\tau) f(S, L)$, with $L = 1 - e^{-r\tau}$.

2. Apply the approximation $(1 - L)Mf_L = 0$, and find a general solution to the resulting PDE describing the approximated early exercise premium.

   This approximation is reasonable in particular for very long and short maturities (Barone-Adesi and Whaley, 1987). The general solution contains the the stock price S, the positive and negative roots of $[q^2 + (N-1)q - M/L]$, denoted by q_1 and q_2, and two unknown parameters denoted a_1 and a_2.

3. Applying parameter constraints on the unknowns, substitute the general solution for the early exercise premium in equation A.2 and solve for the value of the American Call.

   The resulting value for the American call is $C^{A,BS}(S, \tau, K) = C^{E,BS}(S, \tau, K) + La_2 S^{q_2}$. This covers two cases: Holding the American Call until expiry, or exercise early. The critical stock price that separates these two cases is denoted S^*.

4. Find S^*. By definition, at S^* the value of the American call equals $S - K$, both in value and in its first derivative. Solving this system of two equations results in a critical commodity price S^* that satisfies

$$S^* - K = C^{E,BS}(S^*, \tau, K) + \Big\{1 - e^{-d\tau} N\left[d_1(S^*)\right]\Big\} S^*/q_2, \tag{A.3}$$

   where $d_1 = \left[ln(S/K) + \left(\frac{1}{2}\sigma^2 + (r-d)\right)\tau\right]/\sigma\sqrt{\tau}$, and $N\left[.\right]$ is the cumulative distribution function of the univariate normal distribution.

Iteratively Find the Critical Stock Price S^* of the American Call

We now need to solve Equation A.3 iteratively. Therefore we start with a seed value S_1, and calculate the $LHS(S_i) = S_i - X$ as well as the $RHS(S_i) = C^{E,BS}(S_i, \tau, K) + \left\{1 - e^{-d\tau} N\left[d_1(S_i)\right]\right\} S_i/q_2$ for $i = 1$, and make subsequent guesses until the $LHS(S_i)$ is very close to the $RHS(S_i)$.

15 To be consistent throughout my thesis I differ from the notation applied by Barone-Adesi and Whaley (1987).

For the seed value Barone-Adesi and Whaley (1987) propose using either the strike price K, or a starting point closer to the solution to improve convergence speed. Since computation time was a limit in out analysis anyway, we use this alternative seed value defined for the American Call as

$$S_1 = K + [S^*(\infty) - K][1 - e^{h_2}], \tag{A.4}$$

where $h_2 = -((r-d)\tau + \sigma\sqrt{\tau})\,\{K/[S^*(\infty) - K]\}$, and $S^*(\infty) = K/[1 - 1/q_2(\infty)]$, $q_2(\infty) = [-(N-1) + \sqrt{(N-1)^2 + 4M}]/2$.

Then each subsequent guess S_{i+1} can be found as the point where the tangent to the curve $RHS(S_i)$ intersects with the exercise value $S_{i+1} - K$:

$$RHS(S_i) + \partial RHS(S_i)/\partial S_i \times (S_{i+1} - S_i) = S_{i+1} - K. \tag{A.5}$$

Calculating $b_i = \partial RHS(S_i)/\partial S_i$, and isolating S_{i+1} gives

$$S_{i+1} = [K + RHS(S_i) - b_i S_i]/(1 - b_i). \tag{A.6}$$

This will provide a subsequent guess, until the $RHS(S_i)$ and $LHS(S_i)$ are reasonably close. Barone-Adesi and Whaley (1987) propose an acceptable tolerance level of 0.00001, we use 0.0001, hence we iterate until

$$|LHS(S_i) - RHS(S_i)|/K < 0.0001. \tag{A.7}$$

For the American Call the authors provide the value for b_i as

$$b_i^C = e^{-d\tau} N\left[d_1(S_i)\right](1 - 1/q_2) + \left[1 - e^{-d\tau} n\left[d_1(S_i)\right]/\sigma\sqrt{\tau}\right]/q_2, \tag{A.8}$$

where $n[.]$ is the probability density function of the univariate normal distribution.

The Approximation for the American Put Value

Barone-Adesi and Whaley (1987)'s approximation of the American Put option with critical stock value S^{**} is

$$P^{A,BS}(S,\tau,K) = P^{E,BS}(S,\tau,K) + A_1(S/S^{**})^{q_1}, \qquad \text{when } S > S^{**}, \text{ and} \tag{A.9}$$

$$P^{A,BS}(S,\tau,K) = K - S, \qquad \text{when } S \le S^{**}, \tag{A.10}$$

where $A_1 = -(S^{**}/q_1)\left\{1 - e^{-d\tau}N[-d_1(S^{**})]\right\}$ and $q_1 = [-(N-1) - \sqrt{(N-1)^2 + 4M/L}]/2$.

Iteratively Find the Critical Stock Price S^{**} of the American Put

The authors derive the conditions on the critical stock price for the Put, S^{**}, similar to the one ones for the Call described in section A.1. Then S^{**} is determined by

$$K - S^{**} = P^{E,BS}(S^{**},\tau,K) - \left\{1 - e^{-d\tau}N\left[-d_1(S^{**})\right]\right\} S^{**}/q_1. \tag{A.11}$$

We can then similarly calculate b_i as the derivative of the $RHS(S_i)$ with respect to S_i:

$$b_i^P = \frac{\partial RHS(S_i)}{\partial S_i} = \frac{\partial P^E}{\partial S} - \frac{\partial\left\{1 - e^{-d\tau}N\left[-d_1(S_i)\right]\right\} S_i/q_1}{\partial S}. \tag{A.12}$$

The first term is the delta of the put option, which is

$$e^{-d\tau}\left(N[d_1(S_i)] - 1\right) = -e^{-d\tau}N[-d_1(S_i)]. \tag{A.13}$$

The second term (denote it $\partial g(S_i)/\partial S_i$), can be computed with the product and chain rule

$$\frac{\partial g(S_i)}{\partial S_i} = \frac{1 - e^{-d\tau}N[-d_1(S_i)]}{q_1} + \frac{S_i e^{-d\tau}n[-d_1(S_i)]/\sigma\sqrt{\tau}}{S_i q_1} = \frac{\left\{1 + e^{-d\tau}n[-d_1(S_i)]/\sigma\sqrt{\tau}\right\} - e^{-d\tau}N[-d_1(S_i)]}{q_1}. \tag{A.14}$$

Combining equations A.13 and A.14 we obtain

$$b_i^P = -e^{-d\tau}N[-d_1(S_i)]\left(1 - 1/q_1\right) - \left[1 + e^{-d\tau}n[-d_1(S_i)]/\sigma\sqrt{\tau}\right]/q_1. \tag{A.15}$$

Then the subsequent value can again be found by intersecting the tangency to $RHS(S_i)$ with $LHS(S_i)$, though now $LHS(S_i)$ is a decreasing function of the stock price, hence we use

$$S_{i+1} = [K - RHS(S_i) + b_i S_i]/(1 + b_i), \tag{A.16}$$

and again iterate until equation A.7 is satisfied.

A.2 Notes on No Arbitrage in the Implied Volatility Surface

In this section we present the results for the SSVI referenced in Section 3.2. The no-arbitrage conditions for the implied volatility are given by the following two theorems.

Lemma A.1 (No Calendar Arbitrage in the IVS, Lemma 2.1. from Gatheral and Jacquier (2014))**.** *If dividends are proportional to the stock price, the volatility surface is free of calendar spread arbitrage if and only if*

$$\partial_t w(k, \tau) \geq 0, \ \forall \ k \in \mathbb{R} \ \text{and} \ \tau > 0. \tag{A.17}$$

Proof. See Gatheral and Jacquier (2014). □

Lemma A.2 (No butterfly arbitrage in the IVS, Lemma 2.2. from Gatheral and Jacquier (2014))**.** *A slice is free of butterfly arbitrage if and only if* $g(k) \geq 0 \ \forall \ K \in \mathbb{R}$ *and* $\lim_{k \to +\infty} d_+(k) = -\infty$*,*

where $g(k)$ is defined as

$$g(k) := \left(1 - \frac{kw'(k)}{2w(k)}\right)^2 - \frac{w'(k)}{4}\left(\frac{1}{w(k)} + \frac{1}{4}\right) + \frac{w''(k)}{2}. \tag{A.18}$$

Proof. See Gatheral and Jacquier (2014). □

This translates to the following conditions on the SSVI for no calendar spread arbitrage.

Theorem A.1 (No calendar spread arbitrage in the SSVI, Theorem 4.1. from Gatheral and Jacquier (2014))**.** *The SSVI surface from 3.3 is free of calendar spread arbitrage if and only if*

1. $\partial_\tau \theta_\tau \geq 0, \ \forall \ \tau \geq 0$;

2. $0 \leq \partial_\theta(\theta\varphi(\theta)) \leq \frac{1}{\rho^2}\left(1+\sqrt{1-\rho^2}\right)\varphi(\theta), \ \forall\ \theta > 0,$

where the upper bound is infinite then $\rho = 0$.

Proof. See Gatheral and Jacquier (2014). □

As concluded from Definition 3.2, this implies that the skew in implied variance is monotonically increasing in time to maturity. The following Theorem gives the condition under which the SSVI is free of butterfly arbitrage.

