Pricing Climate Change Exposure*

Zacharias Sautner[†] Laurence van Lent[‡] Grigory Vilkov[§] Ruishen Zhang[¶]

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Abstract

We estimate the risk premium for firm-level climate change exposure from 2003 to 2019. Exposure is constructed from discussions of climate-related risks and opportunities in earnings calls. When extracted from realized returns, the unconditional risk premium is zero. This insignificant overall effect masks risk premium increases during the sample period, but with a slump in the financial crisis. Forward-looking proxies deliver an unconditionally positive expected risk premium, with subtle differences in the time series depending on the treatment of tail risks and opportunities. When the underlying model uses variance as the sufficient risk statistic, the premium gradually increases over time. When the model considers tails, the premium declines after 2015, because investors now link climate change exposure to higher opportunities and lower crash risk. This finding arises as the priced part of the risk premium primarily originates from climate-related opportunity shocks rather than downside physical or regulatory shocks.

Keywords: climate finance, climate change exposure, climate risk premium, tail risk, climate change opportunities

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[†]**Frankfurt School of Finance and Management and ECGI**; Postal Address: Adickesallee 32-34, 60322 Frankfurt am Main, Germany; E-mail: z.sautner@fs.de.

[‡]**Frankfurt School of Finance and Management**; Postal Address: Adickesallee 32-34, 60322 Frankfurt am Main, Germany; E-mail: l.vanlent@fs.de.

[§]**Frankfurt School of Finance and Management**; Postal Address: Adickesallee 32-34, 60322 Frankfurt am Main, Germany; E-mail: vilkov@vilkov.net.

[¶]**Shanghai University of Finance and Economics**; Postal Address: Guoding Road 777, 200433, Shanghai, China; E-mail: zhangruishen@sufe.edu.cn.

1 Introduction

Climate change poses huge challenges for financial markets. How should firm-level exposure to climate-related risk and opportunities be measured? How are risk and return quantities affected by climate change exposure? Which firms will benefit from climate change, and why? In light of these challenges, significant resources have recently been allocated to develop the area of climate finance to better grasp how the transition to a low-carbon economy affects financial markets. Yet, this body of literature is still in its infancy, and additional evidence is needed to more fully understand how climate-related risks and opportunities affect stock returns and risks.

Some first steps have recently been taken in this direction, using carbon emissions and ESG scores as proxies for climate change exposure. Bolton and Kacperczyk (2021, 2020) demonstrate the existence of a carbon risk premium, that is, stocks with higher carbon emissions earn higher expected returns, and Ilhan, Sautner, and Vilkov (2021) find that firms with higher carbon emissions exhibit higher tail risk. Engle, Giglio, Kelly, Lee, and Stroebel (2020) develop a procedure to hedge climate change risks, using ESG scores by data vendors to measure firm-level climate risk exposure. Survey evidence in Krueger, Sautner, and Starks (2020) also indicates that institutional investors believe that climate risks, especially those related to carbon emissions, have begun to be priced in financial markets.

The insights from these studies lay the foundation for further work, and the focus on carbon emissions and ESG scores originates from the lack of broad firm-level exposure measures. However, this comes with limitations. Carbon emissions primarily capture downside regulatory (or transition) risks but do not capture physical risks or climate opportunities. In addition, they reflect firms' historic business models, do not allow researchers to distinguish between "good" and "bad" emissions, and suffer from selection bias, as they are voluntarily reported (Matsumura, Prakash, and Vera-Muñoz (2014)).[1] Further complications arise because some of the largest carbon emitters are also key innovators in green technologies (Cohen, Gurun, and Nguyen (2020)), and some of them even issue green bonds to fund climate-friendly projects (Flammer (2021)). Likewise, for ESG scores, a challenge is that they are only available for select firms, and that

[1]Some firms' emissions are "good" in the sense of supporting the transition to a greener economy (these firms are called "climate enablers"). Ramadorai and Zeni (2020) provide an initial analysis of future emissions by examining planned emission abatement data.

they cover rather short periods of time.[2] In a recent review of the climate finance literature, Giglio, Kelly, and Stroebel (2020) therefore highlight the lack of comprehensive measures as a key impediment toward understanding the pricing of climate change exposure.

