Transition risk premiums in option prices

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Abstract

The economy is in a transition process to a low-carbon state. The risk that arises for stock prices due to the uncertainty about the progression of the transition process is referred to as transition risk. Option contracts can be used to hedge equity risks and hence, option prices contain information about the perception and pricing of risks induced by the transition process. Using a measure of transition risk at the individual firm level, the carbon beta developed by Görgen et al. (2020), we analyse delta-hedged returns and measures derived from option prices to examine the relationship between a firm's transition risk and option hedging costs. In contrast to the previous literature, we find a symmetric relationship for brown and green firms, implying that only the absolute value of a firm's exposure to the transition process, and not its sign, is relevant for the expensiveness of options. The increase in expensiveness is caused by several reasons, including higher physical volatilities as well as an increased anticipation of volatility risks for firms with a high absolute value of the carbon beta. We also study anticipated downside tail risks and find evidence that green firms with a negative carbon beta are exposed to higher risks of large value drops than brown firms.

JEL Classification

G12 *Asset Pricing, Trading Volume, Bond Interest Rates*,

G13 *Contingent Pricing, Futures Pricing*,

G15 *International Financial Markets*,

G32 *Financing Policy, Financial Risk and Risk Management, Capital and Ownership Structure, Value of Firms, Goodwill*

Q54 *Climate, Natural Disasters and Their Management, Global Warming*,

Keywords

Transition risk, Carbon risk, Option pricing, Volatility risk, Jump risk, Delta-hedged option returns

1 Introduction

In recent years, public awareness of the dangers of climate change and the need to combat it has increased significantly. Today, there is a broad consensus that our lifestyles and consumption habits need to change in order to mitigate the negative effects of climate change. This change in mindset has major implications for the economy, as it increases the likelihood of strong regulatory constraints in the form of carbon policy changes to reduce emissions of carbon dioxide and other greenhouse gases. In addition, a widespread change in individual consumer behavior could lead to less demand for products from unsustainable companies. This ongoing process of changing economic conditions, which penalizes business models that rely heavily on the use of fossil fuels, is known as the transition process. As a result, the profit prospects of these companies will most likely decline as the transition process progresses.

However, this does not mean that brown assets will necessarily yield negative returns. Under the assumption of an efficient market, the anticipated course of the transition process is already priced in today's asset values and the expected return should be in correspondence with its systematic risk. Since the course of the transition process is unknown and it has an impact on a wide range of assets, the uncertainty induced for asset prices by their dependence on the transition process is a systematic source of risk. The standard approach to describe the relationship between systematic risk factors and expected returns is via linear factor models. A systematic risk factor is there modelled by a risk-mimicking factor portfolio and the exposure of an asset towards a risk factor is determined as the coefficient of a linear regression of the asset returns on the factor returns. In a consecutive step, cross-sectional regressions can determine the risk premiums associated to the systematic risk factors. This approach is applied by Görgen et al. (2020) to quantify the transition risk of a company as the so-called carbon beta coming from a factor model which extends the four-factor model of Carhart by a fifth factor, the Brown-Minus-Green (BMG) factor. The classical way to hedge stocks against equity risks like the transition risk is to buy option contracts. Hence, option prices contain forward looking information about the market's expectations about future risks induced by the transition process.

Options can be expensive for several reasons. First and foremost, the option price rises when the (expected) physical volatility of the underlying increases. In the classical Black-Scholes model, there is no uncertainty with regard to the future volatility of the security, which is assumed to be a constant, and besides the parameters specified in the option contract, the volatility fully determines the price of an option. Nowadays, it is a generally recognized fact that option prices contain volatility and jump risk premiums. The former can be interpreted as a hedge against rising uncertainty, whereas the latter is due to the circumstance that equity risk is not purely diffusive. This corresponds to the image that there are some big news such as policy changes or earning announcements which are instantaneously processed by the market and lead to a significantly different valuation of a company. In the case of downside jumps of large magnitude, the associated risk is often referred to as downside tail risk. Since options provide a hedge against rising volatility and jumps they are more expensive when the uncertainty about the future volatility or the probability of jumps of the underlying stock price process is high. Last but not least, Cao and Han (2013) provide some evidence that option dealers charge a premium for options on stocks with high idiosyncratic volatility. These options are more difficult to hedge and consequently the costs of arbitrage are higher.

In the course of this paper, we study the relationship between the exposure towards transition risk measured via the carbon beta proposed by Görgen et al. (2020) and the hedging costs of option protection on an individual firm level. We examine whether the risks associated with the transition process are priced in the options market for green companies in the same way as for brown ones. The answer to this question provides important insights for risk management as the risks associated with green companies are highlighted. This is particularly relevant in light of the sharp rise in popularity of sustainability funds, which by design are heavily dependent on the transition process of the economy. We present evidence that this one-sided focus results in increased volatility and tail risks.

In order to derive testable implications for the relationship between the carbon beta and higher-order risk premiums, we need a theoretical framework that relates the factor structure of equity returns, i.e. the betas of a firm derived from a factor model, to option prices and in particular the pricing of volatility and jump risks. The foundations of such a framework were laid by Christoffersen et al. (2018), who investigate the implications of a single-factor structure for equity returns on option prices. We apply their results to a multi-factor setting to derive hypotheses about how the carbon beta is related higher-order risks and then test these hypotheses.

In our baseline analysis, we examine the connection between a stock's carbon beta and its option's expensiveness measured via the at-the-money (ATM) Black-Scholes implied volatility (IMPVOL), which is essentially just a scaled version of the option price relative to the Black-Scholes model. We find that the implied volatility rises symmetrically around zero with the absolute value of the carbon beta. This implies that not the sign of the transition risk, i.e. whether a company profits from a slow or fast transition to a low-carbon economy, is relevant for the cost of option protection, but the strength of the dependence on the transition process independent of the sign.

As indicated previously, the real world deviates from the assumptions of the Black-Scholes model in particular due to the presence of stochastic volatility and random jumps which are associated with corresponding risk premiums. Since implied volatilities are derived from market prices for options, there are two ways to interpret them. One the one hand, they are a proxy for the risk-neutral expectation of future volatility. On the other hand, one can think of them as the sum of the expected future volatility under the physical probability measure and the various higher-order risk premiums. A deeper comprehension of the relationship between a firm's exposure towards transition risk and its option's expensiveness requires to examine the connection between the carbon beta and the several risk components included in implied volatilities. In particular, it is important to understand to what extend the increase in option's expensiveness is coming from the market's anticipation of volatility, jump and tail risks.

For this purpose, we analyse daily rebalanced delta-hedged option returns, where the position is initialised 30 days before the expiration date and held until maturity. Delta-hedged option returns have the benefit that they eliminate most of the influence of the underlying stock - in particular potential first-order equity risk premiums - and allow us to focus on higher-order risk premiums. Also in this case, we find statistically significant evidence for a strong negative relationship between the absolute value of a firm's exposure towards transition risk and the delta-neutral returns which indicates a symmetric increase in anticipated higher-order risks for brown and green companies. This result contradicts the previous literature which so-far documented a one-sided relationship in the sense that brown firms are associated with higher uncertainty about future volatility and jump risk compared to green ones (Cao et al. (2023)). At this point, we would like to point out that these apparent contradictions are partially based on the terminological subtlety of what is meant by the terms green and brown and how they are measured. Furthermore, we provide evidence that the perception of transition-related variance risk has evolved over time and that the observed symmetry is a relatively recent phenomenon. This may also explain some of the inconsistencies with the earlier literature. We proceed by studying different measures derived from option prices and returns from option strategies to untangle the higher-order risk premiums and examine the impact of transition risk on volatility, jump and tail risk premiums separately.

To focus on the diffusive risk of a general increase in stock volatility, we study the variance risk premium computed as the difference between the risk-neutral expected volatility extracted from market option prices and the realized volatility as an unbiased estimator of the expected physical volatility over the same time horizon, following the path of Britten-Jones and Neuberger (2000), Carr and Wu (2009) as well as Bollerslev et al. (2009). We conjecture a symmetric relationship between transition risk and the anticipated variance risk. This hypothesis is based on the observation that if stock returns obey the factor structure proposed by Görgen et al. (2020), the variance of both very green and very brown companies, i.e. the ones with a high absolute dependency on the transition process, grows quadratically in and hence independent of the sign of the carbon beta. By looking at the variance risk premium we study the anticipated uncertainty about future volatility. Under the much more restrictive assumptions of the consumption capital asset pricing model (CCAPM) of Breeden (1979), it is shown in Heston (1993) that the variance risk premium should be linear in the current spot variance level. Combining these two considerations yields that the variance risk premium should be an approximately quadratic function of the carbon beta. From a less theoretical point of view, it seems only logical that the uncertainty about the future volatility of the transition process itself impacts brown and green companies in the same way leading to higher option prices.

Subsequently, we apply a measure developed by Kelly et al. (2016) which measures the implied volatility slope of out-of-the-money (OTM) put options to proxy for downside tail risk. In the case of jumps it is much more difficult to provide a theoretical argument for a symmetric risk premium with respect to the carbon beta. This is mainly due to the fact that the distribution of jump sizes can be highly asymmetrical. In particular, it could be that events leading to a strong unexpected acceleration of the transition process are more likely than events causing a strong slowdown. Consequently, the probability of large value drops of brown stocks would be more likely than for green ones and we would expect the downside tail risk of brown firms to be higher.

This line of reasoning is followed by Ilhan et al. (2021), who examine the relationship between a firm's carbon intensity and its downside tail risk as measured by the implied volatility slope. Carbon-intense companies are much more affected by new carbon policies in opposite to firms with low carbon intensities. The authors argue that future carbon policy changes could impose restrictions and significant taxes on carbon emissions, leading to a deterioration of the income prospects of brown assets. In addition, one could make the argument that brown companies are more likely to be associated with bad news in form of environmental scandals.

However, these considerations ignore the possibility that green companies may also be exposed to tail risks that brown companies are not exposed to. High-carbon business models tend to be tried-and-tested, whereas green business models tend to be progressive and much of their valuation is based on potential future rather than actual current profits. Accordingly, these companies should be exposed to the risk of significant asset losses if the economic conditions do not develop as anticipated and the business model therefore fails to deliver profits or only does so significantly later than expected. Such a slowdown of the transition process could be caused, for example, by the sudden realisation that certain technological innovations require more time than originally thought or the demand for green alternatives to existing products is lower than expected.

In fact, we find that for companies with a strongly negative carbon beta, the implied volatility slope is on average much steeper than for companies with comparable positive values. This suggests that the market anticipates larger downside tail risks for firms that are designed for a rapid transition to a low-carbon economy than for firms which profit from a slow transition.

With our work we contribute to the growing strand of literature dealing with the impact of climate change induced risks on financial markets. The work in this field can be categorized mainly according to the type of risk and the class of financial products examined. In terms of risk, a distinction is made primarily between physical climate risk and transition risk, which is often used synonymously with the term carbon risk. In our work we concentrate on the latter. With regard to asset classes, various markets have been studied, with most of the previous work on transition risk focusing on the stock market, drawing a relatively clear picture.

Matsumura et al. (2014) provide evidence that the values of firms in the S&P 500 are negatively related to their carbon emissions and the decision to not disclose them. Alessi et al. (2021) examine stock returns of European companies finding that green and more transparent stocks are associated with lower returns and hence lower costs of capital. Similarly, Bolton and Kacperczyk (2021) study the impact of carbon emissions on stock returns in the US. They find that stocks of firms with higher carbon emissions earn higher returns and interpret this as a carbon premium. In the same spirit, Hsu et al. (2023) investigate the impact of industrial pollution on asset prices and demonstrate a pollution premium paid for stocks with high toxic pollution. Following on from their previous work, Bolton and Kacperczyk (2023) examine global stock returns to estimate the market-based premium associated with carbon-transition risk. Once again they find evidence that firms with higher carbon emissions have higher stock returns in the cross-section. Approaches of hedging climate and carbon risks using low-carbon indices or green bonds are considered for example in Andersson et al. (2016) or Jin et al. (2020).

All aforementioned work uses actual carbon or toxic emissions as proxy for the carbon respectively pollution risk of a company. Most recently, a start has been made on developing other measures that more adequately reflect climate-induced risk on firm-level. Görgen et al. (2020) apply a factor model approach to measure transition risk in a capital-market orientated manner. While the carbon factor they construct can explain cross-sectional variation in stock returns well, they find no evidence of a premium associated with it.

Berkman et al. (2021) use data from 10-K disclosures to construct a firm-specific measure of climate risk and find that it is negatively related to market values of companies. Last but not least, Sautner et al. (2023) extract information from earnings calls about the attention paid by participants to the company's climate risk exposure and show that their measure has pricing implications for options and equity markets.