Theorem A.2 (No butterfly arbitrage in the SSVI, Theorem 4.2. from Gatheral and Jacquier (2014))**.** *The SSVI volatility surface from 3.3 is free of butterfly arbitrage if the following conditions are satisfied for all $\theta > 0$:*

1. $\theta\varphi(\theta)(1+|\rho|) < 4;$

2. $\theta\varphi(\theta)^2(1+|\rho|) \leq 4.$

Proof. See Gatheral and Jacquier (2014). □

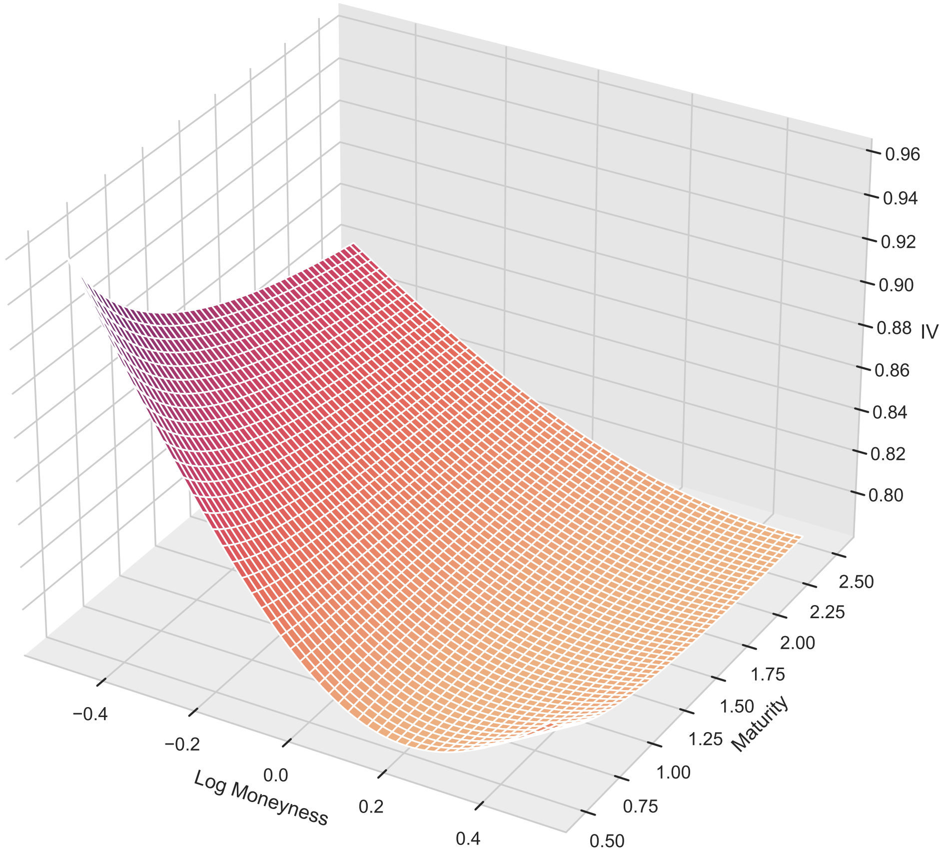


Figure A.1 – An Exemplary Implied Volatility Surface on 30th November 2021 for Tesla Inc. The Implied Volatilitys are estimated from American Options with Barone-Adesi and Whaley (1987)'s approximation for American call value and a bivariate search. The surface is fitted using the Surface SVI parametrization from Gatheral and Jacquier (2014)

Appendix B

Data

B.1 Overview of Dataset

Table B.1 contains an overview of the variables used.

Table B.1 – Overview of Variables

Variable	Definition	Source
Option-implied Measures		
Put Slope	The slope coefficient for regressing IV of out-of-the money put options (i.e. for log-moneyness in range $[-0.5, -0.001]$) with 30 days to maturity on the corresponding log-moneyness and a constant, multiplied by minus one. We multiply with minus one since Ilhan et al. (2021) measure moneyness with delta for which the Put Slope is usually increasing, whereas in log-moneyness the Put Slope is usually decreasing. The value is calculated for options on the last business-day each month.	OptionMetrics[16]
ATM IV	The average over the two IVs closest to a log-moneyness of zero. Since we use a discrete log-moneyness grid of 200 points between $[-0.5, 0.5]$ the two moneyness closest to zero are -0.001 and 0.001. The variable is calculated using options with 30 days to maturity on the last business-day of each month.	OptionMetrics

Continuation...

[16] OptionMetrics (2021)

... Continuation

Variable	Definition	Source
VRP	The difference of risk-neutral expected variance over $[t, t+30]$, and realized variance over $[t, t-30]$. The risk-neutral expected variance is calculated as the square of ATM IV from options on the last business day each month t with 30 days to maturity. The realized variance is computed as the sum of squared log returns over $[t, t-30]$.	OptionMetrics, CRSP[17]
Skew	The curvature of the IV slices. It is computed after Mixon (2011) as the difference between put options at forward log moneyness -0.125, and call options at forward log moneyness 0.125, scaled by the average implied volatility at-the-money. We compute the measure for implied volatility slices with 30 days to maturity on the last business day each month.	OptionMetrics
Call Slope	The steepness of the right-slope of the IV slices that is constructed from out-of-the-money call options. We construct it similarly to the Put Slope by regressing implied volatilities from out-of-the-money call options on the corresponding forward log-moneyness and a constant, based on implied volatility slices with 30 days to maturity on the last business day of each month.	OptionMetrics
Climate Change Variables		
Scope 1/MV Firm	Annual scope 1 carbon emissions of each firm [kt C02 equivalents] (Refinitiv item `ENERDP024`) divided by the firms equity market value [M $] (Compustat item `MKVALT`) at the end of the year.	Refinitiv (Eikon)[18], Compustat[19]
Scope 1/MV Industry	Sum of annual scope 1 carbon emissions of each firm within an industry [kt C02 equivalents] (Refinitiv item `ENERDP024`) divided by the sum of equity market value for each firm within an industry [M $] (Compustat item `MKVALT`) at the end of the year. Industry levels are defined by SIC4 Codes.	Refinitiv (Eikon), Compustat
Carbon Intensity Quantile (QI)	Categorical variable indicating the firms' carbon intensity quartile, defined each year over all firms, or 'Scope 1 not reported' if carbon emissions are not available in the given year.	Refinitiv (Eikon)
Scope 1	Annual scope 1 carbon emissions [kt C02 equivalents] (Refinitiv item `ENERDP024`)	Refinitiv (Eikon)

Continuation...

[17] CRSP (2021)
[18] Refinitiv (2021)
[19] S&P Global Market Intelligence (2021)

... Continuation

Variable	Definition	Source
Firm Carbon Disclosure	Binary variable True if a firm discloses emissions within a given year, False otherwise	Refinitiv (Eikon)
Industry Carbon Disclosure	Fraction of firms disclosing emissions within a given year within an industry (SIC4)	Refinitiv (Eikon)
Control Variables		
Log(Assets)	Logarithm to base e of total assets [M $] (Compustat item `AT`), at the end of the year, winsorized at the 1% level.	Compustat
Div. payout ratio	Dividends total other than stock dividends [M $] (Compustat item `DVT`) divided by net income [M $] (Compustat item `NI`), at the end of the year, winsorized at the 1% level.	Compustat
Debt/Assets	Sum of the book value of long-term debt (Compustat item `DLTT`) and the book value of current liabilities (Compustat item `DLC`), divided by total assets (Compustat item `AT`), all in [M $], at the end of the year, winsorised at the 1% level.	Compustat
Ebit/Assets	Earnings before interest and taxes [M $] (Compustat item `EBIT`), divided by total assets [M $] (Compustat item `AT`), at the end of the year, winsorised at the 1% level.	Compustat
CapEx/Assets	Capital Expenditures [M $] (Compustat item `CAPX`), divided by total assets [M $] (Compustat item `AT`), at the end of the year, winsorised at the 1% level.	Compustat
Book-to-Market	Difference of the common equity (Compustat item `CEQ`) and preferred stock capital (Compustat item `PSTK`) divided by equity market value (Compustat item `MKVALT`), all in [M $], at the end of the year, winsorizsed at the 1% lvel.	
Log(Return)	Logarithm to base e of the annual stock price close at the end of the fiscal year (Compustat item `PRCC_F`), winsorised at the 1% level.	Compustat
Inst. Own	Total institutional ownership as a percentage of shares outstanding (Refinitiv item `instown_perc`).	Refinitiv (Thomson Reuters)
CAPM beta	Sensitivity of monthly stock returns (computed from stock prices, CRSP item `prc` for each stock) to monthly S&P 500 returns (computed from index level, CRSP item `spindx`). We compute for each month m a rolling window regression of 24 months to obtain $\beta_{i,m}$ for each firm from $\mathit{log(Return)}_{i,m,t} = \beta_0 + \beta_{i,m}\mathit{log(S\&P500\ Return)}_t$, winsorized at the 1% level.	CRSP

Continuation...

... Continuation

Variable	Definition	Source
Oil beta	Sensitivity of monthly stock returns (computed from stock prices, CRSP item `prc` for each stock) to monthly oil returns (computed from crude oil WTI prices). We compute for each month m a rolling window regression of 24 months to obtain $\beta_{2,i,m}$ for each firm from $log(Return)_{i,m,t} = \beta_0 + \beta_{i,m} log(S\&P500\ Return)_t + \beta_{2,i,m} log(Oil\ Return)_t$, winsorized at the 1% level.	CRSP, U.S. Energy Information Administration[20]
Volatilty	Standard deviation of stock returns (computed from stock prices, CRSP item `prc` for each stock), computed with a rolling window of 12 month and winsorized at the 1% level.	CRSP
ESG Score	Environmental, Social and Governance scope, based on self-reported information, ranging from the lowest of 0 to the best of 100 (Refinitiv item `TRESGS`), at the end of each year.	Refinitiv (Eikon)
Trends CO2 Tax	Search for 'C02 Tax' as topic for the United States, during 01.01.2007 and 31.12.2021, scaled from zero to one, within the specified search area and time.	Google Trends[21]
Time Trend	Integer, zero for 2007, increasing by one each year.	Self-constructed

The table gives an overview of the variables, including computation and source.

B.2 Additional Assumptions for Data Processing

In the following we list a selection of assumptions made during data processing and data set construction that may limit the generalisability of our results.