In this paper, we make significant progress toward overcoming this impediment. We show how a broad measure of firm-level climate change exposure is related to stock returns and risk quantities. Instead of relying on carbon emissions or ESG scores, we make use of an exposure measure available for a broad sample of firms from 2002 to 2019. The measure is constructed by Sautner, van Lent, Vilkov, and Zhang (2020) (hereinafter SvLVZ), and it is extracted from conversations between analysts and management in earnings conference calls. The measure captures risks *and* opportunities associated with climate change, and it is not subject to the selection bias of prior measures. Intuitively, it reflects the fraction of the conference call discussion that is centered on climate change topics. SvLVZ provide an aggregate measure of overall climate change exposure, and three topic-based measures reflecting exposure to climate-related opportunity, physical, and regulatory shocks. We relate climate change exposure to realized returns, *ex ante* expected returns, and risk quantities capturing the entire return distribution.[3]

Why should climate change exposure command a risk premium? The reason is that the effects of climate change on individual stocks are highly uncertain, and Barnett, Brock, and Hansen (2020) provide a theoretical framework which demonstrates that this uncertainty should be priced. Climate change uncertainty arises because it is highly unclear just how much global temperatures will rise, and also because it is uncertain how strongly emissions must be curbed to limit global warming. This in turn makes it difficult for investors to evaluate how individual stocks will be affected by climate-related physical and regulatory shocks. Moreover, the investment opportunities related to technological innovations facilitating the transition to a low-carbon economy are also highly uncertain (e.g., investments into battery technology or carbon storage). These considerations imply that the measure of overall climate change exposure, which encapsulates all of these aspects, should be associated with a risk premium; the same should hold for each of the three topic-based exposure measures.

[2]The same limitation holds for the carbon risk ratings that recently became available by ISS and Sustainalytics.

[3]The definition of "exposure" used in this paper follows prior literature. It is somewhat different from how risk exposure (e.g., a factor beta) is defined in the asset pricing literature. Hassan, Hollander, van Lent, and Tahoun (2019) provide a discussion of the relationship between these two areas of literature.

We answer three specific questions: First, how is climate change exposure – that is, the attention market participants accord to climate-related topics during earnings calls – related to realized and expected returns? Second, how does compensation for climate change exposure evolve over time, both in terms of realized and expected returns? Third, which risk quantities are associated with climate change exposure, and how do investors with different risk preferences price such risks when configuring return expectations?

In tackling these questions, we provide results that improve our understanding of how climate change affects financial markets. We begin with establishing a new empirical fact: Unconditionally, that is, across the full sample, the *realized* risk premium for climate change exposure is indistinguishable from zero. However, investors who buy stocks with higher climate change exposure *expect* to earn a risk premium *ex ante*. We detected such an expected risk premium using two approaches that exploit option-implied information but differ in terms of the assumed investor preferences used to derive the risk premium estimates. The risk premium proxy by Martin and Wagner (2019) assumes that variance is the sufficient risk statistic for investors – that is, the risk premium is based on the second moments of the returns of the market and of individual stocks. Somewhat differently, Chabi-Yo, Dim, and Vilkov (2020) assume that investors also consider extreme risks and opportunities, so their approach explicitly accounts for returns' higher-order moments in the risk premium estimation. In a nutshell, both approaches use different pieces of information from the options market to estimate expected returns.