The existing literature on the pricing of climate-related risks in the options market is relatively small, even though options can provide valuable insights on the types of risk one is dealing with and the costs of hedging them. Ilhan et al. (2021) provide evidence that the cost of option protection against downside tail risk is larger for carbon-intense companies. On the other hand, they do not find a significant relationship between the carbon-intensity of a firm and the volatility risk premium extracted from option prices. Cao et al. (2023) focus on a related but slightly different notion of risk, the ESG risk, and its implications for option returns. They find that poor corporate social responsibility performance of firms in the form of low ESG ratings is associated with lower delta-hedged and straddle returns, indicating perceived higher volatility and jump risk.

However, the existing literature on the pricing of climate-induced risks in the derivatives market differs from our work in two substantial points. First, the approach to use a capital market orientated indirect measure as main explanatory variable to capture not necessarily how carbon-intense or sustainable a company is, but rather the dependence on the transition process, is new to the best of our knowledge. Second, and related to that, the previous literature documents a non-symmetric relationship in the sense that brown firms are associated with more expensive options and increased anticipated volatility and jump risks.

The last point obviously applies not only to the previous work on the options markets but also to the work on the equity markets referenced above. The existing literature on transition risk mainly focus on the downside risk for carbon-intense business models, so-called "sunset" industries, and neglects potential downside risks of green business models designed for a fast transition as stated in Semieniuk et al. (2021). There are only a few contributions that provide a two-sided view of transition risk and the associated danger of a "green bubble" as for example Borio et al. (2023). With our work, we contribute to closing this gap in the literature by providing a symmetrical view of the risks induced by the transition process for green and brown companies.

The paper proceeds as follows. Section 2 provides a theoretical yet heuristic framework which allows us to motivate our hypothesis, that the physical volatilies as well as the variance risk premiums of stocks should rise symmetrically around zero with increasing absolute values of their carbon betas. Section 3 describes the data and methodology used to compute the carbon betas and the option measures. In Section 4, we present our empirical results and Section 5 concludes.

2 Theoretical foundations

Our theoretical framework aims to establish a connection between the underlying factor structure of a stock and option returns on that stock. Therefore, we extend ideas of Christoffersen et al. (2018), who examine the implications of a stock price process obeying a single-factor structure on the implied volatility surface extracted from option prices. For the beginning, we notice that Görgen et al. (2020) propose a factor structure for equity returns given by

$$\begin{aligned} r_{i,t} - r_{f,t} = &\beta_i^{\text{mkt}} r_{M,t} + \beta_i^{\text{SMB}} \text{SMB}_t + \beta_i^{\text{HML}} \text{HML}_t \\ &+ \beta_i^{\text{WML}} \text{WML}_t + \beta_i^{\text{BMG}} \text{BMG}_t + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where the return of stock i at time t is explained by the factors of the four factor model of Carhart (1997) complemented by the BMG factor and an idiosyncratic component. For the moment, we abstract from this concrete factor model and assume that stocks obey an arbitrary factor structure. Therefore, let Φ denote the finite set of risk factors governing equity returns, inducing the factor structure

$$r_{i,t} - r_{f,t} = \sum_{F \in \Phi} \beta_i^F F_t + \epsilon_{i,t}. \tag{2}$$

If we interpret the systematic factors F_t and the idiosyncratic component $\epsilon_{i,t}$ as random quantities as in the arbitrage pricing theory of Ross (1976) and assume that the factors are uncorrelated with the noise term, we obtain a variance decomposition of the returns

$r_{i,t}$ via

$$
\begin{aligned}
Var(r_{i,t}) &= \sum_{F,\tilde{F}\in\Phi} \beta_i^F \beta_i^{\tilde{F}} Cov(F_t, \tilde{F}_t) + Var(\epsilon_{i,t}) \\
&= \sum_{F\in\Phi} \left(\beta_i^F\right)^2 Var(F_t) + \sum_{\substack{F,\tilde{F}\in\Phi \\ F\neq\tilde{F}}} \beta_i^F \beta_i^{\tilde{F}} Cov(F_t, \tilde{F}_t) + Var(\epsilon_{i,t}).
\end{aligned} \tag{3}
$$

We notice that the overall variance of the stock return is given as the sum of the factor variances weighted with the squared factor loadings, the factor covariances weighted with the product of the corresponding factor loadings and the idiosyncratic variance of the stock. In particular, for a given point in time t, the cross-sectional variance is a function of the factor loadings β_i^F. If we assume that the factor covariances are small compared to the factor variances, which is a plausible assumption since the factors aim to capture orthogonal risk sources, the return variance of stock i is approximately

$$
Var(r_{i,t}) \approx \sum_{F\in\Phi} \left(\beta_i^F\right)^2 Var(F_t) + Var(\epsilon_{i,t}). \tag{4}
$$

In summary, the physical volatility of a stock increases approximately with the square of the factor loadings and, in particular, should be independent of the signs of these factor loadings.

The usual approach in option pricing is to model the underlying stock price by a diffusion process with stochastic volatility and/or random jumps, ignoring the potential factor structure of the underlying stock. However, it is possible to extend the modelling of the stock price process to include the underlying factor structure as demonstrated by Christoffersen et al. (2018). This extension provides a connection between a stock's factor loadings and higher-order risk premiums. In the spirit of the Heston model, we model each risk factor F_t according to a stochastic volatility diffusion process where the variance obeys a Feller square root process:

$$
\begin{aligned}
\frac{dF_t}{F_t} &= \mu_F dt + \sigma_{F,t} dW_t^{(F,1)}, \\
d\sigma_{F,t}^2 &= \kappa_F(\theta_F - \sigma_{F,t}^2)dt + \delta_F \sigma_{F,t} dW_t^{(F,2)}, \qquad F \in \Phi.
\end{aligned} \tag{5}
$$

For the sake of simplicity, we allow the two Wiener processes belonging to the same factor to be correlated but assume that they are uncorrelated for different factors, i.e.

$$\begin{aligned} dW_t^{(F,1)} dW_t^{(F,2)} &= \rho_F dt, \\ dW_t^{(F,n)} dW_t^{(\tilde{F},m)} &= 0, \qquad\qquad n,m \in \{1,2\}, F \neq \tilde{F}. \end{aligned} \tag{6}$$

Combining (5) with the factor structure in (4) implies a model for the stock price process given as

$$\frac{dS_t^i}{S_t^i} = r_f dt + \sum_{F \in \Phi} \beta_i^F \frac{dF_t}{F_t} + \sigma_{i,t} dW_t^{(i,1)}, \tag{7}$$

$$d\sigma_{i,t}^2 = \kappa_i(\theta_i - \sigma_{i,t}^2)dt + \delta_i \sigma_{i,t} dW_t^{(i,2)}. \tag{8}$$

We can rewrite (7) as

$$\frac{dS_t^i}{S_t^i} = \big(r_f + \sum_{F \in \Phi} \beta_i^F \mu_F\big)dt + \sum_{F \in \Phi} \beta_i^F \sigma_{F,t} dW_t^{(F,1)} + \sigma_{i,t} dW_t^{(i,1)}. \tag{9}$$

To derive predictions about higher-order risk premiums in this setting, it is necessary to make an assumption about the concrete from of the stochastic discount factor M_t. Analogously to Christoffersen et al. (2018), following Heston (1993) and many others, we assume a market price of factor volatility risk that is linear in the factor spot volatility level, i.e.

$$Cov\left(\frac{dM_t}{M_t}, d\sigma_{F,t}\right) = \lambda_F \sigma_{F,t} dt \quad \Leftrightarrow \quad Cov\left(\frac{dM_t}{M_t}, d\sigma_{F,t}^2\right) = \tilde{\lambda}_F \sigma_{F,t}^2 dt. \tag{10}$$

Christoffersen et al. (2018) proved that the factor structure governing the stock price process under the $\mathbb{P}$-measure is preserved under the $\mathbb{Q}$-measure. Therefore, we are able to explicitly compute the variance risk premium as the difference between the expected integrated variance of the stock with respect to the $\mathbb{P}$- respectively the $\mathbb{Q}$-measure. Let $V_{i,t}$ therefore denote the spot variance level of stock j at time t. Since we assumed that the factors are uncorrelated, the spot variance becomes

$$V_{i,t} = \sum_{F \in \Phi} \big(\beta_i^F\big)^2 \sigma_{F,t}^2 + \sigma_{i,t}^2. \tag{11}$$

We can compute the difference of the expected integrated variance between t_0 and T conditioned on t_0 with respect to the $\mathbb{P}$- respectively $\mathbb{Q}$-measure as

$$\begin{aligned} &\mathbb{E}_{t_0}^{\mathbb{P}}\left[\int_{t_0}^{T} V_{j,t}dt\right] - \mathbb{E}_{t_0}^{\mathbb{Q}}\left[\int_{t_0}^{T} V_{j,t}dt\right] \\ = &\sum_{F\in\Phi} \left(\beta_i^F\right)^2 \cdot \left(\mathbb{E}_{t_0}^{\mathbb{P}}\left[\int_{t_0}^{T} \sigma_{F,t}^2 dt\right] - \mathbb{E}_{t_0}^{\mathbb{Q}}\left[\int_{t_0}^{T} \sigma_{F,t}^2 dt\right]\right) + \mathbb{E}_{t_0}^{\mathbb{P}}\left[\int_{t_0}^{T} \sigma_{i,t}^2 dt\right] - \mathbb{E}_{t_0}^{\mathbb{Q}}\left[\int_{t_0}^{T} \sigma_{i,t}^2 dt\right] \\ &\sim (T - t_0) \sum_{F\in\Phi} \left(\beta_i^F\right)^2 \cdot \tilde{\lambda}_F \sigma_{F,t_0}^2, \end{aligned} \tag{12}$$

where we assumed for the last equality sign that idiosyncratic variance risk is not priced. Equation (12) provides us with the testable implication of whether the variance risk premium increases quadratically with the carbon beta, as we are able to estimate the LHS of (12) in a model-free manner using liquid option prices by applying the methods developed by Britten-Jones and Neuberger (2000), Jiang and Tian (2005), Carr and Wu (2009) and Bollerslev et al. (2009).

Since the main option measure that we study are delta-hedged gains of ATM options, we are interested in a model prediction for the relationship between the carbon beta and these gains. We refrain from a rigorous derivation - which should be possible in principle in this specific model framework - and instead provide a heuristic argument based on Bakshi and Kapadia (2003). They study the fundamental case of expected delta-hedged gains $\pi_{t_0,T}$ of near-the-money options in the Heston model with a volatility risk premium linear in the spot volatility level and show in Proposition 2 that these positions should earn the volatility risk premium and therefore be proportional to the (systematic) spot volatility level. Transferred to our setting, this suggests that

$$\mathbb{E}_{t_0}^{\mathbb{P}}\left[\pi_{t_0,T}\right] \sim \sqrt{V_{i,t_0} - \sigma_{i,t_0}^2} = \sqrt{\sum_{F\in\Phi} \left(\beta_i^F\right)^2 \sigma_{F,t_0}^2}. \tag{13}$$

This poses some problems since the linear decomposition of the variance as in (3) does not transfer directly to the volatility due to the square root. However, we notice that an application of the well-known inequality for the relationship between the 1- and 2-norm on $\mathbb{R}^n$,

$$\|x\|_2 \leq \|x\|_2 \leq \sqrt{n}\|x\|_2, \tag{14}$$

yields

$$\sqrt{\sum_{F\in\Phi}\left(\beta_i^F\right)^2\sigma_{F,t_0}^2} \leq \sum_{F\in\Phi}|\beta_i^F|\sigma_{F,t_0} \leq \sqrt{|F|}\sqrt{\sum_{F\in\Phi}\left(\beta_i^F\right)^2\sigma_{F,t_0}^2}. \tag{15}$$

Therefore, it should be reasonable to approximate the RHS of (13) via

$$\sqrt{\sum_{F\in\Phi}\left(\beta_i^F\right)^2\sigma_{F,t_0}^2} \approx \sum_{F\in\Phi}|\beta_i^F|\sigma_{F,t_0}. \tag{16}$$

Overall, we obtain the testable implication that it should roughly hold

$$\mathbb{E}_{t_0}^{\mathbb{P}}\left[\pi_{t_0,T}\right] \sim \sum_{F\in\Phi}|\beta_i^F|\sigma_{F,t_0}. \tag{17}$$

In particular, we would expect that the delta-hedged gains increase roughly linear with the absolute value of the carbon beta.