Assumptions made regarding Firm Sensitivity to Carbon Taxation

1. We assume that carbon emissions are available to investors in March of each year. This is consistent with assuming that firms publish their emissions along with their annual reports, which under the 10-K form have to be publish within 90-days after fiscal year end, which is December for most companies.

2. Following Ilhan et al. (2021) we choose to measure a firms sensitive to carbon tax with their carbon consumption relative to market value. While this is a reasonable assumption, other authors argue in favour of using levels and growth rate of emissions, as in order to achieve Net Zero targets, carbon

[20] `https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm`
[21] `https://trends.google.com/trends/`

emissions must be significantly curbed in the next two decades, independent of a companies intensity of fossil fuel consumption (ct. Bolton and Kacperczyk, 2022).

3. Our analysis is focused on scope 1 emissions. This is reasonable, if investors perceive scope 1 emissions as the major source of company vulnerability. However, due to the high magnitude of indirect emissions future carbon reporting might focus increasingly on scope 2 and scope 3 emissions, making firms more sensitive to carbon taxation through their indirect emissions (Hertwich and Wood, 2018).

Possible Improvements for Fitting the SSVI

We had to base some modelling choices on computational feasibility. In the following we give an an overview on possible improvements for fitting the SSVI.

1. For future research we recommend adding weights to the optimisation procedure to account for different reliability of the raw data. We optimise using the l_2 norm in our objective function, indirectly assuming all information is equally relevant. Results might be improved by giving more weight to liquid options by constructing weights inverse proportional to the square of bid-ask spreads; or to options for which a price change is more sensitive to movements in implied volatility, using the option's Vega. (Homescu, 2011).

2. Additionally, Öhman (2019) suggest to interpolate in SVI parameters instead of in total implied variance to limit the number of parameters for interpolation.

3. When improving the initial fit we iterate forward though each slice in maturity and fit the SVI-JW parameters (step 5, Section 3.2.3). Öhman (2019) find that lower residuals can be achieved, when iterating backward in maturity or globally, taking into account the information from all available maturities.

4. Finally, we limit our forward log-moneyness domain to $[-0.5, 0.5]$, following Ilhan et al. (2021). However, as Figure 3.2 shows, this omits possibly relevant information for large strikes, particularly for deep-out-of the money put options. For future research we suggest considering a wider log-moneyness range.

B.3 Determinants of Firm Carbon Intensity

Regession Results for Determinants of Firm Carbon Intensity

Table B.2 – Determinants of Firm Carbon Intensity with Constant: Industry Intensity

	Log(Scope 1/MV Firm)		Log(Scope 1) Firm	
	(1)	(2)	(3)	(4)
Log(Scope 1/MV Ind)	1.002***	0.708***		
	(0.011)	(0.028)		
Log(Scope 1) Ind			0.883***	0.748***
			(0.007)	(0.020)
Log(Assets)		-0.174***		0.092***
		(0.039)		(0.031)
Div. payout ratio		0.381**		0.456***
		(0.193)		(0.139)
Debt/Assets		0.944**		0.883**
		(0.451)		(0.352)
Ebit/Assets		-3.048**		0.071
		(1.196)		(0.846)
CapEx/Assets		18.504***		10.433***
		(2.331)		(1.753)
Book-to-Market		0.776**		0.375
		(0.337)		(0.238)
Log(Return)		-0.279		-0.128
		(0.208)		(0.171)
Inst. Own.		-1.071**		-1.309***
		(0.443)		(0.340)
CAPM beta		-0.077		-0.017
		(0.127)		(0.083)
Oil beta		-0.044		0.013
		(0.234)		(0.182)
Volatility		0.541		-0.224
		(1.146)		(0.928)
Model	OLS	OLS	OLS	OLS
Intercept	No	No	No	No
Fixed Effects	No	No	No	No
Level	Firm	Firm	Firm	Firm
Frequency	Annual	Annual	Annual	Annual
Observations	980	980	980	980
R^2	0.860	0.884	0.957	0.961
Adjusted R^2	0.860	0.883	0.957	0.961
Residual Std. Error	1.867	1.710	1.434	1.368

Continuation. . .

... Continuation

	Log(Scope 1/MV Firm)		Log(Scope 1) Firm	
	(1)	(2)	(3)	(4)
F Statistic	8854.524***	990.332***	15118.539***	2439.668***

Note: Regressions are estimated at the annual level using OLS for S&P 500 constituents during 2007-2021 for which scope 1 GHG emissions are reported. The sampling deadline for the S&P 500 constituents is 31^{th} December each year. *Scope 1/MV Firm* is a firm's carbon intensity, defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Scope 1/MV Industry* is the sum of annual scope 1 GHG emissions of all firms in the same industry, divided by the annual sum of the market value of all firms in the same industry (SIC4). *Scope 1* are unscaled scope 1 GHG emissions (in kt CO2 equivalents). t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table B.3 – Determinants of Firm Carbon Intensity without Constant: Industry Intensity

	Log(Scope 1/MV Firm)		Log(Scope 1) Firm	
	(1)	(2)	(3)	(4)
Log(Scope 1/MV Ind)	0.880***	0.708***		
	(0.019)	(0.029)		
Log(Scope 1) Ind			0.834***	0.748***
			(0.015)	(0.021)
Log(Assets)		-0.270***		0.085
		(0.064)		(0.053)
Div. payout ratio		0.381*		0.485***
		(0.207)		(0.150)
Debt/Assets		0.851*		0.981**
		(0.496)		(0.392)
Ebit/Assets		-4.241***		-0.540
		(1.435)		(1.134)
CapEx/Assets		17.914***		10.146***
		(2.324)		(1.774)
Book-to-Market		0.883***		0.321
		(0.337)		(0.254)
Log(Return)		-0.165		-0.088
		(0.248)		(0.202)
Inst. Own.		-1.805***		-1.359**
		(0.677)		(0.528)
CAPM beta		-0.070		0.003

Continuation...

... Continuation

	Log(Scope 1/MV Firm)		Log(Scope 1) Firm	
	(1)	(2)	(3)	(4)
		(0.127)		(0.084)
Oil beta		-0.115		0.016
		(0.242)		(0.186)
Volatility		0.500		-0.533
		(1.198)		(1.031)
Model	OLS	OLS	OLS	OLS
Intercept	Year	Year	Year	Year
Fixed Effects	No	Year	No	Year
Level	Firm	Firm	Firm	Firm
Frequency	Annual	Annual	Annual	Annual
Observations	980	980	980	980
R^2	0.615	0.674	0.753	0.779
Adjusted R^2	0.614	0.666	0.753	0.774
Residual Std. Error	1.826	1.699	1.425	1.364
F Statistic	2075.044***	141.854***	3107.738***	241.519***

Note: Regressions are estimated at the annual level using OLS for S&P 500 constituents during 2007-2021 for which scope 1 GHG emissions are reported. The sampling deadline for the S&P 500 constituents is 31^{th} December each year. *Scope 1/MV Firm* is a firm's carbon intensity, defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Scope 1/MV Industry* is the sum of annual scope 1 GHG emissions of all firms in the same industry, divided by the annual sum of the market value of all firms in the same industry (SIC4). *Scope 1* are unscaled scope 1 GHG emissions (in kt CO2 equivalents). t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table B.4 – Determinants of Firm Carbon Intensity with Constant: Sector Intensity

	Log(Scope 1/MV Firm)		Log(Scope 1) Firm	
	(1)	(2)	(3)	(4)
Log(Scope 1/MV Sec)	0.953***	0.820***		
	(0.022)	(0.034)		
Log(Scope 1) Sector			0.820***	0.782***
			(0.025)	(0.032)
Log(Assets)		-0.065		0.600***
		(0.068)		(0.063)
Div. payout ratio		0.396**		0.640***

Continuation...

... Continuation

	Log(Scope 1/MV Firm)		Log(Scope 1) Firm	
	(1)	(2)	(3)	(4)
		(0.186)		(0.180)
Debt/Assets		1.265***		0.855*
		(0.461)		(0.441)
Ebit/Assets		-4.059**		-2.421*
		(1.578)		(1.465)
CapEx/Assets		13.750***		13.023***
		(2.351)		(2.344)
Book-to-Market		0.506		-0.676*
		(0.348)		(0.355)
Log(Return)		-0.370		-0.090
		(0.287)		(0.292)
Inst. Own.		-1.434*		-2.269***
		(0.756)		(0.706)
CAPM beta		0.020		-0.064
		(0.141)		(0.151)
Oil beta		-0.499*		-0.842***
		(0.262)		(0.322)
Volatility		2.107**		1.039
		(0.991)		(1.316)
Model	OLS	OLS	OLS	OLS
Intercept	Year	Year	Year	Year
Fixed Effects	No	Year	No	Year
Level	Firm	Firm	Firm	Firm
Frequency	Annual	Annual	Annual	Annual
Observations	980	980	980	980
R^2	0.596	0.644	0.519	0.640
Adjusted R^2	0.596	0.635	0.519	0.631
Residual Std. Error	1.870	1.777	1.987	1.741
F Statistic	1918.634***	95.461***	1098.956***	90.651***

Note: Regressions are estimated at the annual level using OLS for S&P 500 constituents during 2007-2021, for which scope 1 GHG emissions are reported. The sampling deadline for the S&P 500 constituents is 31^{th} December each year. *Scope 1/MV Firm* is a firm's carbon intensity, defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Scope 1/MV Sector* is the sum of annual scope 1 emissions of all firms in the same sector, divided by the annual sum of the market value of all firms in the same sector (GICS). *Scope 1* are unscaled scope 1 GHG emissions (in kt CO2 equivalents). t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table B.5 – Determinants of Firm Carbon Intensity without Constant: Sector Intensity