When considering time-series dynamics, we observe that the divergence between the realized and the expected risk premiums is largely driven by a "crowding out" of the realized premium during the financial crisis. Specifically, realized compensation for climate change exposure rises steadily over the sample period, from zero in 2003 to 2% p.a. before the financial crisis. The realized premium then declines sharply into negative terrain between 2007 and 2009, and it subsequently resumes its upward trend until 2019 (with a positive premium since 2015/2016). The patterns for the two proxies for the expected risk premium look different, relative to the realized premium, and also relative to each other. For investors using variance as the sufficient risk statistic (Martin and Wagner (2019)), the expected risk premium increases from an initial level of zero to 0.5% in 2012, and it then plateaus (or slightly increases) around this level for the next decade. Until 2015, this pattern is similar if we construct the premium for investors also considering extreme risks and opportunities (Chabi-Yo, Dim, and Vilkov (2020)). However, we observe a remarkably different pattern after 2015: for investors with higher-order risk preferences, there has been a steady *decline* in the premium since that year to zero in 2019.

What can we learn from these diverging patterns? An initial conclusion is that climate change exposure has nuanced effects: the associated risk premiums exhibit non-monotone effects that change over time depending on which investor risk preferences are assumed in the risk premium estimations.[4] A second conclusion is that our understanding of how climate change exposure affects financial markets requires a detailed analysis of how exposure affects risk quantities *beyond* the second moment. A third conclusion is that we need to acquire a better understanding of how climate change exposure maps to financial risk quantities *since 2015*.

These insights prompt us to explore in detail how climate exposure affects higher-order moments and tail risks, conditional on different time periods. We demonstrate that the dynamics of the two expected risk premiums can be attributed to how investors map climate exposure into variance and higher-order risks: beginning around 2015, investors started to associate relatively smaller crash risks and relatively higher opportunities with climate change exposure. This reallocation of likelihood from left- to right-tail events reduces the required compensation for climate exposure in the eyes of investors with preferences that take higher-order risks into account. We capture these effects as our exposure measure reflects upside *and* downside aspects. Moreover, these effects arise as large parts of the expected risk premium for climate change exposure – and of the risks associated with this exposure – originate from climate-related opportunity shocks; such opportunities are risky, as they require significant and uncertain investments. There is also a positive risk premium effect of regulatory shocks, but overall, the effect of upside opportunity shocks dominates that of downside regulatory shocks (we cannot detect a risk premium for physical shocks). What are the implications of this for the two expected risk premium proxies? Firms with better climate-related opportunities may command a higher risk premium because of a higher expected variance (as we find for the proxy by Martin and Wagner (2019)). How-

[4] This conclusion is consistent with Bolton and Kacperczyk (2020), whose analysis also reveals nuanced effects of the carbon risk premium over time and across countries.

ever, the proxy by Chabi-Yo, Dim, and Vilkov (2020) may be reduced to zero if higher climate exposure means better growth potential and smaller downside crash risk.

This answer this leaves open the question of what happened in 2015, the year in which the Chabi-Yo, Dim, and Vilkov (2020) proxy began its decline to zero. We offer two non-mutually exclusive explanations. First, 2015 was the year of the Paris Agreement, and markets may have in turn updated their views on the likelihood of the success of climate-related investment opportunities; this should lower downside crash risk and increase upside financial potential for firms with high climate-related opportunities.[5] Second, Azar, Duro, Kadach, and Ormazabal (2021) document that since 2015, there has been increased climate-related engagement by the "Big Three" (BlackRock, Vanguard, and State Street), which has lead to emission reductions. This effect may in turn have reduced downside tail risks of firms with high regulatory exposure.

In this paper, we address two challenges identified by Giglio, Kelly, and Stroebel (2020) in the analysis of how climate change affects asset prices. The first challenge is to obtain a firm-level exposure measure, which separates between physical and transition climate risks and captures climate-related upside and downside potential. The second challenge is the short time period for which climate exposure data is usually available, and, importantly, changes in investors' recognition and perception of climate-related risks during that short period.