So far, we focussed exclusively on the link between exposure to the transition process and volatility risk and predicted a symmetric relationship. We would also be interested to derive predictions how the carbon beta is related to jump and in particular downside tail risk premiums. Our main measure for downside tail risk is the slope of the implied volatility moneyness curve for OTM put options, which is determined by the risk-neutral equity skewness. In their model, Christoffersen et al. (2018) derive a relation between the risk-neutral equity skewness on the one side and the betas of the stock and the risk-neutral factor skewnesses on the other side. Expressed in terms of our extended setting, they show that it holds

$$\begin{aligned} Sk^{\mathbb{Q}}\left(\int_{t_0}^{T}\frac{dS_t^i}{S_t^i}\right) = &\sum_{F\in\Phi}\left(\beta_i^F\right)^3\left(\frac{\mathbb{E}_{t_0}^{\mathbb{Q}}\left[\int_{t_0}^{T}\sigma_{F,t}^2 dt\right]}{\mathbb{E}_{t_0}^{\mathbb{Q}}\left[\int_{t_0}^{T}V_{i,t}dt\right]}\right)^{3/2}\cdot Sk^{\mathbb{Q}}\left(\int_{t_0}^{T}\frac{dF_t}{F_t}\right) \\ &+\left(\frac{\mathbb{E}_{t_0}^{\mathbb{Q}}\left[\int_{t_0}^{T}\sigma_{i,t}^2 dt\right]}{\mathbb{E}_{t_0}^{\mathbb{Q}}\left[\int_{t_0}^{T}V_{i,t}dt\right]}\right)^{3/2}\cdot Sk^{\mathbb{Q}}\left(\int_{t_0}^{T}\sigma_{i,t}dW_t^{(i,1)}\right). \end{aligned} \tag{18}$$

From equation (18) we expect an asymmetric relationship around zero between the carbon beta and the anticipated downside tail risk, since the risk-neutral skew is proportional to the cubic factor sensitivities and hence the sign of beta matters. However, to make a prediction about the direction of this relationship - i.e. whether brown or green firms are exposed to higher tail risks - we would need the risk-neutral skew of the BMG factor. The factor skew is determined by the physical probabilities of large upward and downward jumps of the BMG-factor and investors' preferences for the respective states of the world. A priori, it is not clear whether a sudden slow-down or speed-up of the transition process is more likely and whether investors like or dislike the associated states.

3 Data and methodology

3.1 Carbon beta

Our main proxy for a firm's exposure towards transition risk is the carbon beta proposed by Görgen et al. (2020). The carbon beta is determined as the regression coefficient in front of the BMG factor in the equation

$$\begin{aligned} r_{i,t} - r_{f,t} = &\alpha_i + \beta_i^{\text{mkt}} r_{M,t} + \beta_i^{\text{SMB}} \text{SMB}_t + \beta_i^{\text{HML}} \text{HML}_t \\ &+ \beta_i^{\text{WML}} \text{WML}_t + \beta_i^{\text{BMG}} \text{BMG}_t + \epsilon_{i,t}, \end{aligned} \tag{19}$$

The BMG factor is constructed as the return of a long-short portfolio that is long in brown assets, which profit from a slow transition towards a low-carbon economy, and short in green assets, which conversely benefit from a fast transition. Hence, a positive value of the carbon beta indicates a brown company whereas a negative carbon beta is associated with a firm designed for a fast transition. The regression equation in (19) is evaluated on the basis of daily stock returns in the year prior to the corresponding initialisation date on which the option measures are calculated or, in the case of returns, the option position is built up. The four daily factors of the factor model of Carhart are obtained from the data library of Kenneth R. French. The BMG factor is publicly available on a daily basis from the beginning of 2010 until the end of 2019. Furthermore,Görgen et al. (2020) provided us with an updated version of the BMG factor up to April 2023. Hence, we are able to compute carbon betas from the beginning of 2011 until April 2023. We obtain split-adjusted daily stock returns from the OptionMetrics database for the US market. We exclude a carbon beta if one of the following two criteria was met: (i) at least one day for which OptionMetrics was not able to compute a daily return, (ii) less than 240 daily returns available in the prior year to evaluate (19).

3.2 Option measures

3.2.1 Implied volatility

Equity options usually expire at the third Friday of every month. All our option measures are calculated on a monthly basis from option prices exactly thirty days before expiration T. If the exchange was closed at that particular day, we choose the next day on which the exchange was open. We call these dates t_0 initialisation dates. Due to the limited availability of our main explanatory variable, the carbon beta, we concentrate on initialisation dates in the time period from January 2011 until February 2023 yielding a total of 146 initialisation dates. For our first measure, the implied volatility $IMPVOL$, we select for each security for which options are available exactly one ATM option, i.e. the one for which the strike is closest to the current spot price. Subsequently, we filter the option universe according to the following filter criteria: (i) the security is a common stock, (ii) the option has a standard settlement, (iii) the open interest is greater than zero, (iv) the option's midprice is at least 1/8 \$, (v) there exists a best bid greater than zero and less than or equal to the best offer, (vi) the option's Black-Scholes delta exists and has an absolute value less than or equal to 1, (vii) the option's underlying security does not pay any dividends until expiration, (viii) the option's midprice satisfies the usual upper and lower arbitrage bounds, (ix) the option's moneyness is greater than 0.9 and less than 1.1. For condition (viii), we need risk-free rates. Here and in other situations where we need riskless interest rates, we use the zero curve rates provided by OptionMetrics, linearly inter- or extrapolated if necessary.

For the options satisfying the above filter criteria, we select the Black-Scholes implied volatility provided by OptionMetrics as our first option variable measuring the option's expensiveness relative to the Black-Scholes model. We also consider the implied variance, which is simply the square of the implied volatility, as our model yields more rigorous predictions in the variance case.

3.2.2 Delta-hedged return

We initialise the delta-neutral positions at the above mentioned initialisation dates t_0 thirty days prior to expiration T. We apply the same filter criteria as in the case of the implied volatility, hence obtaining the same option universe. The portfolio consists of a long position in the option, which is delta-hedged with the underlying security. The fraction of the stock is rebalanced daily and the position is closed at expiration date. If there was no delta available for a certain trading day, the position is not rebalanced and we use the latest delta available. The net gain of the delta-neutral position is given as

$$\pi_{t_0,T} = V_T - V_{t_0} - \sum_{j=1}^{n} \left[\Delta_{t_j}(S_{t_{j+1}} - S_{t_j}) + (V_{t_j} - \Delta_{t_j} S_{t_j}) \left(e^{r_{t_j}(\tau_j) \cdot \tau_j} - 1 \right) \right]. \tag{20}$$

V_t is the option's value measured as the midprice, whereas S_t is the stock price, Δ_t the option's Black-Scholes delta and $r_t(\tau)$ the risk-free rate at time t for a runtime τ. For comparison, we rescale the net gains of the delta-hedged position by dividing through the absolute value of the position at initialisation date: [1]

$$r^{\Delta}_{t_0,T} = \frac{\pi_{t_0,T}}{|V_{t_0} - \Delta_{t_0} S_{t_0}|} = \begin{cases} \pi_{t_0,T} / (\Delta_{c,t_0} S_{t_0} - C_{t_0}), \\ \pi_{t_0,T} / (P_{t_0} - \Delta_{p,t_0} S_{t_0}). \end{cases} \tag{21}$$

3.2.3 Variance risk premium

A commonly used definition of the variance risk premium is as the difference of the expected variance under the physical $\mathbb{P}$-measure and the risk-neutral $\mathbb{Q}$-measure. Under the assumption that the stock price process S_t is given as a diffusion process with stochastic volatility σ_t, we can define the realized variance of the stock from time t_0 up to T as

$$RV_{t_0,T} := \int_{t_0}^{T} \sigma_t^2 dt = \int_{t_0}^{T} \left(\frac{dS_t}{S_t} \right)^2. \tag{22}$$

[1] The results are robust to alternatively scaling by the spot price of the underlying at initialisation date.

The annualized variance risk premium between t_0 and T can now be defined as

$$VRP_{t_0,T} := \frac{1}{T-t_0}\Big(\mathbb{E}^{\mathbb{P}}_{t_0}[RV_{t_0,T}] - \mathbb{E}^{\mathbb{Q}}_{t_0}[RV_{t_0,T}]\Big), \tag{23}$$

where $\mathbb{E}^{\mathbb{P}}_{t_0}$ and $\mathbb{E}^{\mathbb{Q}}_{t_0}$ are the expected values with respect to the probability measures $\mathbb{P}$ respectively $\mathbb{Q}$ conditioned on the current time t_0.

Britten-Jones and Neuberger (2000) established a connection between the risk-neutral expectation of the variance and the market prices of European call options. They show that under suitable assumptions, it holds

$$\mathbb{E}^{\mathbb{Q}}_{t_0}\left[RV_{t_0,T}\right] = 2\int_0^\infty \frac{C_{t_0}(T,K)/B(t_0,T) - \max(S_{t_0}/B(t_0,T) - K, 0)}{K^2} dK, \tag{24}$$

where

$$B(t_0,T) = e^{-r_{t_0}(T-t_0)\cdot(T-t_0)}$$

is the price of a zero bond at t_0 that pays off one dollar at time T and $C_{t_0}(T,K)$ is the market price of a European call option with strike K and maturity T at time t_0. Hence, we require a continuum of call option prices with respect to the strike price K expiring in T to compute the risk-neutral expected variance. To estimate $\mathbb{E}^{\mathbb{Q}}_{t_0}\left[RV_{t_0,T}\right]$ empirically, we generate a fine grid of synthetic call option prices extracted from actual market prices to evaluate the integral in (24) using the trapezoid rule following the approaches of Carr and Wu (2009) as well as Jiang and Tian (2005). To ensure that the approximation is reasonable, we filter the security universe at each initialisation date t_0 according to the following criteria: (i) at least five call options with open interest greater 0 and expiration T in thirty days, (ii) at least two of these options being OTM ($S_t/K < 1$), (iii) at least two of these options being ITM ($S_t/K > 1$) and (iv) at least one of these options being close to ATM ($0.8 < S_t/K < 1.2$). For further details on the computation, we refer to Appendix B.

As an empirical counterpart to $\mathbb{E}^{\mathbb{P}}_{t_0}[RV_{t_0,T}]$, we choose the observed realized variance of the stock over the same time horizon from initialisation date t_0 until expiration T using daily log-returns:

$$\widehat{\mathbb{E}}_{t_0}^{\mathbb{P}}[RV_{t_0,T}] := \frac{1}{n-1}\sum_{j=1}^{n} \log\left(\frac{S_{t_j}}{S_{t_{j-1}}}\right), \qquad t_0 < \cdots < t_n = T. \tag{25}$$

We remark that (25) provides an unbiased estimator of the expected variance under the physical measure. Hence, we are able to compute an empirical estimate of the variance risk premium $VRP_{t_0,T}$ of the stocks that fulfil the filter criteria stated above.

3.2.4 Implied volatility slope

The implied volatility slope is a measure introduced by Kelly et al. (2016) to capture the downside tail risk associated with a security. The function which relates option moneyness to implied volatility is not flat as suggested by the Black-Scholes model but rather exhibits a skew. In the case of put options, the implied volatility typically increases as the option gets more OTM. This is due to the fact that far OTM put options provide a hedge against large value drops of the stock (i.e. the downside tail risk). The steeper the slope of this implied volatility function, the more expensive it is to purchase a hedge against downside tail risk and the higher the anticipated risk.

In this case, we measure the moneyness via the option delta following the precise approach of Kelly et al. (2016). We filter our security universe by considering only stocks for which, at a given initialisation date t_0, there are at least three put options expiring thirty days later, which satisfy both (i) $0.5 < \Delta < -0.1$ and (ii) the open interest being greater than zero. Then, the measure for downside tail risk *slopeD* is computed as the coefficient of an OLS regression of the implied volatilities of all the options surviving the filter criteria on their deltas.

4 Empirical results

4.1 Implied volatility

We start our analysis by studying the relationship between a firm's carbon beta and its option implied volatility. As argued before, the implied volatility is essentially a scaled version of the option price relative to the Black-Scholes model. Since it is obtained from market prices, implied volatility captures not only the market's expectation about future volatility of the underlying but includes also various potential higher-order risk premiums contained in option prices such as volatility and jump risk premiums. It can thus be interpreted as a proxy for risk-neutral expected volatility of the stock over the lifetime of the option.

From section 3, we know that the factor structure is preserved under the $\mathbb{Q}$-measure and hence the variance decomposition in equation (3) holds also for the implied variance. Therefore, we would expect a linear relationship between the squared carbon beta and the implied variance of the stock. We test this hypothesis in table 7, finding a highly significant relationship with a coefficient of 0.023 in the univariate regression (t-statistic of 13.179) which decreases to 0.011 after adding control variables but remains highly significant (10.065). This shows that options tend to be more expensive as the carbon beta of the underlying grows in absolute value.

As argued before, the expected linear relationship between the squared carbon beta and (implied) variance approximately translates to a linear relationship between the absolute value of the carbon beta and (implied) volatility. It has some benefits to empirically work with the volatility instead of the variance even though the predictions are not completely rigorous in this case. The main reasons for this are that volatility is easier to interpret and that the regression results are not that much driven by the tail values of the implied volatility and the carbon beta as in the case of squared values.

Table 8 contains the regression results of ATM implied volatility on the absolute value of carbon beta. The univariate regression indicates an increase in the implied volatility of call options of 8.8 percentage points (t-statistic = 23.603) when the absolute value of the carbon beta increases by 1. This relationship slightly decreaes to 4.2 percentage points but remains highly significant (16.192) after including several control variables typically used to explain implied volatilities, as well as the absolute values of the other betas from the factor model. We obtain almost the same results when considering put options.