	Log(Scope 1/MV Firm)		Log(Scope 1) Firm	
	(1)	(2)	(3)	(4)
Log(Scope 1/MV Sec)	1.076***	0.811***		
	(0.013)	(0.033)		
Log(Scope 1) Sector			0.679***	0.700***
			(0.007)	(0.029)
Log(Assets)		-0.083**		0.315***
		(0.037)		(0.038)
Div. payout ratio		0.383**		0.493***
		(0.178)		(0.176)
Debt/Assets		1.184***		0.138
		(0.416)		(0.394)
Ebit/Assets		-4.713***		-5.196***
		(1.237)		(1.270)
CapEx/Assets		14.199***		15.120***
		(2.341)		(2.288)
Book-to-Market		0.368		-0.597*
		(0.344)		(0.348)
Log(Return)		-0.456*		-0.184
		(0.253)		(0.254)
Inst. Own.		-1.646***		-4.688***
		(0.453)		(0.441)
CAPM beta		0.021		-0.114
		(0.139)		(0.149)
Oil beta		-0.470*		-0.809**
		(0.257)		(0.316)
Volatility		1.919*		0.816
		(0.985)		(1.353)
Model	OLS	OLS	OLS	OLS
Intercept	No	No	No	No
Fixed Effects	No	No	No	No
Level	Firm	Firm	Firm	Firm
Frequency	Annual	Annual	Annual	Annual
Observations	980	980	980	980
R^2	0.855	0.875	0.915	0.936
Adjusted R^2	0.855	0.873	0.914	0.935
Residual Std. Error	1.902	1.777	2.020	1.761
F Statistic	7138.590***	706.723***	8984.705***	1394.291***

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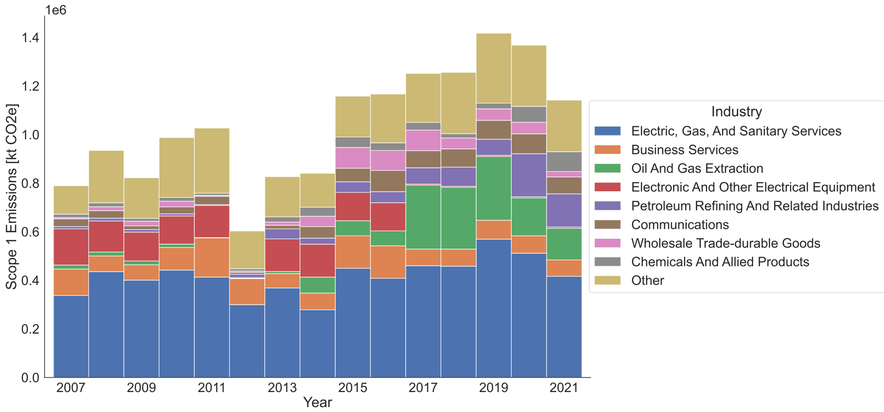
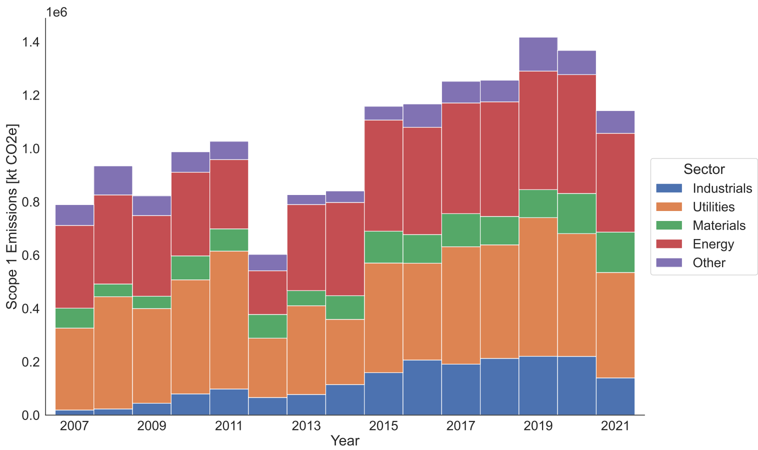
	Log(Scope 1/MV Firm)		Log(Scope 1) Firm	
	(1)	(2)	(3)	(4)

Note: Regressions are estimated at the annual level using OLS for S&P 500 constituents during 2007-2021, for which scope 1 GHG emissions are reported. The sampling deadline for the S&P 500 constituents is 31^{th} December each year. *Scope 1/MV Firm* is a firm's carbon intensity, defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Scope 1/MV Sector* is the sum of annual scope 1 emissions of all firms in the same sector, divided by the annual sum of the market value of all firms in the same sector (GICS). *Scope 1* are unscaled scope 1 GHG emissions (in kt CO2 equivalents). t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Composition of Carbon Emissions per Sector and Industry



(a) Sum of Emissions per Industry



(b) Sum of Emissions per Sector

Figure B.1 – Sum of Scope 1 GHG Emissions per Industry and Sector over Time. The figures show the composition of GHG emissions grouped by industry (SIC2) and sector (GICS). Industries and sectors that together account for less than 40% of overall emissions are grouped in 'Other'. For sectors, these include Communication Services, 'Consumer Discretionary, Consumer Staples, Financials, Health Care, Information Technology and Real Estate. For industries, there are too many to list. The figure is based on end-of-year values of self-reported company emissions generated between 2007 and 2021 for an of S&P 500 constituents with reported GHG scope 1 emissions and sufficient data availability to match databases and construct implied volatility surfaces. This corresponds to 456 out of 818 companies and a total of 2958 observations.

Appendix C

Extended Results

C.1 Full Results for the Main Models

Table C.1 – Full Results for the First Model: Panel Model

	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
Intercept	0.113***	0.774***	0.562***	0.184***	-0.122***
	(0.019)	(0.020)	(0.036)	(0.016)	(0.023)
Scope 1/MV Firm Q2	0.019***	-0.002	0.007	-0.030***	-0.019***
	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)
Scope 1/MV Firm Q3	0.014***	0.008*	0.012*	-0.023***	-0.039***
	(0.005)	(0.004)	(0.007)	(0.004)	(0.006)
Scope 1/MV Firm Q4	0.014**	0.001	0.001	-0.017***	-0.016**
	(0.005)	(0.005)	(0.008)	(0.005)	(0.007)
Scope 1 not reported	0.018***	-0.002	0.010	-0.017***	-0.012**
	(0.004)	(0.003)	(0.006)	(0.003)	(0.005)
Trends CO2 Tax	0.031***	0.126***	0.178***	-0.040***	-0.217***
	(0.010)	(0.008)	(0.015)	(0.009)	(0.014)
ESG Score	0.002	-0.039***	-0.019	-0.017**	0.031***
	(0.009)	(0.007)	(0.014)	(0.008)	(0.011)
Log(Assets)	0.024***	-0.033***	-0.033***	-0.037***	0.021***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Div. payout ratio	0.012***	-0.008***	-0.012***	-0.017***	-0.010***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Debt/Assets	0.038***	0.094***	0.160***	0.025***	-0.001
	(0.007)	(0.007)	(0.013)	(0.006)	(0.009)
Ebit/Assets	0.173***	-0.378***	-0.508***	-0.308***	0.039*

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	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
	(0.019)	(0.018)	(0.035)	(0.015)	(0.022)
CapEx/Assets	-0.178***	0.141***	0.178**	0.220***	0.123***
	(0.035)	(0.034)	(0.078)	(0.028)	(0.042)
Book-to-Market	-0.026***	0.058***	0.071***	0.038***	-0.020***
	(0.006)	(0.006)	(0.012)	(0.004)	(0.007)
Log(Return)	-0.001	-0.010**	-0.028***	0.013***	0.027***
	(0.004)	(0.004)	(0.007)	(0.003)	(0.005)
Inst. Own.	0.012	0.010	-0.008	0.018**	0.000
	(0.009)	(0.008)	(0.015)	(0.007)	(0.011)
CAPM beta	-0.002	0.017***	0.017***	0.012***	0.005*
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
Oil beta	-0.022***	0.031***	0.023**	0.041***	-0.003
	(0.006)	(0.006)	(0.011)	(0.004)	(0.006)
Volatility	0.095***	1.483***	2.092***	0.403***	-0.452***
	(0.024)	(0.056)	(0.093)	(0.022)	(0.033)
Time Trend	0.014***	-0.014***	-0.021***	-0.008***	0.014***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Model	OLS	OLS	OLS	OLS	OLS
Fixed Effects	Sector	Sector	Sector	Sector	Sector
Frequency	Monthly	Monthly	Monthly	Monthly	Monthly
Observations	55,888	55,888	55,888	55,888	55,888
R^2	0.077	0.292	0.182	0.112	0.070
Adjusted R^2	0.076	0.291	0.182	0.111	0.070
Residual Std. Error	0.264	0.227	0.418	0.239	0.331
F Statistic	175.814***	443.321***	168.856***	283.806***	147.457***

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	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)

Note: This table extends Table 5.1. Regressions are estimated at firm-month level using OLS for S&P 500 constituents during 2007-2021. *Scope 1/MV Firm Q2-Q4* is each a binary variable indicating the quartile of a firm's carbon intensity relative to all other firms in the same year. A firm's carbon intensity is defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Scope 1 not reported* equals one if a firm's carbon emissions are not available in a given year, and zero else. We assume emission data is published in March each year. *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The measures are based on the Surface SVI. Additionally we include the Call slope, which is the slope coefficient for regressing out-of-the-money calls (log-moneyess in $[0.001, 0.5]$ on the respective log-moneyness and a constant). The variable is included for discussion of the robustness. The dependent variables are lagged by one to twelve months with respect to the independent variables. Standard errors are calculated using the heteroscedasticity robust HC3 covariance estimator from MacKinnon and White (1985). t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table C.2 – Full Results for the Second Model: Cross-sectional Model with Sample Correction

	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)
Intercept	0.353	0.720	0.775	0.119	0.555
	(0.374)	(0.491)	(0.820)	(0.311)	(0.559)
Log(Scope 1/MV Firm)	0.001	-0.006	-0.009	-0.010***	-0.012**
	(0.004)	(0.005)	(0.008)	(0.003)	(0.005)
Log(Assets)	0.023***	-0.047***	-0.070***	-0.025***	0.033***
	(0.007)	(0.009)	(0.015)	(0.006)	(0.010)
Div. payout ratio	0.003	-0.009	-0.018	-0.007	-0.012
	(0.007)	(0.009)	(0.015)	(0.006)	(0.010)
Debt/Assets	0.103***	0.141***	0.251***	-0.008	-0.010
	(0.037)	(0.049)	(0.081)	(0.031)	(0.055)
Ebit/Assets	0.056	-0.947***	-1.434***	-0.413***	0.260
	(0.121)	(0.159)	(0.265)	(0.100)	(0.180)
CapEx/Assets	-0.207	1.015***	1.778***	0.632***	0.751**
	(0.232)	(0.304)	(0.508)	(0.192)	(0.346)
Book-to-Market	-0.001	0.093**	0.136**	0.023	-0.055
	(0.028)	(0.036)	(0.061)	(0.023)	(0.041)

Continuation...