We offer a partial solution to both challenges. First, we use a firm-level exposure measure to quantify investor attention to (or preoccupation with) climate-related topics. We are able to split exposure into opportunity, regulatory, and physical shocks, and to trace the financial market effects of these facets of climate change. Second, instead of relying solely on a noisy measure of realized returns, we make use of conditional forward-looking proxies of expected returns constructed from option prices. Such proxies have been shown to work well as unbiased predictors of unconditional expected excess returns, and they can serve as conditional predictors under most economic conditions (Back, Crotty, and Kazempour (2020)). The use of different expected return proxies allows us to disentangle the effects of second-order (variance) risks from those of tail and higher-order risks not spanned by the variance.[6]

[5] The Paris Agreement contains legally binding commitments to allocate large amounts of capital toward climate-friendly projects.

[6] For example, they allow us to consider the relative effects of crash risk, represented by the left tail, versus those of opportunities, reflected by the right tail.

A further advantage is that our exposure measure is adaptive, in the sense that it does not represent an observable quantity linked to climate change.[7] Instead, it reflects the revealed need for information by, and attention of, investors with regard to climate topics considered relevant for their investment decisions. As a result, the exposure measure varies within-firm and reflects a range of issues potentially driving returns (e.g., temperature changes, ESG awareness of investors, or climate beliefs). The compensation for climate change exposure inherits these adaptive dynamics, and it reflects, at any point in time, the *current mapping* by market participants from information flows in earnings calls into return and risk quantities.[8]

These features open interesting channels for the development of climate finance models. For example, the diminishing risk premium of climate exposure for some investors since 2015 can be linked to the ESG-CAPM framework of Pedersen, Fitzgibbons, and Pomorski (2020) and the increasing awareness of climate topics among investors. The positive unconditional risk premium lends support to the models that Giglio, Kelly, and Stroebel (2020) categorize as models with "uncertainty about the path of climate change." In these models, a high exposure to climate change commands a risk premium. However, a decreasing conditional risk premium due to the attribution of higher opportunities for firms with higher exposure also means that these models need an extra dynamic component linking climate change exposure to growth opportunities.

2 Data, Estimation Choices, and Procedures

2.1 Data on Firm-Level Climate Change Exposure

2.1.1 Firm-level Climate Change Metrics

We use the measures of climate change exposure recently developed by SvLVZ, who construct their measures from the transcripts of quarterly earnings conference calls. Earnings calls allow market participants to listen to management and inquire about material current and future developments (Hollander, Pronk, and Roelofsen (2010)). Most relevant for our setting, earnings

[7]This is different from the use of emissions as in Bolton and Kacperczyk (2021), the use of a draught index as in Hong, Li, and Xu (2019), or the use of elevations above sea level as in Giglio, Maggiori, Rao, Stroebel, and Weber (2018).

[8]A step in the same direction is provided by Kölbel, Leippold, Rillaerts, and Wang (2020), who show that a 10-K-based measure of climate change exposure affects the CDS term structure.

calls provide a forum for market participants to query firms' exposure to the risks and opportunities related to climate change. We restrict our analysis to U.S. firms in the S&P 500 to ensure that we meet data quality requirements with respect to our measures of expected returns and risk. The data are available for the years 2002 to 2019.[9]

To capture exposure, that is, the proportion of the earnings call devoted to talk about climate change, SvLVZ develop a computational linguistics algorithm that identifies when the discussion between analysts and executives turns to climate change.[10] The innovation in SvLVZ is to adapt the keyword discovery algorithm by King, Lam, and Roberts (2017) to produce a set of bigrams $\mathbb{C}$ that are unique to climate change discussions. Furthermore, SvLVZ refine their overall measure of exposure by separating out three categories of specific bigrams related to climate-related opportunity, regulatory, and physical shocks ($\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, and $\mathbb{C}^{Phy}$, respectively).