Overall, the results show that the option price measured via implied volatility increases symmetrically around zero in the absolute vale of carbon beta. Therefore, options on firms that depend strongly on the transition process tend to be more expensive independent of whether they profit from a fast or slow transition. A large fraction of this increase is likely due to increased expected physical volatilities for firms with a large absolute value of carbon beta as suggested by the variance decomposition in (3). To further investigate the connection between carbon beta and perceived volatility and jump risk, we move to option-based measures that allow us to isolate these higher-order risk components from the expected physical variance.

4.2 Delta-hedged returns

4.2.1 Baseline results

In a Black-Scholes world, delta-hedged gains are zero when the hedge is rebalanced continuously and (asymptotically) zero in expectation when the rebalancing is executed discretely as was shown in Bertsimas et al. (2000). When additional sources of uncertainty affect the stock price process, such as random volatility or jumps, delta-hedged gains can have a non-zero physical expectation, as the position is still exposed to the additional risks which may be associated with non-zero risk premiums. For this reason, delta-hedged returns provide the ideal environment to study these higher-order risk premiums.

As argued before, in a stochastic volatility setting, delta-hedged gains are proportional to the volatility risk premium, which in turn is often assumed to be negative and linear in the spot volatility level. The factor structure of stock returns induces a decomposition of the spot variance which approximately allows a decomposition of the spot volatility level. All together, this suggests that delta-hedged returns should roughly be linear in the absolute value of the carbon beta as stated in (17).

We test this prediction by performing regressions of ATM delta-hedged gains over 30 days prior to expiration on the absolute value of the carbon beta computed for stock returns over the year prior to initialisation of the delta-neutral position. Table 9 provides the regression results revealing a strong linear relationship indicating that an increase in the absolute value of carbon beta of one corresponds to a decrease in the scaled delta-hedged gains for call options of 0.361 with a t-statistic of -5.971. Some fraction of this relationship can be explained by control variables but even after adding controls, the regression coefficient is still -0.193 with a t-statistic of -3.345. The regression results for put options are similar.

The results indicate that anticipated volatility risk, measured via delta-hedged returns, grows as the exposure towards the transition process, measured via the carbon beta, increases independently of the sign of beta. Once again, we highlight that this result should not be surprising from an intuitive point of view, as uncertainty about the future volatility of the transition process affects brown and green companies in the same way. Companies with a high absolute value of the carbon beta will be exposed to volatility risk induced by the transition process and therefore options on these companies are more expensive as the charged volatility risk premium is higher.

4.2.2 Evolution over time

The change of economic conditions leading to the transition to a low-carbon economy is a relatively recent phenomenon. Therefore, it is a natural question to ask whether the reception of risks induced by the transition process has changed over time as investors develop a better understanding of them. In particular, we are interested in whether the documented symmetric relationship between the carbon beta and higher-order risk premiums captured via delta-hedged gains has evolved as time progressed.

A first indication that this could be the case are the results of Fama-MacBeth regressions of delta-hedged gains on the absolute value of carbon beta and control variables, which we run as robustness tests on the exact same dataset as before the panel regressions. These results, reported in Table 10, show that the symmetric relation between the carbon beta and delta-hedged gains decreases from -0.361 to -0.297 in the univariate case and becomes insignificant (coefficient of -0.078 with a t-statistic of -1.102) when adding control variables. However, the ESG score as a proxy for sustainability risk is much more significant compared to the panel regressions as it increases from 0.414 (2.654) to 0.43 (4.930). Of course, we need to be careful when comparing t-statistics of panel regressions with time fixed effects to those of Fama-MacBeth regressions, but the results indicate that there are some differences between the regression results that need to be investigated.

One major difference between panel and Fama-MacBeth regressions is that in the former case, each observation contributes to the regression in an equal manner, whereas in the latter case, for each point in time a cross-sectional regression is performed and these cross-sectional regression coefficients contribute equally to the overall coefficient. Therefore, one possible explanation for differences in the results of panel and Fama-MacBeth regressions can occur if the number of observations changes strongly over time. In our panel data set, the number of valid observations increases steadily from roughly 700 in January 2011 to round about 1800 at the end of our observation period in February 2023 as displayed in figure 3. Hence, the observations from the beginning of our observation window are massively overweighted in the Fama-MacBeth regressions compared to the panel regressions. This indicates that the explanatory power of the absolute value of carbon beta for delta-hedged returns gains strength as time progresses, whereas the ESG score loses significance.

To test this hypothesis, we divide our sample into two subsamples and run panel regressions on these subsamples separately. The first subsample contains all observations made before January 1, 2018 whereas the second subsample consists of all observations made after that date. The choice of the split date has two reasons. First, it divides the full sample into two relatively equally sized subgroups. Second, the time window before and slightly after the split date contains a series of events which should have led to a stronger perception of risks induced by the transition process. Notable events in this context are the signing of the Paris Agreement in April 2016, the election of Donald Trump to US president in November 2016, the US withdrawal from the Paris agreement in June 2017 and the momentum gain of the climate movement around the "Fridays for Future" protests starting in August 2018.

As expected from the Fama-MacBeth regression results, the relationship between the carbon beta and delta-hedged returns is much less pronounced for the subperiod from 2011 until 2017. We obtain regression coefficients of -0.101 (t-statistic of -1.497) in the univariate case and of -0.014 (t-statistic of -0.219) after adding control variables. In contrast to that, we find some strong and highly significant relationship for the time period from 2018 until 2023 with a coefficient of -0.62 (t-statistic of -7.532) in the univariate case reducing to -0.251 (t-statistic of -3.552) after controlling for other variables. For the ESG score, we document the opposite effect as it loses its significance in the more recent subperiod.

To summarise, we found evidence that the anticipation of higher-order risks for firms that depend heavily on the transition process has increased significantly in recent years. Volatility can be interpreted as a measure for the intensity with which price-relevant information appear on the market. Volatility risk can therefore be regarded as the risk that this intensity increases. An economic explanation for the increase of the volatility risk premium induced by the transition process could hence be that investors have been sensitized for the relevance and the possibility of increasing volatility of the transition process due to the aforementioned events taking place between April 2016 and August 2018.

4.3 The model-free variance risk premium

As a supplementary option-based measure for variance risk, we consider the model-free variance risk premium, computed as the difference between the realized variance and the fair price of a synthetic variance swap rate over the same time horizon. The variance swap can be duplicated by a portfolio consisting of a continuum of call options with respect to the strike K, thus enabling us to derive its fair market value using market prices for options.

The advantage of analysing the model-free variance risk premium instead of delta-hedged returns is that the former captures more exclusively diffusive variance risk, whereas the latter is also affected by potential jump risk premiums. Additionally, our model predictions are more rigorous for the model-free variance risk premium than for delta-hedged returns as we do not have to rely on the approximation in (16).

As argued in equation (12), we expect that the model-free variance risk premium grows quadratically in the carbon beta. This hypothesis is tested via panel regressions of the variance risk premium on the squared carbon beta and control variables. The regressions results documented in table 13 reveal a strong negative relationship showing that the anticipated variance risk increases strongly in the squared beta. We obtain a highly significant coefficient of -0.007 with a t-statistic of -4.42 in the univariate case which slightly decreases to -0.004 with a t-statistic of -2.901 after adding control variables.

The results provide supplementary evidence that transition induced variance risk is priced symmetrically for firms benefiting from a fast respectively slow transition.

4.4 Implied volatility slope

Having analysed the relationship between carbon beta and variance risk, we next want to examine how exposure towards transition risk is associated with anticipated jump and downside tail risks in particular. According to our model, we expect an asymmetric relationship as stated in equation (18), whereby the direction of asymmetry is determined by the risk-neutral skewness of the BMG factor and is a priori unclear. The option measure we apply to capture the risk-neutral skewness of the return distribution of the underlying security is the option-implied volatility moneyness slope for OTM put options. This slope measures the increase in expensiveness as the put options become more OTM and therefore a higher slope indicates a risk-neutral return distribution that is more left-skewed, thus having a heavier left tail.

In our baseline panel regression in table 14, we observe an asymmetric relationship between the carbon beta and the implied volatility slope with a coefficient of -0.013, which is significant with a t-statistic of -2.879. The first conclusion we can draw is that the anticipated downside tail risk is larger for green firms than for brown ones. Furthermore, from equation (18) we can deduce that the risk-neutral distribution of the BMG factor should be right-skewed in order to match our observations. This means, that in the risk-neutral world, a sudden deceleration of the transition process, resulting in an upward jump of the BMG factor, is more likely than an abrupt acceleration corresponding to a downward jump. However, this does not necessarily mean that the same holds true for the real world as the risk-neutral distribution also accounts for risk attitudes. Besides asymmetric physical probabilities for upward and downward jumps, it could also be that investors have preferences for states of the world in which the transition process speeds up and dislike states in which it slows down, thus requiring a compensation in form of a risk premium.

We also test the alternative hypothesis of a symmetric relationship by regressing the implied volatility slope on the absolute value of carbon beta, finding no significant relationship. Additionally, we study the impact of a firm's carbon intensity on *slopeD* as done before by Ilhan et al. (2021), finding a highly significant linear relationship with a regression coefficient of 0.007 and a t-statistic of 3.783 matching the previous results of Ilhan et al. (2021). This seems contradictory at first sight, as column (1) of table 14 essentially tells us that firms with a lower carbon beta, which profit from a fast transition to a low-carbon economy, are exposed to higher downside tail risks, whereas column (3) makes the analogous statement for firms with a high carbon intensity. However, these explanatory variables should intuitively have a significant positive correlation since carbon-intense firms should be negatively affected by an acceleration of the transition processes that might induce some regulatory risks for these companies.

This paradox observation provides a hint that the correlation between the carbon beta and the carbon intensity might not be as high as expected and that the variables actually capture different concepts and hence are associated with different interpretations of the notions brown and green. For the full sample, we find a moderate correlation of 0.38 between those two variables. We proceed to compute the conditional covariances where we condition on $\beta_{BMG} > 0$ respectively $\beta_{BMG} < 0$. In the former case, we obtain a medium correlation of 0.37, indicating that for companies identified as rather profiting from a slow transition, increasing carbon intensity corresponds to a stronger sensitivity towards the transition process. However, conditioned on the latter case, the variables are uncorrelated as the correlation coefficient is given by -0.03. This means that for firms which rather benefit from a fast transition, we cannot observe a connection between their carbon beta and their carbon intensity. Therefore, the carbon intensity is not able to identify the firms which are actually very green in the sense that they benefit from a fast transition as these companies are not significantly less carbon-intense than firms which are not sensitive towards the transition process at all. We suspect that this non-trivial correlation structure, which emphasises that the two variables measure different concepts of brown and green, is responsible for the contradicting results.

Additionally, we want to stress that relationship between the carbon beta and the implied volatility slope is robust to the inclusion of several control variables as documented in the columns (5) and (6) of table 14, whereas the explanatory power of the carbon intensity, at least in our sample, completely vanishes.

5 Conclusion

We have analysed the link between the carbon beta proposed by Görgen et al. (2020) and various option measures to examine whether there exists a relationship between a firm's exposure to the transition process and the market expectations about higher-order risks. We begin our analysis by examining the connection between the carbon beta and the implied volatility, which is essentially just a scaled version of the option price and thus contains various risk premiums. We find that the price of an option increase when the underlying asset has a higher exposure to the transition process independent of the sign. To analyse the extent to which this increase is driven by higher-order risk premiums, we study delta-hedged returns, the model-free variance risk premium and the option implied volatility slope to differentiate between variance and downside tail risk.

In the case of variance risk, we documented a symmetric relationship in the sense that the variance risk premium increases with the square of the carbon beta. From an economic perspective, this only makes sense as uncertainty about the future volatility of the transition process should affect firms that benefit from a fast respectively slow transition to a low-carbon economy in the same way.

We then examined the development of this relationship over time and were able to show that it has become considerably stronger in recent years. One explanation for this increase could be that investors have developed an increasingly better understanding of the risks induced by the transition process. This seems plausible, as the relevance of the transition process for asset prices has become clearer due to several events in the time period from 2016 until 2018.

Finally, we analysed the impact of transition risk on the risk of large losses in value, as measured by the increase in the implied volatility of put options when they are progressively further OTM. We found that business models with a negative exposure towards the transition process are associated with higher anticipated downside tail risks than firms with a positive exposure. This suggests that the risk-neutral distribution of the BMG factor that captures transition risk is right-skewed, which in turn may be caused either by higher physical probabilities for a strong deceleration than an acceleration of the transition process or by investor preferences for a rapid transition towards a low-carbon economy.

Furthermore, we investigated the apparent contradiction to the existing literature that documented higher tail risks for carbon-intense firms. We resolve this paradox by looking at the correlation structure of the carbon beta and the carbon intensity, demonstrating that they measure different concepts, in particular for companies that benefit from an accelerated transition process.