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	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
Log(Return)	-0.007	-0.164***	-0.251***	-0.059**	-0.026
	(0.029)	(0.038)	(0.063)	(0.024)	(0.043)
Inst. Own.	-0.126**	0.060	0.004	0.101**	-0.124
	(0.060)	(0.079)	(0.132)	(0.050)	(0.090)
CAPM beta	-0.006	0.102***	0.133***	0.045***	-0.041*
	(0.014)	(0.019)	(0.031)	(0.012)	(0.021)
Oil beta	0.047*	0.130***	0.204***	0.018	-0.004
	(0.028)	(0.037)	(0.062)	(0.023)	(0.042)
Volatility	-0.582***	0.208	0.218	0.393**	-0.049
	(0.188)	(0.247)	(0.411)	(0.156)	(0.280)
ESG Score	-0.011	-0.163**	-0.227**	-0.044	0.149*
	(0.052)	(0.068)	(0.113)	(0.043)	(0.077)
Trends CO2 Tax	1.173	1.339	1.374	-1.440	-4.474
	(1.978)	(2.597)	(4.334)	(1.642)	(2.952)
Inverse Mills	0.013	-0.038	-0.063	0.001	0.072*
	(0.027)	(0.035)	(0.058)	(0.022)	(0.040)
Model	IV2SLS	IV2SLS	IV2SLS	IV2SLS	IV2SLS
Fixed Effects	None	None	None	None	None
Year (t)	2019	2019	2019	2019	2019
Observations	316	316	316	316	316
R^2	0.174	0.565	0.501	0.397	0.162
Adjusted R^2	0.133	0.543	0.476	0.367	0.120
Residual Std. Error	0.104	0.136	0.227	0.086	0.155
F Statistic	4.216***	26.172***	20.186***	13.981***	4.309***

Note: This table extends Table 5.2. Regressions are estimated at firm-year level using 2SLS for S&P 500 constituents during 2019-2021 with reported scope 1 GHG emissions. *Log(Scope 1/MV Firm)* is a firm's carbon intensity, defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The Inverse Mills ratio is the conditional estimate of firm disclosure from a Probit model on all firms to control for a possible sample selection bias. The independent variables are calculated from April 2019 to March 2020, the dependent variables are observed from April 2020 to March 2021. Additionally we include the Call slope, which is the slope coefficient for regressing out-of-the-money calls (log-moneyess in $[0.001, 0.5]$ on the respective log-moneyness and a constant). The variable is included for discussion of the robustness. t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

C.2 Robustness Tests for the Panel Model

Table C.3 – Robustness Test for OptionMetrics Volatility Surface

	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
Intercept	0.323***	0.337***	0.081***	-0.052***	0.257***
	(0.014)	(0.010)	(0.013)	(0.014)	(0.011)
Scope 1/MV Firm Q2	0.026***	-0.001	0.009***	-0.010***	0.015***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Scope 1/MV Firm Q3	0.019***	0.003	0.008***	-0.005	0.005**
	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
Scope 1/MV Firm Q4	0.004	0.006**	0.011***	0.003	-0.003
	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)
Scope 1 not reported	0.007***	0.003*	0.009***	0.001	0.005***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Trends CO2 Tax	-0.039***	0.081***	0.061***	-0.014**	-0.047***
	(0.006)	(0.004)	(0.005)	(0.006)	(0.005)
ESG Score	-0.034***	-0.030***	-0.016***	-0.015**	-0.019***
	(0.005)	(0.004)	(0.004)	(0.006)	(0.004)
Log(Assets)	-0.029***	-0.011***	-0.004***	-0.023***	-0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Div. payout ratio	-0.001	-0.005***	-0.004***	-0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Debt/Assets	0.060***	0.044***	0.047***	0.007	0.027***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
Ebit/Assets	-0.168***	-0.208***	-0.190***	-0.189***	-0.115***
	(0.012)	(0.010)	(0.015)	(0.013)	(0.010)
CapEx/Assets	-0.237***	0.184***	0.126***	0.188***	-0.130***
	(0.023)	(0.018)	(0.021)	(0.022)	(0.019)
Book-to-Market	0.043***	0.016***	-0.003	0.026***	0.045***
	(0.004)	(0.003)	(0.006)	(0.003)	(0.003)
Log(Return)	-0.006**	-0.017***	-0.024***	-0.012***	-0.006***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Inst. Own.	0.008	0.014***	0.002	-0.012*	-0.011**
	(0.007)	(0.005)	(0.005)	(0.006)	(0.005)
CAPM beta	0.005***	0.014***	0.010***	0.012***	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Oil beta	-0.002	0.019***	0.006	0.030***	0.015***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.002)
Volatility	0.410***	1.087***	0.951***	0.348***	-0.149***
	(0.020)	(0.036)	(0.041)	(0.017)	(0.014)
Time Trend	0.016***	-0.005***	-0.005***	0.002***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Model	OLS	OLS	OLS	OLS	OLS

Continuation...

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	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
Fixed Effects	Sector	Sector	Sector	Sector	Sector
Frequency	Monthly	Monthly	Monthly	Monthly	Monthly
Observations	72,446	72,446	72,446	72,446	72,446
R^2	0.142	0.331	0.175	0.049	0.162
Adjusted R^2	0.142	0.330	0.175	0.049	0.162
Residual Std. Error	0.199	0.130	0.164	0.220	0.148
F Statistic	277.034***	617.040***	243.419***	197.329***	352.708***

Note: Regressions are estimated at firm-month level using OLS for S&P 500 constituents during 2007-2021. *Scope 1/MV Firm Q2-Q4* is each a binary variable indicating the quartile of a firm's carbon intensity relative to all other firms in the same year. A firm's carbon intensity is defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Scope 1 not reported* equals one if a firm's carbon emissions are not available in a given year, and zero else. We assume emission data is published in March each year. *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The measures are based on the implied volatility surface from the OptionMetrics Surface file. Additionally to the main model we include the Call slope, which is the slope coefficient for regressing out-of-the-money calls (log-moneyess in $[0.001, 0.5]$ on the respective log-moneyness and a constant). The variable is included for discussion of the robustness. The dependent variables are lagged by one to twelve months with respect to the independent variables. Standard errors are calculated using the heteroscedasticity robust HC3 covariance estimator from MacKinnon and White (1985). t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table C.4 – Robustness Test for Observing Carbon Emissions in September

	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
Intercept	0.141***	0.729***	0.492***	0.152***	-0.142***
	(0.020)	(0.021)	(0.036)	(0.017)	(0.025)
Scope 1/MV Firm Q2	0.021***	0.007*	0.024***	-0.036***	-0.030***
	(0.004)	(0.004)	(0.007)	(0.004)	(0.006)
Scope 1/MV Firm Q3	0.013**	0.019***	0.031***	-0.025***	-0.046***
	(0.005)	(0.004)	(0.007)	(0.005)	(0.006)
Scope 1/MV Firm Q4	0.015***	0.008*	0.015*	-0.017***	-0.025***

Continuation...

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	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
	(0.006)	(0.005)	(0.008)	(0.005)	(0.007)
Scope 1 not reported	0.019***	0.011***	0.025***	-0.018***	-0.020***
	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)
Trends CO2 Tax	-0.015	0.093***	0.123***	-0.008	-0.170***
	(0.010)	(0.008)	(0.014)	(0.010)	(0.015)
ESG Score	0.003	-0.036***	-0.025*	-0.016**	0.025**
	(0.009)	(0.008)	(0.015)	(0.008)	(0.012)
Log(Assets)	0.027***	-0.029***	-0.026***	-0.039***	0.020***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)
Div. payout ratio	0.012***	-0.008***	-0.011***	-0.017***	-0.011***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Debt/Assets	0.032***	0.091***	0.155***	0.030***	0.002
	(0.007)	(0.007)	(0.015)	(0.006)	(0.009)
Ebit/Assets	0.173***	-0.358***	-0.470***	-0.304***	0.037
	(0.019)	(0.019)	(0.036)	(0.015)	(0.023)
CapEx/Assets	-0.191***	0.124***	0.112*	0.235***	0.138***
	(0.037)	(0.035)	(0.067)	(0.030)	(0.045)
Book-to-Market	-0.023***	0.042***	0.039***	0.038***	-0.019***
	(0.006)	(0.006)	(0.013)	(0.005)	(0.007)
Log(Return)	0.000	-0.012***	-0.034***	0.016***	0.031***
	(0.004)	(0.004)	(0.008)	(0.003)	(0.005)
Inst. Own.	0.009	0.017*	0.005	0.026***	0.004
	(0.009)	(0.009)	(0.016)	(0.008)	(0.012)
CAPM beta	-0.003	0.016***	0.016***	0.013***	0.005*
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
Oil beta	-0.029***	0.037***	0.028**	0.044***	-0.004
	(0.006)	(0.006)	(0.011)	(0.004)	(0.007)
Volatility	0.057**	1.628***	2.307***	0.504***	-0.493***
	(0.026)	(0.053)	(0.089)	(0.024)	(0.035)
Time Trend	0.011***	-0.015***	-0.023***	-0.006***	0.016***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Model	OLS	OLS	OLS	OLS	OLS
Fixed Effects	Sector	Sector	Sector	Sector	Sector
Frequency	Monthly	Monthly	Monthly	Monthly	Monthly
Observations	47,975	47,975	47,975	47,975	47,975
R^2	0.066	0.320	0.205	0.120	0.087
Adjusted R^2	0.066	0.320	0.204	0.119	0.086
Residual Std. Error	0.251	0.221	0.407	0.234	0.325
F Statistic	125.910***	428.129***	163.725***	255.478***	157.390***

Continuation...