Based on each of these four sets of bigrams, SvLVZ construct four metrics to quantify, for each quarter, a firm's exposure to climate change. These metrics have a straightforward interpretation: they capture how frequently a set of climate change bigrams appears in a conference call transcript, scaled by the length of the conference call transcript, and thus can be interpreted as the share of the conversation devoted to climate change:

$$CCExposure_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} (1[b \in \mathbb{C}]), \tag{1}$$

where $b = 0, 1, ...B_{it}$ are the bigrams appearing in the transcript of firm i in quarter t, where $1[\cdot]$ is the indicator function, and where $\mathbb{C}$ is a given set of climate change bigrams ($\mathbb{C}$, $\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, or $\mathbb{C}^{Phy}$). The measure of total exposure is labelled as $CCExposure$, and the three topic-based measures as $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$, respectively.[11] OA Table 1 provides the top-100 bigrams used to create $CCExposure$, and OA Table 2 to 4 those used for the three topic-based exposure measures.

[9] The SvLVZ data can be accessed on https://osf.io/fd6jq/.

[10] In order to identify such discussions, the algorithm determines the salient word combinations that are used in talks about climate change. As SvLVZ explain, this step is not obvious to implement, as the language used in earnings calls tends to be tailored to the specific business models and ecosystems of firms.

[11] We use "exposure" not in the traditional asset pricing sense, but consistent with the terminology introduced in Hassan, Hollander, van Lent, and Tahoun (2019).

To investigate whether exposure is firm-specific or is instead driven by investor attitudes toward particular industries, we compute a measure of industry-level exposure ($CCExposure^{Ind}$) by averaging $CCExposure$ across all firm years in an industry. We then compute for each firm month the firm-specific component $CCExposure^{Res}$ ($CCExposure$ - $CCExposure^{Ind}$).

2.2 Time Structure and Matching of Climate Change Exposure Data

For three reasons, we transform the exposure metrics in order to match them with return and risk variables. First, we want to ensure that there is no look-ahead bias – in other words, that the exposure measures are available at the time we construct the risk and return quantities. Second, the exposure measures are observed at the quarterly frequency, while data on returns and risk quantities are available monthly. Third, when specific climate topics are discussed in an earnings call, subsequent calls may not inspire interest in the same topic, implying that subsequent transcripts may not contain climate bigrams.[12] To address these data features, we process the exposure measures in two steps. In the first step, we match the month of a given transcript date with the end-of-month data in the Monthly Stock File from CRSP. We then merge the two datasets while retaining the monthly frequency of the data. This allows us to eliminate look-ahead bias, because information from earnings calls is now available to investors before the stock data date. In the second step, we exponentially smooth *monthly* observations of the exposure measures using a half-life of six months.[13] Hence, we replace each exposure measure x_t with its exponentially weighted moving average y_t:

$$y_t = \frac{\sum_{z=0}^{t} x_{t-z}(1-\alpha)^z}{\sum_{z=0}^{t}(1-\alpha)^z},$$

where the decay α is related to half-life τ as $\alpha = 1 - \exp(-\ln(2)/\tau)$.

Before employing these smoothed exposure measures, we standardize the measures for each month using $\frac{x-\mu_x}{100\sigma_x}$; this allows us to express risk premiums in percentages.

[12] SvLVZ circumvent this issue by using annual averages of quarterly transcript-based exposure measures.

[13] Results are not sensitive to the parameters of the smoothing, and using half-lives between three and 12 months yields similar results.

2.3 Data on Expected Returns and Risk Characteristics

We collect data on returns and risk quantities for S&P 500 stocks that belonged to the index between 2000 and 2019. Data on climate change exposure are available since 2002, but our subsequent tests start in January 2003 to allow for a burn-in period – that is, to ensure that a reasonable number of stocks obtain non-zero climate change exposure values at the beginning of the estimation. Data on the S&P 500 constituents and on firm fundamentals are from Compustat, and data on returns and stock prices are from CRSP.[14]

We estimate standard multi-factor models at the end of each month using daily returns over the past 12 months (Fama and French (1993), Carhart (1997), Fama and French (2015)). For company characteristics, we use size, book-to-market ratio, momentum, profitability, and investment. Size is the log of the year-end market cap for the year preceding the month of interest. Book-to-market ratio is the log of the ratio of the book value of equity to the market cap at the end of the preceding fiscal year. Investment and profitability are computed as in Hou, Xue, and Zhang (2015): investment equals the annual change in total assets scaled by lagged total assets, and profitability is income before extraordinary items (year preceding the month of interest) divided by the book value of equity. To ensure that the fundamentals are based on available data, we assume at least a six-month gap between the end of the fiscal year and the time at which the fiscal-year-end data become publicly available (Fama and French (1992)).