Appendix A Variance risk premium

The evaluation of (24) requires the knowledge of call option prices with respect to a continuum of strike prices K ranging from 0 to infinity. Since we can only observe the option market prices for a finite number of strikes, we need a standardised procedure to interpolate these prices. Therefore, we closely follow the approach outlined in Jiang and Tian (2005) as well as Carr and Wu (2009). The basic idea is not to interpolate the prices directly, but rather the associated implied volatilities, which are then converted back into option prices using the Black-Scholes formula. To standardise this procedure, we notice that OptionMetrics provides for each day and each security a standardised volatility surface containing the strikes of synthetic call options expiring thirty days later with deltas ranging from 0.10 to 0.90 in steps of size 0.05 yielding a total number of 17 data points. They extract these synthetic options from actually traded options using a methodology based on a kernel smoothing algorithm. We take these 17 data points consisting of strike and delta and perform a change of variable by substituting the strike K by the natural logarithm of the strike divided by the price of a synthetic forward expiring in 30 days which is provided by the forward price file of OptionMetrics. Subsequently, we interpolate the data points consisting of $\log(K/F_{t_0}(T))$ as x-variable and the corresponding implied volatility σ_{imp} as y-variable by a cubic spline. This interpolation is only performed in between the points, whereas we extrapolate for strikes K outside the range by simply taking the implied volatility to be constantly equal to the respective boundary point.

Next, we generate a fine grid of 2000 strike prices K in the interval

$$K \in [\exp(ln(S_{t_0}) - 2\sigma), \exp(ln(S_{t_0}) + 2\sigma)],$$

where the standard deviation σ is chosen as the mean of all 17 synthetic implied volatilities provided by the implied volatility surface.[2] We then generate synthetic call option prices for these strikes by evaluating the Black-Scholes formula on the previously interpolated implied volatilities corresponding to the respective strikes. Equation (24) can then be evaluated numerically on the strike grid using the trapezoid rule.

[2] We computed the synthetic variance swap rates using different choices for the interval boundaries and found that the above choice provided a good trade-off between the truncation and the discretisation error.

Appendix B Variable definitions

Option measures	Definition	Source
IMPVOL	The Black-Scholes implied volatility of the option at the initialisation date.	OptionMetrics
IMPVAR	The square of the Black-Scholes implied volatility of the option at the initialisation date.	OptionMetrics
delta-hedged returns	The net gains of a daily rebalanced delta-hedged position where one buys the option and hedges with the underlying, scaled by the stock price at initialisation date. The positon is initialised the soonest trading day which is at most 30 days prior to the expiry date and held until expiration.	OptionMetrics
VRP	The model-free ex-post variance risk premium computed as the difference between the risk-neutral expected variance over the 30-days-period from initialisation until expiration and the realized volatility based on daily returns over the same time window (Britten-Jones and Neuberger (2000), Jiang and Tian (2005), Carr and Wu (2009), Bollerslev et al. (2009)). The risk-neutral expected variance is extracted from market prices for call options at initialisation date that expire 30 days later.	OptionMetrics
slopeD	The regression coefficient of an ordinary linear regression that regresses the implied volatility (essentially a scaled version of the option price) on the moneyness of the option measured via the option's delta. The regression is based on OTM put options ($-0.5 < \Delta < -0.1$). Put options usually become more expensive the further they are out of the money because they then provide a hedge against tail risks. Hence, this variable is usually positive and a higher value is interpreted as increased anticipated tail risks.	OptionMetrics

Option characteristics	Definition	Source
OpenInterestScaled	The open interest for the option, i.e. the number of contracts outstanding at initialisation date, multiplied by 10^3 and divided by the stock trading volume (in shares) over the previous 30 days.	OptionMetrics
BidAskScaled	The difference of the bid and ask quotes of the option divided by their arithmetic mean, the mid-price, at initialisation date.	OptionMetrics

Stock characteristics	Definition	Source
Market equity	The firm's market capitalisation (LSEG data item TR.CompanyMarketCap)	LSEG
Book-to-market	The ratio between a firm's book value and its market equity (Reciprocal of the LSEG data item TR.F.PriceToBookValuePerShr).	LSEG
Ret212m	The cumulative return of the stock over the time period from one year up to 30 days prior to initialisation date.	OptionMetrics
Ret1m	The cumulative return of the stock over the 30 days prior to initialisation date.	OptionMetrics
Ret1Y	The return of the stock over the year prior to initialisation date.	OptionMetrics
AMIHUD	The stock illiquidity measure from Amihud (2002) computed as the arithmetic mean of the ratios of the daily absolute relative returns and the daily dollar trading volume over the previous 30 days multiplied by 10^6.	OptionMetrics
INSTOWN	The percentage of shares outstanding owned by institutional investors (LSEG data item TR.CategoryOwnershipPct) as a number between 0 and 1.	LSEG
IVOL	The stock's idiosyncratic volatility computed as the annualized standard deviation of the residuals coming from a linear regression of the daily stock returns on the three factors of Fama and French over the previous 30 days (Ang et al. (2006)).	Kenneth French's data library, OptionMetrics
Assets	The firm's total assets (LSEG data item TR.F.TotAssets).	LSEG
Dvidends/net profit	The total amount of dividends paid to common and preferred stockholders in the previous quarter (LSEG data item TR.F.DivPaidCashTotCF) divided by the firms net income (LSEG data item TR.NetProfitMean).	LSEG
Debt/assets	The firm's net debt (LSEG data item TR.NeTDebtMean) divided by the firm's total assets.	LSEG
EBIT/assets	The firm's EBIT (LSEG data item TR.EBITMean) divided by the firm's total assets.	LSEG
CapEx/assets	The firm's total capital expenditures (LSEG data item TR.F.CAPEXTot) divided by the firm's total assets.	LSEG
ROE	The net income divided by the total equity of common shares (LSEG data item TR.ROEMean).	LSEG
CAPM beta	The coefficient of a linear regression of the daily stock returns on the market factor over the previous year.	Kenneth French's data library, OptionMetrics
Volatility	The annualised standard deviation of daily log returns over the previous 30 days.	OptionMetrics

Carbon risk proxies	Definition	Source
β_{BMG}	The carbon beta is computed as the regression coefficient of the carbon risk factor using a five-factor model developed by Görgen et al. (2020), which is essentially the four-factor model of Carhart extended by a fifth factor mimicking carbon risk, the so-called Brown-Minus-Green (BMG) factor. The regression is performed using daily stock returns over the year prior to initialisation date.	University of Augsburg, Kenneth French's data library, OptionMetrics
Scope1/market cap	The direct of CO_2 and CO_2 equivalent emissions in tonnes from sources that are owned or controlled by the firm (LSEG data item TR.CO2DirectScope1), scaled by the firm's total market equity.	LSEG
ESG score	The firm's Refinitiv ESG score(LSEG data item TR.TRESGScore) divided by 100.	LSEG

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Table 1. ***Summary statistics of implied volatility and variance for call options.*** *This table contains summary statistics of the implied volatility and variance for all ATM-call options in panel A that survived the data filter criteria and all controls exist.*

	Mean	Std	10th	25th	Median	75th	90th
Panel A: Call options (134,108 observations)							
Implied volatility	0.40	0.20	0.20	0.25	0.35	0.49	0.67
Implied variance	0.20	0.23	0.04	0.06	0.12	0.24	0.45
Moneyness	1.00	0.03	0.97	0.99	1.00	1.01	1.04

Table 2. ***Summary statistics of delta-hedged returns for call options.*** *This table contains summary statistics on the delta-hedged gain and option characteristics for all ATM-call options in the full sample of Panel B that survived the data filter criteria.*

	Mean	Std	10th	25th	Median	75th	90th
Panel B: Call options (251,853 observations)							
Delta-hedged gain	-0.56	6.27	-6.32	-3.08	-0.78	1.62	5.38
Moneyness	1.00	0.03	0.96	0.98	1.00	1.02	1.05
Open interest	0.03	0.07	0.00	0.00	0.01	0.03	0.08
Bid-ask spread	0.34	0.37	0.05	0.10	0.20	0.42	0.86

Table 3. ***Summary statistics of the model-free variance risk premium.*** *This table contains summary statistics on the model-free variance risk premium and the number of liquid options existing at initialisation date. At least five such options were required to compute the VRP.*

	Mean	Std	10th	25th	Median	75th	90th
Panel C: VRP (92,512 observations)							
VRP	-0.11	0.33	-0.41	-0.17	-0.07	-0.01	0.07
#Liquid options	11.92	12.20	5	6	9	13	21

Table 4. ***Summary statistics of the implied volatility slope for OTM put options.*** *This table contains summary statistics on the option implied volatility moneyness slope computed for OTM put options. The second line provides information on the number of liquid put options that were used for the estimation of the slope. At least three such options were required.*

	Mean	Std	10th	25th	Median	75th	90th
Panel D: Implied volatility slope (105,030 observations)							
slopeD	0.32	0.34	0.08	0.13	0.20	0.34	0.78
#Liquid options	4.87	3.38	3	3	4	5	8

Table 5. ***Summary statistics of Panel B.*** *This table reports descriptive statistics on the explanatory variables of Panel B (call options). The sample is restricted on the subset of observations for which all control variables exist.*

Panel B: call options (128,802 observations)							
	Mean	Std	10th	25th	Median	75th	90th
β_{BMG}	0.10	0.92	-0.79	-0.41	-0.04	0.41	1.09
β_{mkt}	1.04	0.36	0.61	0.82	1.03	1.26	1.49
β_{SMB}	0.58	0.66	-0.18	0.08	0.48	0.96	1.45
β_{HML}	0.08	0.69	-0.78	-0.33	0.08	0.51	0.95
β_{WML}	-0.06	0.46	-0.62	-0.29	-0.04	0.21	0.45
ESG	0.42	0.19	0.19	0.27	0.40	0.56	0.71
ln(ME)	8.48	1.57	6.49	7.41	8.39	9.50	10.57
ln(BM)	-1.14	0.95	-2.37	-1.66	-1.03	-0.47	-0.06
Ret1	0.02	0.12	-0.11	-0.04	0.02	0.07	0.15
Ret212	0.18	0.63	-0.36	-0.14	0.08	0.33	0.71
IVOL	0.27	0.19	0.10	0.14	0.21	0.33	0.50
ln(AMHD)	-7.77	1.82	-10.03	-9.06	-7.84	-6.56	-5.38
OI	0.03	0.05	0.00	0.00	0.01	0.03	0.06
BA	0.29	0.35	0.04	0.08	0.15	0.33	0.75

Table 6. ***Correlogram for Panel B.*** *This table reports the Pearson correlation coefficients of all explanatory variables in Panel B. The correlations are computed only on the subset of observations for which all control variables exist. This is the subsample used for the regressions corresponding to column (3) of the tables 9 and 10.*

Panel B: Correlogram for call options (128,802 observations)														
	$\|\beta_{BMG}\|$	$\|\beta_{mkt}\|$	$\|\beta_{SMB}\|$	$\|\beta_{HML}\|$	$\|\beta_{WML}\|$	ESG	ln(ME)	ln(BM)	Ret1	Ret212	IVOL	ln(AM)	OI	BA
$\|\beta_{BMG}\|$	1.00	0.16	0.21	0.20	0.26	-0.06	-0.17	0.13	0.03	0.10	0.32	0.18	0.01	-0.02
$\|\beta_{mkt}\|$	0.16	1.00	0.21	0.25	0.18	-0.08	-0.06	-0.01	0.04	0.08	0.15	0.05	-0.03	-0.12
$\|\beta_{SMB}\|$	0.21	0.21	1.00	0.30	0.19	-0.33	-0.56	-0.01	0.07	0.10	0.48	0.55	0.01	0.19
$\|\beta_{HML}\|$	0.20	0.25	0.30	1.00	0.18	-0.12	-0.14	0.07	0.04	0.05	0.20	0.13	-0.02	0.03
$\|\beta_{WML}\|$	0.26	0.18	0.19	0.18	1.00	-0.11	-0.15	0.04	0.04	0.00	0.28	0.10	0.00	-0.07
ESG	-0.06	-0.08	-0.33	-0.12	-0.11	1.00	0.54	0.03	-0.03	-0.08	-0.25	-0.50	-0.03	-0.23
ln(ME)	-0.17	-0.06	-0.56	-0.14	-0.15	0.54	1.00	-0.21	-0.02	0.01	-0.42	-0.93	-0.04	-0.44
ln(BM)	0.13	-0.01	-0.01	0.07	0.04	0.03	-0.21	1.00	0.02	-0.06	-0.05	0.20	0.03	0.12
Ret1	0.03	0.04	0.07	0.04	0.04	-0.03	-0.02	0.02	1.00	-0.03	0.14	0.07	0.08	-0.01
Ret212	0.10	0.08	0.10	0.05	0.00	-0.08	0.01	-0.06	-0.03	1.00	0.08	-0.03	0.02	-0.04
IVOL	0.32	0.15	0.48	0.20	0.28	-0.25	-0.42	-0.05	0.14	0.08	1.00	0.42	-0.02	0.08
ln(AMHD)	0.18	0.05	0.55	0.13	0.10	-0.50	-0.93	0.20	0.07	-0.03	0.42	1.00	0.05	0.50
OI	0.01	-0.03	0.01	-0.02	0.00	-0.03	-0.04	0.03	0.08	0.02	-0.02	0.05	1.00	-0.07
BA	-0.02	-0.12	0.19	0.03	-0.07	-0.23	-0.44	0.12	-0.01	-0.04	0.08	0.50	-0.07	1.00