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	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)

Note: This table extends Table 5.1. Regressions are estimated at firm-month level using OLS for S&P 500 constituents during 2007-2021. *Scope 1/MV Firm Q2-Q4* is each a binary variable indicating the quartile of a firm's carbon intensity relative to all other firms in the same year. A firm's carbon intensity is defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Scope 1 not reported* equals one if a firm's carbon emissions are not available in a given year, and zero else. Hence the intercept of the reference group (Q1 carbon intensity) is the intercept for the entire model. We assume emission data is published in september each year. *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The measures are based on the Surface SVI. Additionally to the main model we include the Call slope, which is the slope coefficient for regressing out-of-the-money calls (log-moneyess in $[0.001, 0.5]$ on the respective log-moneyness and a constant). The variable is included for discussion of the robustness. The dependent variables are lagged by one to twelve months with respect to the independent variables. Standard errors are calculated using the heteroscedasticity robust HC3 covariance estimator from MacKinnon and White (1985). t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table C.5 – Robustness Test Starting the Panel in 2010

	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)
Intercept	0.166***	0.786***	0.577***	0.169***	-0.177***
	(0.020)	(0.018)	(0.025)	(0.018)	(0.024)
Scope 1/MV Firm Q2	0.016***	-0.007**	-0.004	-0.033***	-0.019***
	(0.004)	(0.003)	(0.005)	(0.004)	(0.006)
Scope 1/MV Firm Q3	0.012**	0.003	0.006	-0.030***	-0.038***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)
Scope 1/MV Firm Q4	0.008	-0.001	0.000	-0.020***	-0.015**
	(0.006)	(0.004)	(0.007)	(0.005)	(0.007)
Scope 1 not reported	0.008*	-0.020***	-0.018***	-0.023***	-0.001
	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)
Trends CO2 Tax	-0.015	-0.003	0.002	-0.062***	-0.139***
	(0.010)	(0.008)	(0.013)	(0.010)	(0.015)
ESG Score	-0.024**	-0.035***	-0.009	-0.004	0.048***
	(0.009)	(0.007)	(0.011)	(0.009)	(0.012)

Continuation. . .

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	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
Log(Assets)	0.025***	-0.042***	-0.044***	-0.045***	0.029***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Div. payout ratio	0.012***	-0.006***	-0.007***	-0.016***	-0.011***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Debt/Assets	0.015**	0.053***	0.078***	0.027***	0.018*
	(0.007)	(0.005)	(0.008)	(0.007)	(0.009)
Ebit/Assets	0.210***	-0.317***	-0.354***	-0.331***	0.045*
	(0.020)	(0.017)	(0.027)	(0.017)	(0.024)
CapEx/Assets	-0.224***	0.146***	0.173***	0.276***	0.103**
	(0.038)	(0.031)	(0.050)	(0.033)	(0.046)
Book-to-Market	-0.030***	0.100***	0.121***	0.067***	-0.048***
	(0.006)	(0.005)	(0.009)	(0.005)	(0.007)
Log(Return)	0.007*	0.006	-0.009	0.022***	0.025***
	(0.005)	(0.004)	(0.006)	(0.004)	(0.005)
Inst. Own.	0.003	-0.000	-0.027**	0.034***	0.017
	(0.009)	(0.008)	(0.011)	(0.008)	(0.011)
CAPM beta	-0.000	0.026***	0.031***	0.016***	-0.001
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)
Oil beta	-0.001	0.036***	0.037***	0.031***	-0.015**
	(0.006)	(0.006)	(0.009)	(0.005)	(0.007)
Volatility	-0.049*	1.102***	1.349***	0.434***	-0.263***
	(0.027)	(0.056)	(0.075)	(0.028)	(0.034)
Time Trend	0.015***	-0.001***	-0.003***	-0.003***	0.007***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Model	OLS	OLS	OLS	OLS	OLS
Fixed Effects	Sector	Sector	Sector	Sector	Sector
Frequency	Monthly	Monthly	Monthly	Monthly	Monthly
Observations	45,864	45,864	45,864	45,864	45,864
R^2	0.062	0.244	0.160	0.102	0.034
Adjusted R^2	0.061	0.244	0.159	0.102	0.034
Residual Std. Error	0.254	0.187	0.278	0.246	0.320
F Statistic	104.912***	317.598***	138.757***	187.887***	57.702***

Continuation...

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	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)

Note: Regressions are estimated at firm-month level using OLS for S&P 500 constituents during 2010-2021. *Scope 1/MV Firm Q2-Q4* is each a binary variable indicating the quartile of a firm's carbon intensity relative to all other firms in the same year. A firm's carbon intensity is defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Scope 1 not reported* equals one if a firm's carbon emissions are not available in a given year, and zero else. We assume emission data is published in March each year. *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The measures are based on the Surface SVI. Additionally we include the Call slope, which is the slope coefficient for regressing out-of-the-money calls (log-moneyess in $[0.001, 0.5]$ on the respective log-moneyness and a constant). The variable is included for discussion of the robustness. The dependent variables are lagged by one to twelve months with respect to the independent variables. Standard errors are calculated using the heteroscedasticity robust HC3 covariance estimator from MacKinnon and White (1985). t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table C.6 – Robustness Test Industry Intensity

	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)
Intercept	0.115***	0.674***	0.445***	0.149***	-0.029
	(0.017)	(0.018)	(0.033)	(0.015)	(0.021)
Scope 1/MV Ind Q2	0.003	-0.012***	-0.017***	-0.020***	0.000
	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)
Scope 1/MV Ind Q3	0.014***	-0.008**	-0.012**	-0.032***	-0.024***
	(0.004)	(0.003)	(0.006)	(0.004)	(0.005)
Scope 1/MV Ind Q4	0.011**	-0.024***	-0.037***	-0.036***	-0.019***
	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)
Scope 1 not reported	0.015***	-0.007**	-0.003	-0.018***	-0.007
	(0.004)	(0.003)	(0.006)	(0.003)	(0.005)
Trends CO2 Tax	0.032***	0.127***	0.178***	-0.041***	-0.218***
	(0.010)	(0.008)	(0.015)	(0.009)	(0.014)
ESG Score	0.006	-0.061***	-0.047***	-0.032***	0.041***
	(0.008)	(0.007)	(0.014)	(0.008)	(0.010)
Log(Assets)	0.025***	-0.026***	-0.024***	-0.033***	0.013***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)

Continuation. . .

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	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
Div. payout ratio	0.015***	-0.011***	-0.014***	-0.025***	-0.018***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Debt/Assets	0.045***	0.059***	0.124***	-0.009*	-0.017**
	(0.006)	(0.006)	(0.012)	(0.006)	(0.008)
Ebit/Assets	0.161***	-0.380***	-0.517***	-0.256***	0.130***
	(0.018)	(0.017)	(0.033)	(0.015)	(0.022)
CapEx/Assets	-0.228***	0.155***	0.156***	0.176***	0.115***
	(0.029)	(0.029)	(0.059)	(0.023)	(0.035)
Book-to-Market	-0.024***	0.062***	0.078***	0.032***	-0.035***
	(0.006)	(0.005)	(0.012)	(0.004)	(0.007)
Log(Return)	-0.001	-0.009**	-0.028***	0.012***	0.026***
	(0.004)	(0.004)	(0.007)	(0.003)	(0.005)
Inst. Own.	0.015*	0.034***	0.019	0.029***	-0.014
	(0.009)	(0.009)	(0.015)	(0.007)	(0.011)
CAPM beta	0.001	0.029***	0.031***	0.017***	0.002
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
Oil beta	-0.027***	0.040***	0.033***	0.041***	-0.005
	(0.005)	(0.006)	(0.011)	(0.004)	(0.006)
Volatility	0.076***	1.507***	2.118***	0.439***	-0.426***
	(0.024)	(0.058)	(0.095)	(0.023)	(0.033)
Time Trend	0.013***	-0.013***	-0.021***	-0.008***	0.014***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Model	OLS	OLS	OLS	OLS	OLS
Frequency	Monthly	Monthly	Monthly	Monthly	Monthly
Observations	55,888	55,888	55,888	55,888	55,888
R^2	0.073	0.279	0.175	0.099	0.060
Adjusted R^2	0.072	0.279	0.175	0.099	0.060
Residual Std. Error	0.265	0.229	0.420	0.241	0.333
F Statistic	259.089***	561.239***	209.984***	392.269***	189.161***

Continuation...