Figure 1. *This figure shows a condensed scatter plot where all data points consisting of a carbon beta and the corresponding implied volatility are ordered and sorted into thirty quantiles according to their carbon beta. For each of the thirty buckets, we compute the average carbon beta and the average implied volatility and plot this condensed data point. Hence the figure provides an intuition for the expected relationship between carbon beta and implied volatility.*

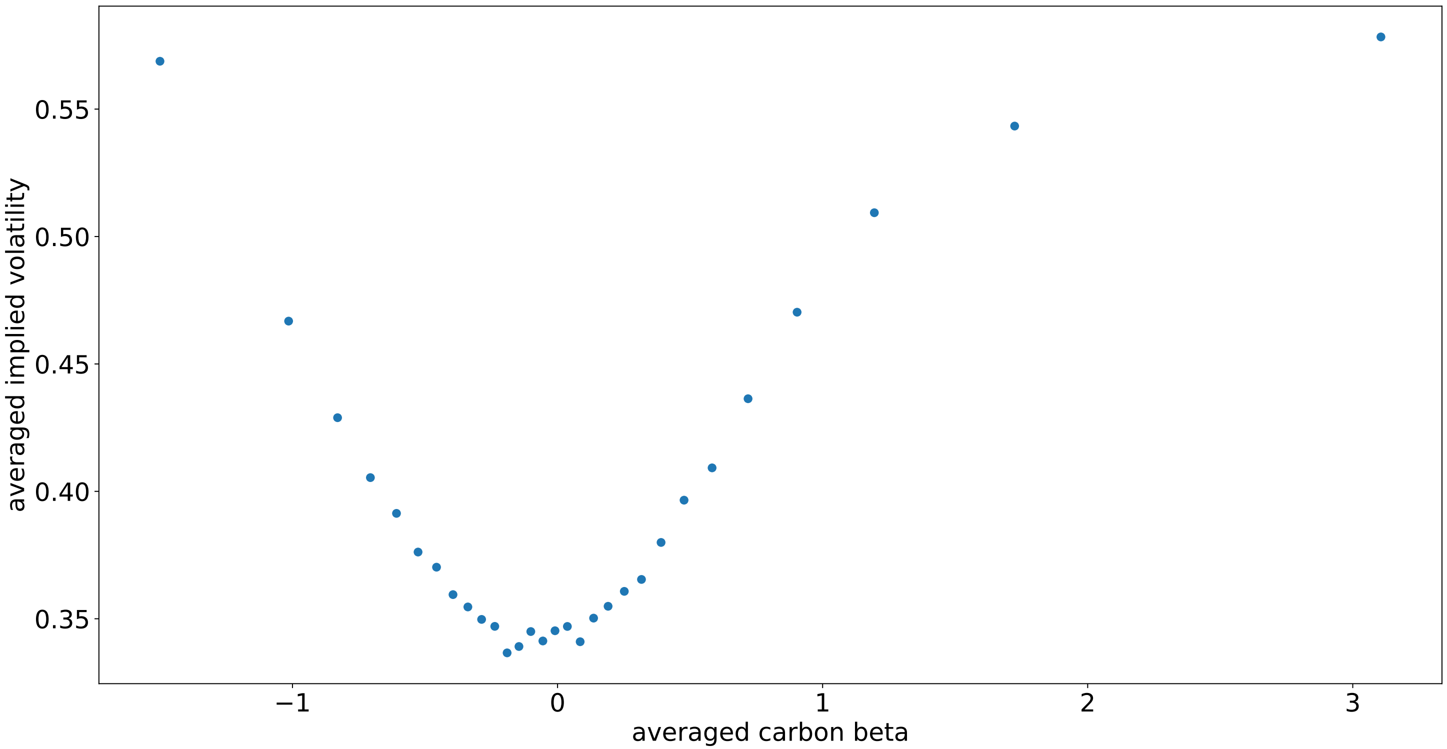

Table 7. ***Panel regressions of implied variance on squared carbon beta with time fixed effects.*** *This table reports the results of panel regressions of the ATM option implied variance as dependent variable on the squared carbon beta as main explanatory variable and control variables. The regression data sets in the first two columns for calls and puts are restricted on the observations for which the standard control variables (without the ESG score) exist. The third columns are additionally limited to observations for which the ESG score was also available. To evaluate the covariance matrix, we use two-way clustered robust standard errors.*

Panel A: Panel regressions of option implied variance on β^2_{BMG}

	Call options			Put options		
	(1)	(2)	(3)	(4)	(5)	(6)
β^2_{BMG}	0.023***	0.018***	0.011***	0.023***	0.018***	0.011***
	(13.179)	(12.853)	(10.065)	(12.750)	(11.851)	(9.533)
β^2_{mkt}			0.054***			0.054***
			(7.114)			(6.442)
β^2_{SMB}			0.115***			0.115***
			(15.020)			(14.623)
β^2_{HML}			0.016**			0.02***
			(3.242)			(3.564)
β^2_{WML}			0.093***			0.096***
			(11.704)			(11.395)
ESG score			−0.001			−0.005
			(−0.06)			(−0.468)
ln(market cap)		−0.055***	−0.034***		−0.058***	−0.034***
		(−21.605)	(−12.503)		(−21.403)	(−12.403)
ln(book-to-market)		−0.049***	−0.039***		−0.051***	−0.039***
		(−12.043)	(−11.884)		(−11.399)	(−10.769)
Ret1		−0.028	−0.057		−0.010	−0.048
		(−0.769)	(−1.660)		(−0.254)	(−1.161)
Ret212		0.010	−0.005		0.011	−0.005
		(1.123)	(−0.549)		(1.247)	(−0.589)
INSTOWN		−0.117***	−0.115***		−0.137***	−0.125***
		(−8.727)	(−9.139)		(−8.796)	(−8.873)
ROE		−0.18***	−0.131***		−0.181***	−0.128***
		(−17.721)	(−14.517)		(−17.507)	(−14.311)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No	No
Clustered	2-ways	2-ways	2-ways	2-ways	2-ways	2-ways
Observations	134108	134108	110910	125702	125702	104896
R^2 overall	4.5%	28.6%	40.0%	3.9%	26.3%	36.2%

*, **, *** means significance at the 5, 1, 0.1% level

Table 8. ***Panel regressions of implied volatility on carbon beta with time fixed effects.*** *This table reports the results of panel regressions of the ATM option implied volatility as dependent variable on the squared carbon beta as main explanatory variable and control variables. The regression data sets in the first two columns for calls and puts are restricted on the observations for which the standard control variables (without the ESG score) exist. The third columns are additionally limited to observations for which the ESG score was also available. To evaluate the covariance matrix, we use two-way clustered robust standard errors.*

Panel A: Panel regressions of option implied volatility on $\lvert\beta_{BMG}\rvert$						
	Call options			Put options		
	(1)	(2)	(3)	(4)	(5)	(6)
$\lvert\beta_{BMG}\rvert$	0.088***	0.069***	0.042***	0.089***	0.068***	0.041***
	(23.603)	(25.89)	(16.192)	(22.705)	(24.021)	(16.036)
$\lvert\beta_{mkt}\rvert$			0.071***			0.07***
			(11.523)			(10.886)
$\lvert\beta_{SMB}\rvert$			0.092***			0.092***
			(17.050)			(16.846)
$\lvert\beta_{HML}\rvert$			0.019***			0.022***
			(4.981)			(5.42)
$\lvert\beta_{WML}\rvert$			0.089***			0.091***
			(16.544)			(16.268)
ESG score			−0.018*			−0.023*
			(−1.961)			(−2.431)
ln(market cap)		−0.056***	−0.035***		−0.058***	−0.036***
		(−34.030)	(−19.442)		(−34.343)	(−19.863)
ln(book-to-market)		−0.045***	−0.034***		−0.046***	−0.035***
		(−14.633)	(−14.915)		(−14.298)	(−14.133)
Ret1		−0.016	−0.046*		0.003	−0.032
		(−0.662)	(−2.125)		(0.118)	(−1.352)
Ret212		0.016*	0.002		0.017**	0.002
		(2.445)	(0.404)		(2.624)	(0.376)
INTSOWN		−0.063***	−0.064***		−0.072***	−0.068***
		(−5.969)	(−7.047)		(−6.201)	(−7.008)
ROE		−0.138***	−0.096***		−0.137***	−0.094***
		(−22.057)	(−17.855)		(−21.654)	(−17.754)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No	No
Clustered	2-ways	2-ways	2-ways	2-ways	2-ways	2-ways
Observations	134108	134108	110910	125702	125702	104896
R^2 overall	9.8%	37.2%	50.0%	9.4%	36.5%	48.3%

*, **, *** means significance at the 5, 1, 0.1% level

Figure 2. *This figure shows a condensed scatter plot where all data points consisting of a carbon beta and the corresponding delta-hedged gain are ordered and sorted into thirty quantiles according to their carbon beta. For each of the thirty buckets, we compute the average carbon beta and the average delta-hedged gain and plot this condensed data point. Hence the figure provides an intuition for the expected relationship between carbon beta and delta-hedged gain.*

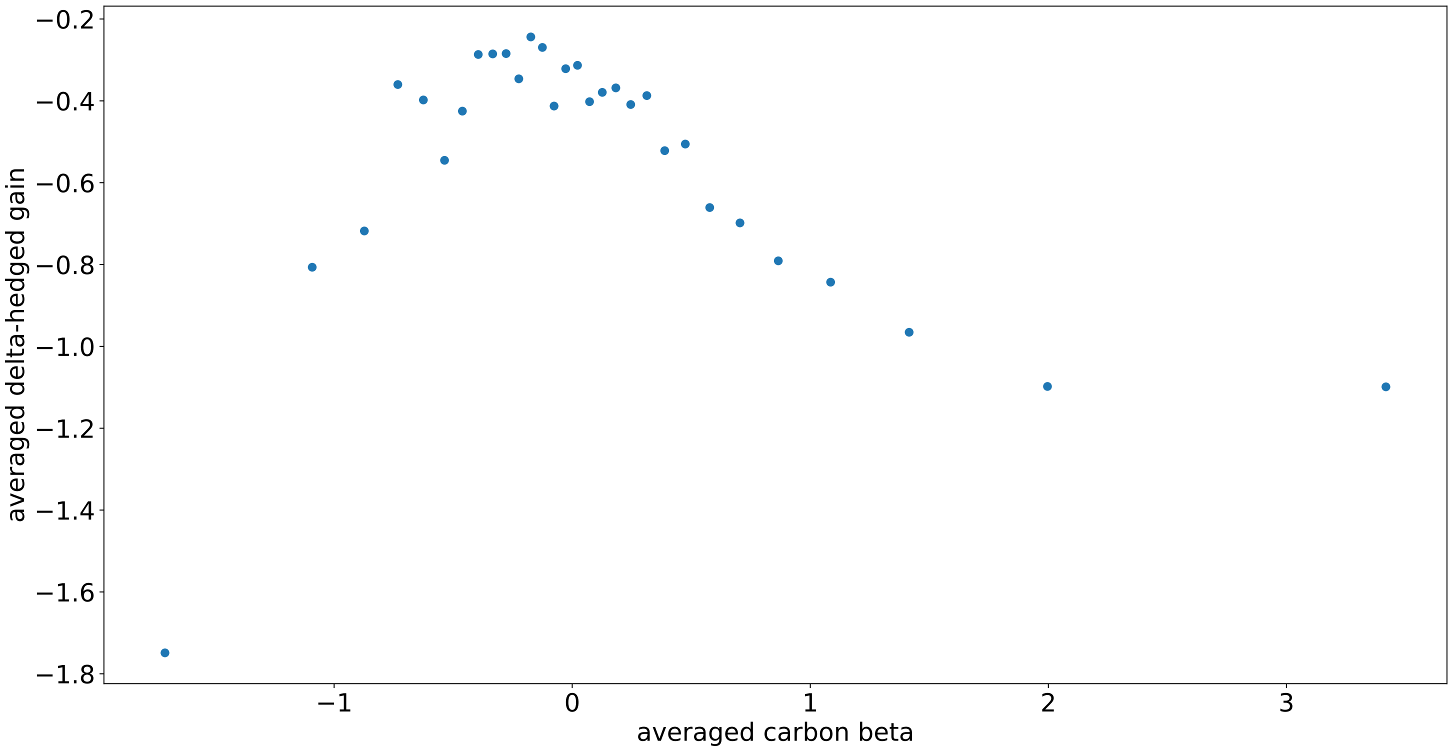

Table 9. ***Panel regressions of delta-hedged option return on carbon beta with time fixed effects.*** *This table reports the regression results of panel regressions on the firm-month level. The dependent variable is the daily rebalanced delta-hedged option return when buying the option and hedging with the stock over the 30 days prior to expiration. The net return is scaled by $\Delta_t S_t - C_t$ in the case of call and $P_t - \Delta_t S_t$ in the case of put options. The main explanatory variable is $|\beta_{BMG}|$, the absolute value of the carbon beta, which measures the exposure towards transition risk of the underlying firm. The regressions (2) and (3) respectively (5) and (6) are evaluated only on the subset of company-date-observations for which the respective control variables were available. The covariance matrix is estimated using two-way clustered robust standard errors.*