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	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)

Note: Regressions are estimated at firm-month level using OLS for S&P 500 constituents during 2007-2021. *Scope 1/MV Industry Q2-Q4* is each a binary variable indicating the quartile of a firm's industry carbon intensity relative to all other firms in the same year. A firm's industry carbon intensity is defined as the sum of scope 1 GHG emissions (in kt CO2 equivalents) of all firms in the industry (SIC4), divided by firm market value (in M$) of all firms in the industry. *Scope 1 not reported* equals one if a firm's carbon emissions are not available in a given year, and zero else. We assume emission data is published in March each year. *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The measures are based on the Surface SVI. Additionally we include the Call slope, which is the slope coefficient for regressing out-of-the-money calls (log-moneyess in $[0.001, 0.5]$ on the respective log-moneyness and a constant). The variable is included for discussion of the robustness. The dependent variables are lagged by one to twelve months with respect to the independent variables. Standard errors are calculated using the heteroscedasticity robust HC3 covariance estimator from MacKinnon and White (1985). t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

C.3 Robustness Tests in the Cross-Section

Table C.7 – Robustness Test Sample Correction Model, Year 2018

	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
Intercept	0.102	0.315	0.228	-0.129	-0.065
	(0.215)	(0.215)	(0.306)	(0.234)	(0.280)
Log(Scope 1/MV Firm)	0.004	-0.001	0.000	-0.008**	-0.002
	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)
Log(Assets)	0.027***	-0.040***	-0.050***	-0.043***	0.021**
	(0.006)	(0.007)	(0.009)	(0.007)	(0.008)
Div. payout ratio	0.001	-0.009	-0.013	-0.015**	-0.018**
	(0.006)	(0.006)	(0.009)	(0.007)	(0.008)
Debt/Assets	0.072*	-0.000	0.017	-0.072*	0.033
	(0.038)	(0.038)	(0.054)	(0.041)	(0.049)
Ebit/Assets	0.143	-0.124	-0.111	-0.304**	0.104

Continuation...

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	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
	(0.113)	(0.114)	(0.162)	(0.124)	(0.148)
CapEx/Assets	-0.118	-0.059	-0.315	0.241	0.145
	(0.200)	(0.201)	(0.285)	(0.219)	(0.261)
Book-to-Market	-0.052*	0.174***	0.249***	0.089**	-0.041
	(0.032)	(0.032)	(0.045)	(0.034)	(0.041)
Log(Return)	0.015	-0.030	-0.047	0.007	0.055
	(0.027)	(0.027)	(0.039)	(0.030)	(0.035)
Inst. Own.	-0.047	0.088	0.001	0.133**	-0.085
	(0.055)	(0.055)	(0.078)	(0.060)	(0.071)
CAPM beta	-0.016	0.026**	0.028*	0.028**	-0.014
	(0.012)	(0.012)	(0.017)	(0.013)	(0.015)
Oil beta	0.006	0.080***	0.097**	-0.002	-0.091**
	(0.027)	(0.027)	(0.039)	(0.030)	(0.036)
Volatility	-0.331	2.330***	2.791***	1.294***	-0.781**
	(0.279)	(0.280)	(0.397)	(0.305)	(0.364)
ESG Score	0.005	0.007	0.014	0.033	0.054
	(0.052)	(0.052)	(0.074)	(0.057)	(0.068)
Trends CO2 Tax	0.957	0.867	0.887	0.091	0.066
	(0.649)	(0.651)	(0.923)	(0.709)	(0.847)
Inverse Mills	-0.016	-0.022	-0.041	0.010	0.030
	(0.022)	(0.022)	(0.031)	(0.024)	(0.028)
Model	IV2SLS	IV2SLS	IV2SLS	IV2SLS	IV2SLS
Fixed Effects	None	None	None	None	None
Year (t)	2018	2018	2018	2018	2018
Observations	281	281	281	281	281
R^2	0.188	0.582	0.506	0.390	0.207
Adjusted R^2	0.143	0.558	0.478	0.355	0.162
Residual Std. Error	0.095	0.095	0.135	0.104	0.124
F Statistic	4.296***	24.570***	18.102***	11.514***	4.595***

Continuation...

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	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)

Note: Regressions are estimated at firm-year level using 2SLS for S&P 500 constituents during 2018-2020 with reported scope 1 carbon emissions. *Log(Scope 1/MV Firm)* is a firm's carbon intensity, defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The Inverse Mills ratio is the conditional estimate of firm disclosure from a Probit model on all firms to control for a possible sample selection bias. The independent variables are calculated from April 2018 to March 2019, the dependent variables are observed from April 2019 to March 2020. Additionally to the main model we include the Call slope, which is the slope coefficient for regressing out-of-the-money calls (log-moneyess in $[0.001, 0.5]$ on the respective log-moneyness and a constant). The variable is included for discussion of the robustness. t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table C.8 – Robustness Test Sample Correction Model, Year 2017

	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)
Intercept	0.000	0.582***	0.430***	-0.096	-0.041
	(0.146)	(0.126)	(0.161)	(0.184)	(0.173)
Log(Scope 1/MV Firm)	0.006	-0.005	-0.001	-0.015***	-0.004
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Log(Assets)	0.023***	-0.040***	-0.040***	-0.028***	0.023**
	(0.008)	(0.007)	(0.009)	(0.011)	(0.010)
Div. payout ratio	0.015**	-0.016**	-0.015*	-0.024***	-0.008
	(0.007)	(0.006)	(0.008)	(0.009)	(0.009)
Debt/Assets	0.066	-0.014	0.014	-0.072	0.018
	(0.047)	(0.041)	(0.052)	(0.060)	(0.056)
Ebit/Assets	0.347**	-0.228*	-0.175	-0.298	0.381**
	(0.146)	(0.126)	(0.161)	(0.184)	(0.173)
CapEx/Assets	-1.010***	0.670**	0.611*	1.051***	0.164
	(0.307)	(0.266)	(0.339)	(0.388)	(0.363)
Book-to-Market	-0.014	0.121***	0.159***	0.071	-0.009
	(0.043)	(0.037)	(0.047)	(0.054)	(0.051)
Log(Return)	0.012	-0.024	-0.025	0.003	0.043
	(0.037)	(0.032)	(0.041)	(0.047)	(0.044)
Inst. Own.	-0.057	-0.020	-0.069	0.058	-0.054
	(0.068)	(0.059)	(0.075)	(0.086)	(0.081)

Continuation...

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	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)
CAPM beta	0.009	0.038***	0.047***	0.032*	0.018
	(0.013)	(0.011)	(0.014)	(0.016)	(0.015)
Oil beta	-0.066*	0.046	0.097**	-0.013	-0.008
	(0.037)	(0.032)	(0.041)	(0.047)	(0.044)
Volatility	-0.518**	1.271***	1.204***	1.180***	-0.438
	(0.260)	(0.225)	(0.287)	(0.328)	(0.308)
ESG Score	-0.050	-0.054	-0.018	0.079	0.218***
	(0.067)	(0.058)	(0.074)	(0.085)	(0.079)
Trends CO2 Tax	1.875***	0.565	0.191	-0.641	-1.057**
	(0.429)	(0.372)	(0.474)	(0.542)	(0.508)
Inverse Mills	0.023	0.031	0.058**	-0.010	0.053*
	(0.025)	(0.022)	(0.028)	(0.032)	(0.030)
Model	IV2SLS	IV2SLS	IV2SLS	IV2SLS	IV2SLS
Fixed Effects	None	None	None	None	None
Year (t)	2017	2017	2017	2017	2017
Observations	257	257	257	257	257
R^2	0.246	0.511	0.427	0.238	0.152
Adjusted R^2	0.199	0.480	0.391	0.190	0.099
Residual Std. Error	0.112	0.097	0.124	0.142	0.133
F Statistic	5.501***	16.691***	11.934***	5.390***	2.915***

Note: Regressions are estimated at firm-year level using 2SLS for S&P 500 constituents during 2017-2019 with reported scope 1 carbon emissions. *Log(Scope 1/MV Firm)* is a firm's carbon intensity, defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The Inverse Mills ratio is the conditional estimate of firm disclosure from a Probit model on all firms to control for a possible sample selection bias. The independent variables are calculated from April 2017 to March 2018, the dependent variables are observed from April 2018 to March 2019. Additionally to the main model we include the Call slope, which is the slope coefficient for regressing out-of-the-money calls (log-moneyess in $[0.001, 0.5]$ on the respective log-moneyness and a constant). The variable is included for discussion of the robustness. t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table C.9 – Robustness Test Sample Correction Model, Year 2016

	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
Intercept	-0.058	0.784***	0.517**	0.166	-0.650***
	(0.142)	(0.115)	(0.203)	(0.201)	(0.198)
Log(Scope 1/MV Firm)	0.004	-0.006**	0.001	-0.021***	-0.003
	(0.004)	(0.003)	(0.005)	(0.005)	(0.005)
Log(Assets)	0.043***	-0.043***	-0.037***	-0.056***	0.041***
	(0.007)	(0.006)	(0.010)	(0.010)	(0.010)
Div. payout ratio	0.008	-0.008	0.000	-0.030***	-0.007
	(0.008)	(0.006)	(0.011)	(0.011)	(0.011)
Debt/Assets	0.018	0.011	-0.001	-0.058	-0.123**
	(0.044)	(0.036)	(0.063)	(0.063)	(0.062)
Ebit/Assets	0.472***	-0.261***	-0.131	-0.225	0.641***
	(0.112)	(0.091)	(0.161)	(0.160)	(0.157)
CapEx/Assets	-0.499**	0.334*	0.002	0.745**	-0.102
	(0.220)	(0.178)	(0.314)	(0.312)	(0.307)
Book-to-Market	-0.021	0.086***	0.110***	0.071*	-0.065*
	(0.027)	(0.022)	(0.038)	(0.038)	(0.038)
Log(Return)	0.012	-0.012	-0.014	-0.000	0.014
	(0.032)	(0.026)	(0.046)	(0.046)	(0.045)
Inst. Own.	0.134**	-0.009	-0.049	0.020	0.105
	(0.062)	(0.051)	(0.089)	(0.089)	(0.087)
CAPM beta	0.030**	0.002	0.024	-0.025	0.024
	(0.015)	(0.012)	(0.021)	(0.021)	(0.021)
Oil beta	-0.012	-0.009	0.058	-0.045	0.088
	(0.039)	(0.032)	(0.056)	(0.055)	(0.055)
Volatility	-0.825***	1.685***	1.679***	1.843***	-0.533
	(0.273)	(0.222)	(0.389)	(0.387)	(0.381)
ESG Score	0.035	-0.037	0.068	-0.140	0.063
	(0.063)	(0.051)	(0.089)	(0.089)	(0.087)
Trends CO2 Tax	0.180	-0.572*	-0.735	0.003	1.377**
	(0.398)	(0.323)	(0.568)	(0.565)	(0.556)
Inverse Mills	-0.018	0.014	0.033	-0.007	-0.011
	(0.021)	(0.017)	(0.030)	(0.030)	(0.029)
Model	IV2SLS	IV2SLS	IV2SLS	IV2SLS	IV2SLS
Fixed Effects	None	None	None	None	None
Year (t)	2016	2016	2016	2016	2016
Observations	233	233	233	233	233
R^2	0.353	0.605	0.361	0.380	0.247
Adjusted R^2	0.308	0.578	0.317	0.337	0.195
Residual Std. Error	0.096	0.078	0.137	0.137	0.134
F Statistic	7.859***	22.466***	8.196***	9.634***	4.803***

Continuation. . .

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	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)

Note: Regressions are estimated at firm-year level using 2SLS for S&P 500 constituents during 2016-2018 with reported scope 1 carbon emissions. *Log(Scope 1/MV Firm)* is a firm's carbon intensity, defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The Inverse Mills ratio is the conditional estimate of firm disclosure from a Probit model on all firms to control for a possible sample selection bias. The independent variables are calculated from April 2016 to March 2017, the dependent variables are observed from April 2017 to March 2018. Additionally to the main model we include the Call slope, which is the slope coefficient for regressing out-of-the-money calls (log-moneyess in $[0.001, 0.5]$ on the respective log-moneyness and a constant). The variable is included for discussion of the robustness. t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table C.10 – Robustness Test Sample Correction Model, Year 2015

	Put Slope	ATM IV	VRP	Skew	Call Slope
	(1)	(2)	(3)	(4)	(5)
Intercept	0.071	0.732***	0.408	0.808*	0.047
	(0.248)	(0.243)	(0.274)	(0.426)	(0.414)
Log(Scope 1/MV Firm)	0.007	-0.018***	-0.019***	-0.026***	-0.004
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)
Log(Assets)	0.034***	-0.053***	-0.048***	-0.089***	0.013
	(0.008)	(0.008)	(0.009)	(0.013)	(0.013)
Div. payout ratio	0.018**	-0.008	-0.009	-0.040***	-0.036***
	(0.008)	(0.008)	(0.009)	(0.014)	(0.014)
Debt/Assets	0.059	0.033	0.035	-0.047	-0.027
	(0.052)	(0.051)	(0.057)	(0.089)	(0.086)
Ebit/Assets	0.122	-0.482***	-0.376***	-0.702***	0.284
	(0.123)	(0.120)	(0.136)	(0.211)	(0.205)
CapEx/Assets	-0.034	0.513**	0.681***	0.398	0.220
	(0.231)	(0.226)	(0.255)	(0.397)	(0.385)
Book-to-Market	-0.028	0.134***	0.148***	0.104*	-0.046
	(0.031)	(0.030)	(0.034)	(0.053)	(0.052)
Log(Return)	-0.011	-0.104***	-0.130***	-0.015	0.076
	(0.032)	(0.031)	(0.035)	(0.055)	(0.053)
Inst. Own.	0.047	-0.022	-0.055	0.073	0.154

Continuation...

... Continuation

	Put Slope (1)	ATM IV (2)	VRP (3)	Skew (4)	Call Slope (5)
	(0.068)	(0.067)	(0.075)	(0.117)	(0.114)
CAPM beta	0.031**	0.012	0.013	-0.005	0.001
	(0.014)	(0.014)	(0.015)	(0.024)	(0.023)
Oil beta	-0.073*	0.040	0.036	0.069	0.022
	(0.039)	(0.038)	(0.043)	(0.067)	(0.065)
Volatility	-0.162	0.228**	0.171	0.537***	0.235
	(0.118)	(0.115)	(0.130)	(0.202)	(0.196)
ESG Score	-0.020	-0.073	-0.010	-0.163	0.181*
	(0.062)	(0.061)	(0.068)	(0.107)	(0.104)
Trends CO2 Tax	0.421	0.416	0.466	-1.095	-1.155
	(0.768)	(0.751)	(0.847)	(1.319)	(1.281)
Inverse Mills	0.037*	-0.032	-0.017	-0.097***	-0.025
	(0.022)	(0.021)	(0.024)	(0.037)	(0.036)
Model	IV2SLS	IV2SLS	IV2SLS	IV2SLS	IV2SLS
Fixed Effects	None	None	None	None	None
Year (t)	2015	2015	2015	2015	2015
Observations	223	223	223	223	223
R^2	0.173	0.437	0.368	0.352	0.110
Adjusted R^2	0.113	0.397	0.322	0.305	0.046
Residual Std. Error	0.106	0.103	0.116	0.181	0.176
F Statistic	2.898***	13.043***	9.942***	8.289***	1.613*

Note: Regressions are estimated at firm-year level using 2SLS for S&P 500 constituents during 2015-2017 with reported scope 1 carbon emissions. *Log(Scope 1/MV Firm)* is a firm's carbon intensity, defined as scope 1 GHG emissions (in kt CO2 equivalents) divided by firm market value (in M$). *Put Slope, ATM IV, VRP* and *Skew* are calculated from the IVS and measure downside tail risk, price risk, variance risk, and jump risk respectively. The Inverse Mills ratio is the conditional estimate of firm disclosure from a Probit model on all firms to control for a possible sample selection bias. The independent variables are calculated from April 2015 to March 2016, the dependent variables are observed from April 2016 to March 2017. Additionally to the main model we include the Call slope, which is the slope coefficient for regressing out-of-the-money calls (log-moneyess in $[0.001, 0.5]$ on the respective log-moneyness and a constant). The variable is included for discussion of the robustness. t-statistics are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Appendix D

Deviation From Reference Paper

Table D.1 – Overview of Deviations from Lead Paper (Ilhan et al. (2021))

Lead Paper	Our Choice	Reasoning
Main Deviations		
Get IVS from IvDB Surface Dataset from OptionMetrics, interpolate in moneyness dimension with cubic splines and extrapolate with value on boundary.	Estimate IV form price dataset of IvDB OptionMetrics with binary-search and BAW's American option price approximation, compute IVS with thhe SSVI parameterisation, interpolate in maturity.	Without imposing certain criteria on the cubic spline interpolation, interpolating on the surface file can introduce arbitrage (Fengler, 2009) and setting the Implied Volatility to some constant outside the observed moneyness region introduces unstable behaviour at the boundary (Homescu, 2011)-
Estimate a panel model for sample selection model as in Heckman (1976) using full information maximum likelihood (I think).	Estimate one panel model with categorical emissions intensity, and a second model with accounting for selection bias in the explanatory variables in the cross-section.	We could not find enough details to replicate the model approach from Ilhan et al. (2021). In particular, as Wooldridge (2010) point out, the Heckman (1976) model is valid for the cross-section under sample selection based on the dependent variable. While the extension to sample selection based on the independent variables in the cross-section is straight-forward, it is not in the panel data case. As a key feature, the endogeneity in the independent variables has to be accounted for using an instrumental variable approach.

Use industry carbon intensity as the main explanatory variable.	Use firm carbon intensity as the main explanatory variable and add sector-fixed effects.	Ilhan et al. (2021) find that firm carbon intensity is well explained by industry carbon intensity at SIC4 level. Since we can not confirm these findings, we decide to use firm carbon intensity as our main explanatory variable.
Time the emission variables for year t to September of year. $t+1$	Time to March of year $t+1$.	Ilhan et al. (2021) obtain the firm emission data from the Carbon Disclosure Project which according to the authors published emission data in September each year. We obtain emission data from Refinitiv Eikon and assume emissions are published along with annual reports, which are due in March for most firms. We estimate a robustness test for publication date in September.
Other Deviations		
Get emission data from the Carbon Disclosure Project.	Get emission data from Refinitiv Eikon.	Since we did not have access to the non-public datasets of the Carbon Disclosure Project, we obtain emission data from Refinitiv Eikon.
Use all controls at annual level.	If possible, use controls at monthly level.	We do not average *Volatility, CAPM beta* and *Oil beta* to preserve within-year variability.
Control for investor attention using Google Search Volume for 'Climate Change' and the news index from Engle et al. (2020) in a separate model.	Include investor attention with search volume for 'CO2 Tax' in main model, control for a firms ESG rating.	Since we investigate carbon tax uncertainty, we decided to use the Search Volume for "CO2 Tax".
Compute VRP from a model-free IV and realised variance over the life of the option $[t, t+30]$.	Use the IV from the Black-Scholes model and realised variance from the past observed prices $[t-30, t]$.	Since the information from $[t, t+30]$ is not available to investors in t, we use the ex-post version of VRP. The model-free IVs are more involved to compute and can be noisier for sigle-stock data (KPV)
Use the model-free skewness of the risk-neutral density.	Use the skewness of the implied volatility slice.	We use the implied volatility Skew since it provides the convenient interpretation for jump risk, as given by Mixon (2011).
Estimate the model during 2010-2017.	Estimate the models for 2007-2021.	We have an extended data set available. We estimate a robustness test excluding the years 2007-2010, where emission reporting was more scarce.
Use year-quarter fixed effects.	Use sector fixed-effects.	Since we do not use industry carbon intensity we use sector fixed-effects to account for clusteing of emissions within sectors and industries.

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