Panel B: Panel regressions of delta-hedged option return on $\lvert\beta_{BMG}\rvert$						
	Call options			Put options		
	(1)	(2)	(3)	(4)	(5)	(6)
$\lvert\beta_{BMG}\rvert$	−0.361***	−0.225***	−0.193***	−0.480***	−0.221***	−0.159*
	(−5.971)	(−4.28)	(−3.345)	(−6.311)	(−3.438)	(−2.340)
$\lvert\beta_{mkt}\rvert$			0.088			0.468***
			(0.779)			(3.631)
$\lvert\beta_{SMB}\rvert$			−0.521***			−0.604***
			(−7.845)			(−7.767)
$\lvert\beta_{HML}\rvert$			0.024			−0.097
			(0.270)			(−0.996)
$\lvert\beta_{WML}\rvert$			0.002			−0.124
			(0.024)			(−1.188)
ESG score			0.414**			0.449*
			(2.654)			(2.509)
ln(market cap)		0.695***	0.587***		0.778***	0.603***
		(10.058)	(8.194)		(9.374)	(7.234)
ln(book-to-market)		0.226***	0.166***		0.163***	0.091*
		(5.873)	(4.173)		(3.852)	(2.197)
Ret1		0.779*	1.017**		0.713	1.13**
		(2.429)	(2.806)		(1.825)	(2.715)
Ret212		−0.293***	−0.257**		−0.438***	−0.423***
		(−4.353)	(−2.809)		(−5.654)	(−4.472)
IVOL		−0.695*	−0.540		−0.875*	−0.334
		(−2.328)	(−1.719)		(−2.497)	(−0.892)
ln(AMIHUD)		0.443***	0.496***		0.509***	0.478***
		(8.135)	(8.381)		(7.107)	(6.454)
Open interest		−4.305***	−5.081***		−4.239***	−3.788***
		(−12.002)	(−11.612)		(−9.823)	(−8.328)
Bid-ask spread		0.116	0.246*		0.220*	0.259*
		(1.100)	(2.005)		(1.992)	(2.050)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No	No
Clustered	2-ways	2-ways	2-ways	2-ways	2-ways	2-ways
Observations	251853	161343	128802	234201	149828	120969
R^2 overall	0.2%	1.3%	1.5%	0.3%	1.5%	1.5%

*, **, *** means significance at the 5, 1, 0.1% level

Table 10. ***Fama-MacBeth regressions of delta-hedged option return on carbon beta.*** *This table reports the regression results of Fama-MacBeth regressions on the firm-month level. The dependent variable is the daily rebalanced delta-hedged option return when buying the option and hedging with the stock over the 30 days prior to expiration. The net return is scaled by $\Delta_t S_t - C_t$ in the case of call and $P_t - \Delta_t S_t$ in the case of put options. The main explanatory variable is $|\beta_{BMG}|$, the absolute value of the carbon beta, which measures the exposure towards transition risk of the underlying firm. The covariance matrix is estimated using HAC standard errors.*

Panel B: Fama-MacBeth regressions of delta-hedged option return on $|\beta_{BMG}|$

	Call options			Put options		
	(1)	(2)	(3)	(4)	(5)	(6)
$\|\beta_{BMG}\|$	−0.297***	−0.131*	−0.078	−0.439***	−0.115	−0.053
	(−3.293)	(−2.242)	(−1.102)	(−4.923)	(−1.76)	(−0.843)
$\|\beta_{mkt}\|$			−0.126			0.204
			(−0.879)			(1.632)
$\|\beta_{SMB}\|$			−0.417***			−0.486***
			(−4.554)			(−6.408)
$\|\beta_{HML}\|$			−0.041			−0.109
			(−0.686)			(−1.608)
$\|\beta_{WML}\|$			−0.055			−0.178*
			(−0.709)			(−2.073)
ESG score			0.43***			0.469***
			(4.930)			(4.513)
ln(market cap)		0.608***	0.46***		0.656***	0.447***
		(8.728)	(6.457)		(7.991)	(8.156)
ln(book-to-market)		0.225***	0.139***		0.186***	0.098***
		(7.921)	(5.068)		(5.354)	(3.658)
Ret1		1.053**	1.1**		0.826	0.677
		(3.126)	(2.917)		(1.790)	(1.747)
Ret212		−0.189**	−0.191**		−0.333***	−0.258***
		(−2.750)	(−2.752)		(−3.491)	(−3.343)
IVOL		−0.426	0.149		−0.748*	0.302
		(−1.315)	(0.395)		(−2.391)	(0.974)
ln(AMIHUD)		0.388***	0.394***		0.435***	0.382***
		(6.954)	(6.512)		(6.306)	(7.219)
Open interest		−4.787***	−4.565***		−4.652***	−3.368***
		(−6.257)	(−5.222)		(−7.230)	(−7.607)
Bid-ask spread		0.048	0.196		0.208*	0.182
		(0.474)	(1.59)		(2.044)	(1.668)
Clustered	HAC	HAC	HAC	HAC	HAC	HAC
Observations	251853	161343	128802	234201	149828	120969
R^2 overall	0.2%	1.1%	1.3%	0.3%	1.4%	1.4%

*, **, *** means significance at the 5, 1, 0.1% level

Figure 3. ***Time series evolution of the number of observations in Panel B.*** *The figure displays the number of valid observations consisting of a delta-hedged gain for an option surviving the filter criteria and a valid carbon beta of the underlying for all months in our sample period from January 2011 until February 2023. Furthermore, all control variables must exist for a data-point in order to be counted.*

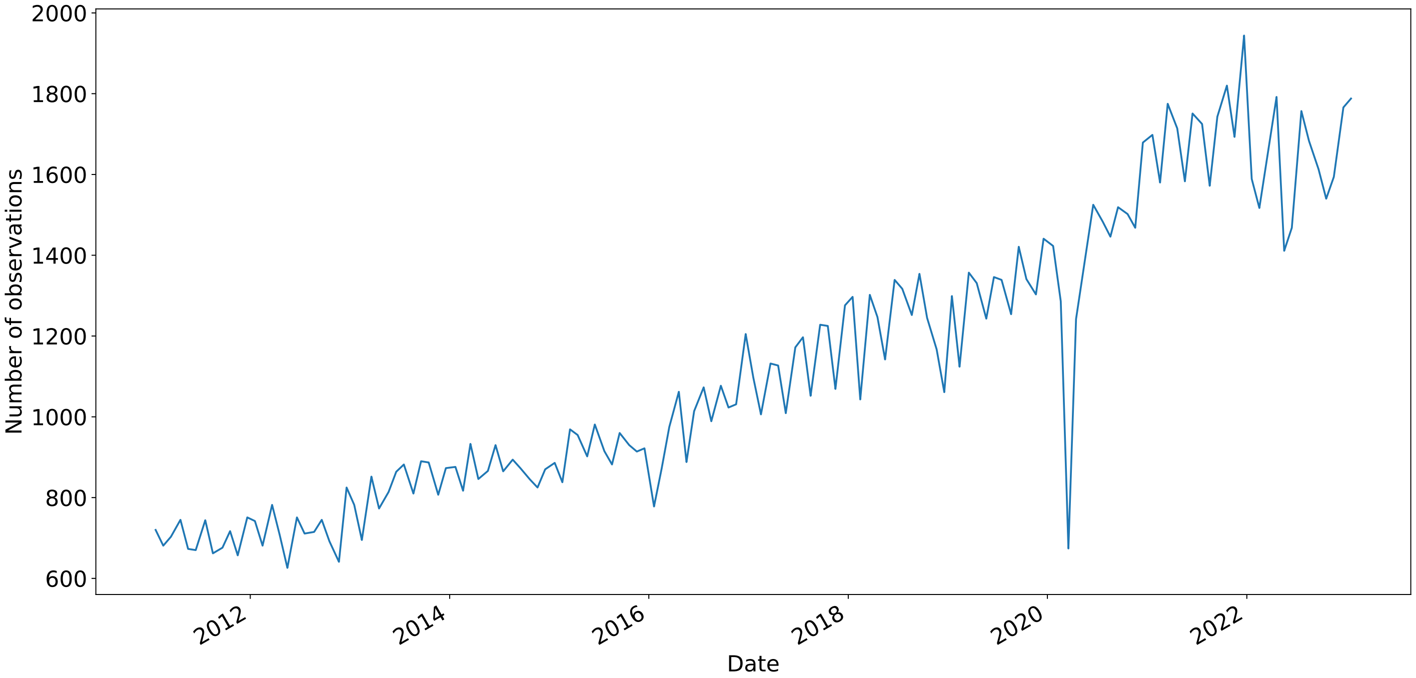

Table 11. *Panel regressions of delta-hedged option return on carbon beta with time fixed effects restricted on the years 2011-2017.* *This table reports the regression results of panel regressions on the firm-month level. The dependent variable is the daily rebalanced delta-hedged option return when buying the option and hedging with the stock over the 30 days prior to expiration. The net return is scaled by* $\Delta_t S_t - C_t$ *in the case of call and* $P_t - \Delta_t S_t$ *in the case of put options. The main explanatory variable is* $|\beta_{BMG}|$*, the absolute value of the carbon beta, which measures the exposure towards transition risk of the underlying firm. The covariance matrix is estimated using two-way clustered robust standard errors.*

Panel B1: Panel regressions of delta-hedged option return on $\|\beta_{BMG}\|$ from 2011 to 2017						
	Call options			Put options		
	(1)	(2)	(3)	(4)	(5)	(6)
$\|\beta_{BMG}\|$	−0.101	−0.069	−0.014	−0.238**	−0.098	0.023
	(−1.497)	(−1.090)	(−0.219)	(−2.597)	(−1.234)	(0.312)
β_{BMG}			0.015			−0.038
			(0.282)			(−0.663)
$\|\beta_{mkt}\|$			−0.428***			−0.249*
			(−4.523)			(−2.177)
$\|\beta_{SMB}\|$			−0.346***			−0.471***
			(−4.045)			(−4.569)
$\|\beta_{HML}\|$			−0.161*			−0.228**
			(−2.063)			(−2.858)
$\|\beta_{WML}\|$			−0.157			−0.243
			(−1.434)			(−1.946)
ESG score			0.431***			0.509***
			(3.468)			(4.211)
ln(market cap)		0.420***	0.273***		0.466***	0.271***
		(7.229)	(5.3)		(6.799)	(4.388)
ln(book-to-market)		0.227***	0.130***		0.239***	0.116**
		(6.067)	(4.212)		(5.306)	(2.919)
Ret1		0.111	0.068		−0.895	−1.358**
		(0.269)	(0.159)		(−1.945)	(−2.588)
Ret212		−0.045	−0.081		−0.073	−0.095
		(−0.581)	(−0.939)		(−0.845)	(−0.945)
IVOL		0.43	1.367***		0.260	1.519***
		(1.445)	(4.563)		(0.746)	(4.333)
ln(AMIHUD)		0.214***	0.231***		0.291***	0.272***
		(4.445)	(4.662)		(4.961)	(4.621)
Open interest		−2.894***	−2.547***		−3.691***	−2.566***
		(−7.128)	(−5.726)		(−7.220)	(−5.174)
Bid-ask spread		−0.068	0.084		0.177	0.154
		(−0.673)	(0.699)		(1.552)	(1.225)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No	No
Clustered	2-ways	2-ways	2-ways	2-ways	2-ways	2-ways
Observations	138333	74015	45818	128898	68797	43852
R^2 overall	0.0%	0.7%	1.3%	0.1%	1.0%	1.6%

*, **, *** means significance at the 5, 1, 0.1% level

Table 12. ***Panel regressions of delta-hedged option return on carbon beta with time fixed effects restricted on the years 2018-2023.*** *This table reports the regression results of panel regressions on the firm-month level. The dependent variable is the daily rebalanced delta-hedged option return when buying the option and hedging with the stock over the 30 days prior to expiration. The net return is scaled by* $\Delta_t S_t - C_t$ *in the case of call and* $P_t - \Delta_t S_t$ *in the case of put options. The main explanatory variable is* $|\beta_{BMG}|$*, the absolute value of the carbon beta, which measures the exposure towards transition risk of the underlying firm. The covariance matrix is estimated using two-way clustered robust standard errors.*

Panel B2: Panel regressions of delta-hedged option return on $|\beta_{BMG}|$ from 2018 to 2023

	Call options			Put options		
	(1)	(2)	(3)	(4)	(5)	(6)
$\lvert\beta_{BMG}\rvert$	−0.62***	−0.326***	−0.251***	−0.739***	−0.29***	−0.243**
	(−7.532)	(−4.952)	(−3.552)	(−6.883)	(−3.478)	(−2.917)
β_{BMG}			−0.104			−0.050
			(−1.783)			(−0.678)
$\lvert\beta_{mkt}\rvert$			0.366*			0.810***
			(2.360)			(4.790)
$\lvert\beta_{SMB}\rvert$			−0.519***			−0.59***
			(−6.564)			(−6.249)
$\lvert\beta_{HML}\rvert$			0.075			−0.045
			(0.598)			(−0.327)
$\lvert\beta_{WML}\rvert$			0.004			−0.106
			(0.031)			(−0.696)
ESG score			0.342			0.408
			(1.512)			(1.504)
ln(market cap)		0.885***	0.762***		0.992***	0.786***
		(9.014)	(7.965)		(8.014)	(6.903)
ln(book-to-market)		0.245***	0.205***		0.143*	0.103
		(4.323)	(3.788)		(2.300)	(1.786)
Ret1		1.147**	1.254**		1.567**	1.772***
		(2.711)	(2.825)		(3.000)	(3.457)
Ret212		−0.34***	−0.259*		−0.543***	−0.461***
		(−3.736)	(−2.509)		(−5.026)	(−4.081)
IVOL		−1.269**	−0.957*		−1.638***	−0.950*
		(−3.062)	(−2.514)		(−3.368)	(−2.040)
ln(AMIHUD)		0.591***	0.625***		0.645***	0.597***
		(7.396)	(7.892)		(5.701)	(5.835)
Open interest		−5.587***	−6.137***		−4.392***	−4.025***
		(−10.294)	(−10.605)		(−6.403)	(−6.202)
Bid-ask spread		0.246	0.265		0.275	0.307*
		(1.571)	(1.716)		(1.663)	(1.973)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No	No
Clustered	2-ways	2-ways	2-ways	2-ways	2-ways	2-ways
Observations	113520	87328	82984	105303	81031	77117
R^2 overall	0.5%	1.9%	1.8%	0.5%	2.1%	1.9%

*, **, *** means significance at the 5, 1, 0.1% level

Figure 4. *This figure shows a condensed scatter plot where all data points consisting of a carbon beta and the corresponding variance risk premium are ordered and sorted into twenty quantiles according to their carbon beta. For each of the twenty buckets, we compute the average carbon beta and the average variance risk premium and plot this condensed data point. Hence the figure provides an intuition for the expected relationship between carbon beta and variance risk premium.*

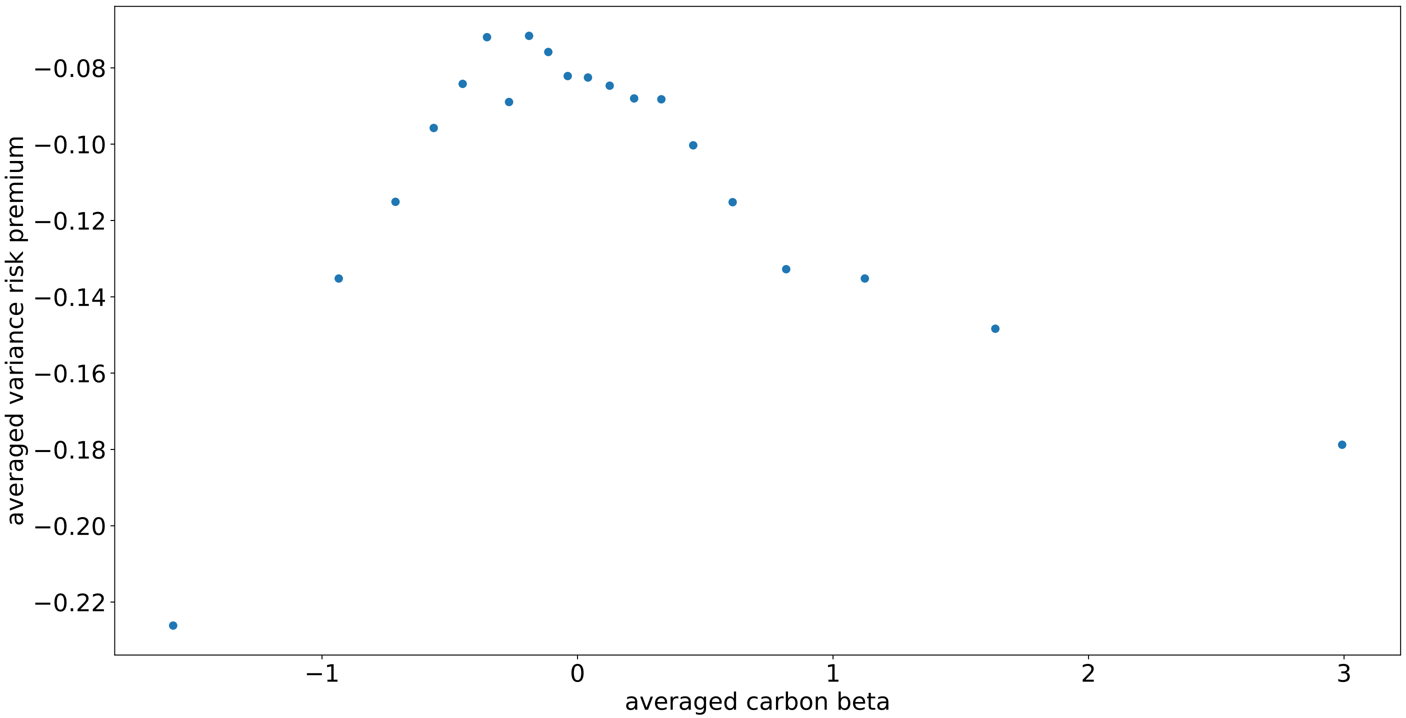

Table 13. *Panel regressions of the model-free variance risk premium on squared carbon beta with time fixed effects.* *This table reports the results of panel regressions of the model-free variance risk premium as dependent variable on the squared carbon beta as main explanatory variable. The covariance matrix is estimated using two-way clustered robust standard errors.*

Panel C: Panel regressions of variance risk premium on β^2_{BMG}				
	(1)	(2)	(3)	(4)
β^2_{BMG}	-0.007^{***}	-0.004^{**}	-0.005^{***}	-0.004^{**}
	(-4.42)	(-3.059)	(-3.661)	(-2.901)
β^2_{mkt}			-0.002	-0.001
			(-0.467)	(-0.269)
β^2_{SMB}			-0.022^{***}	-0.015^{***}
			(-6.206)	(-4.478)
β^2_{HML}			0.003	0.003
			(0.750)	(0.672)
β^2_{WML}			-0.009	0.001
			(-1.205)	(0.148)
ln(market cap)		0.062^{***}		0.058^{***}
		(5.827)		(5.536)
ln(book-to-market)		0.002		0.001
		(0.317)		(0.161)
Ret1		-0.027		-0.020
		(-0.545)		(-0.418)
Ret212		0.01		0.011
		(1.285)		(1.422)
INSTOWN		0.100^{**}		0.092^{*}
		(2.772)		(2.515)
ROE		0.015		0.013
		(1.836)		(1.608)
Month fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No
Clustered	2-ways	2-ways	2-ways	2-ways
Observations	92512	60661	92512	60661
R^2 overall	0.6%	7.5%	3.9%	8.2%

*, **, *** means significance at the 5, 1, 0.1% level

Figure 5. *This figure shows a condensed scatter plot where all data points consisting of a carbon beta and the corresponding implied volatility slope slopeD are ordered and sorted into thirty quantiles according to their carbon beta. For each of the thirty buckets, we compute the average carbon beta and the average slopeD and plot this condensed data point. Hence the figure provides an intuition for the expected relationship between carbon beta and slopeD.*

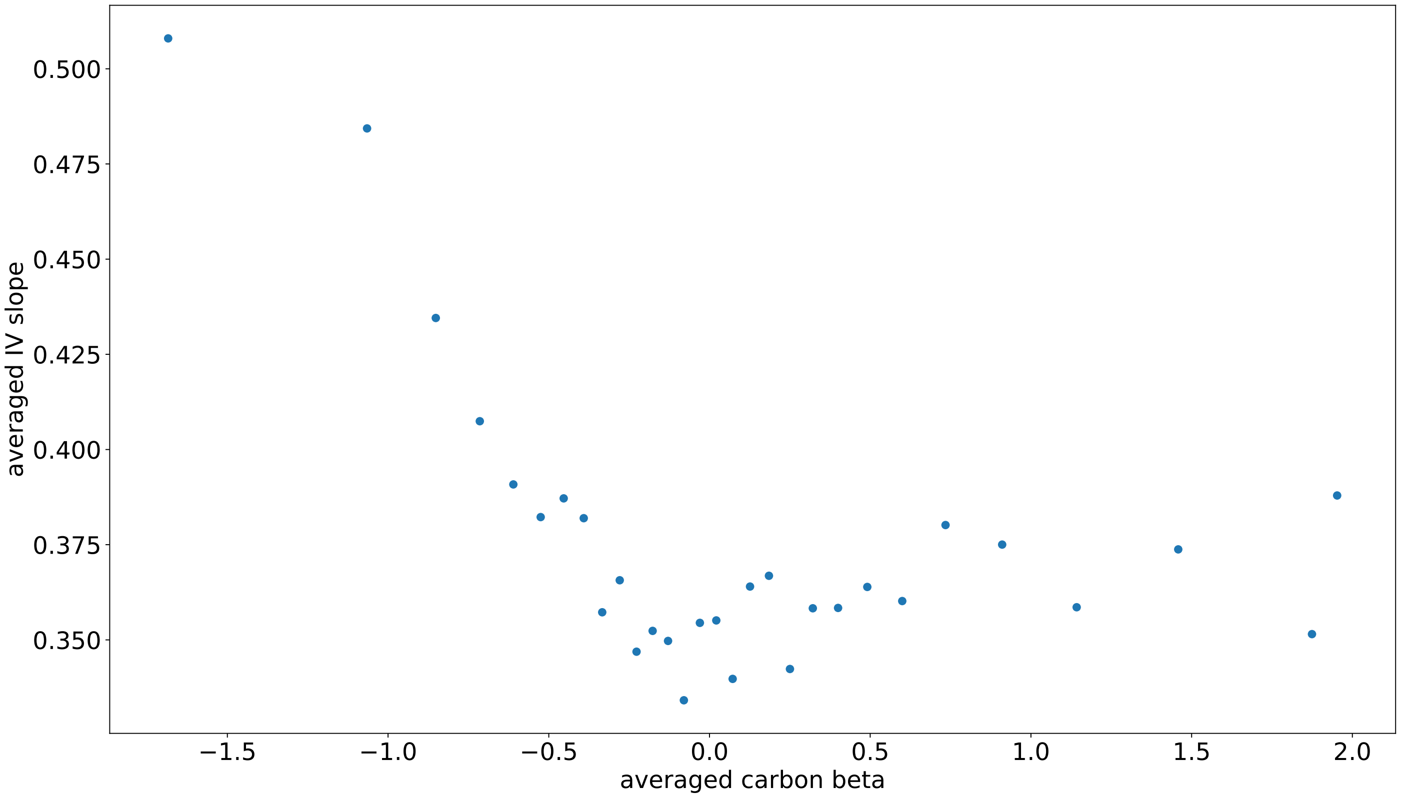

Table 14. *Panel regressions of implied volatility slope of OTM put options on carbon beta with time fixed effects.* *This table reports the results of panel regression with the implied volatility slope as dependent variable. Main explanatory variables are the carbon beta, the absolute value of the carbon beta and the natural logarithm of a firm's carbon intensity. The covariance matrix is estimated using two-way clustered robust standard errors.*

Panel D: Panel regressions of implied volatilty slope on β_{BMG}					
	(1)	(2)	(3)	(4)	(5)
β_{BMG}	-0.013^{**}			-0.036^{***}	-0.029^{**}
	(-2.879)			(-3.875)	(-3.202)
$\lvert\beta_{BMG}\rvert$		0.01		0.029^{**}	0.005
		(1.581)		(2.813)	(0.574)
ln(Scope 1/Market Cap)			0.007^{***}	0.009^{***}	-0.002
			(3.783)	(4.306)	(-0.786)
ln(Assets)					-0.060^{***}
					(-8.501)
Dividends/net income					0.014
					(1.713)
Debt/asset					0.091^{**}
					(3.290)
EBIT/assets					-0.326^{***}
					(-4.028)
CapEx/assets					0.007
					(0.047)
ln(book-to-market)					0.039^{***}
					(4.686)
Returns					-0.038^{***}
					(-3.706)
Institutional Ownership					-0.101^{*}
					(-2.258)
CAPM beta					0.040^{**}
					(2.973)
Volatility					-0.063
					(-1.293)
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No
Clustered	2-ways	2-ways	2-ways	2-ways	2-ways
Observations	105034	105034	35903	35765	20700
R^2 overall	0.1%	0.0%	0.0%	0.5%	4.3%

*, **, *** means significance at the 5, 1, 0.1% level