2.3.1 Measures of Expected Returns

Due to our short sample period, and the infrequently observed climate change metrics, it is important to use up-to-date conditional expected return proxies. Notably, the use of *realized* excess returns as a proxy for expected excess returns may not work well in terms of producing reasonable risk premiums. As Edwin J. Elton noted in his Presidential Address (Elton (1999)): *"Almost all the testing I am aware of involves using realized returns as a proxy for expected*

[14] We merge the two datasets through the CCM Linking Table using GVKEY and IID to link to PERMNO, following the corresponding "second-best" method from Dobelman, Kang, and Park (2014).

returns. [It] relies on a belief that [..] realized returns are therefore an unbiased estimate of expected returns. However, I believe that there is ample evidence that this belief is misplaced."[15]

To address this estimation challenge, we construct proxies for expected returns from forward-looking, always up-to-date, option-implied quantities as proposed by Martin and Wagner (2019), Kadan and Tang (2020), and Chabi-Yo, Dim, and Vilkov (2020).[16] Though similar, there are differences across the three proxies with implications for understanding the effects of climate change exposure. Martin and Wagner (2019) and Kadan and Tang (2020) (hereinafter MW and KT) derive their proxies as lower bounds $\mathcal{LB}_t$ for the conditional expected excess return under assumptions for option-based quantities – that is, as $E_t[R_{t+1}] - R_{f,t} \geq \mathcal{LB}_t$. While the derivations make a statement about the lowest estimate of the conditional expected return, and not about the expected return itself, one can test whether the bound is valid (the expected excess returns cannot be lower than the bound) and tight (the bound is an unbiased predictor of the expected excess return). Important for us is that the bounds by MW and KT are based on the second-order, risk-neutral moments of the return distribution, and thus, to some extent, do not consider the effects of (priced) tail risks and asymmetry in the return distribution (in the portion not spanned by the variance). In other words, the bounds by MW and KT capture the expected returns of investors who consider second moments to be a sufficient risk statistic.

The MW proxy for the expected excess return is constructed for stock i at the end of month t by using the variances of an index and its components:

$$MW_{i,t,t+\Delta t}/R_{f,t} = IV_{t,t+\Delta t} + \frac{1}{2}\left(IV_{i,t,t+\Delta t} - \sum_{i=1}^{N} w_{i,t} IV_{i,t,t+\Delta t}\right), \tag{2}$$

[15] Researchers developed remedies for this parameter estimation problem because early tests rejected the CAPM (Black, Jensen, and Scholes (1972)) and because the performance of optimized portfolios using historical returns as proxies for expected returns was unsatisfactory. In the meantime, a number of corrections exist for beta estimates, from simple fixes as in Elton, Gruber, and Urich (1978), to more complex remedies (Buss and Vilkov (2012), Boloorforoosh, Christoffersen, Fournier, and Gouriéroux (2019). For expected returns, researchers propose the correction of historical averages to reduce the noise (e.g., shrinkage), or to build a proxy for expected returns from less noisy information (Elton (1999), Cochrane (2011)).

[16] Several expected return proxies have also recently been developed for the market index (e.g., Martin (2017), Chabi-Yo and Loudis (2020), or Schneider and Trojani (2019)). Although the use of option-based bounds as a proxy for expected returns is nascent, there are several applications: Cieslak, Morse, and Vissing-Jørgensen (2019) use the equity risk premium proxy by Martin (2017), and Ai, Han, Pan, and Xu (2019) take an implied variance measure (log contract of Bakshi, Kapadia, and Madan (2003)) as a proxy for stocks' expected returns.

where $w_{i,t}$ is the value-weight of stock i, where $IV_{t,t+\Delta t}$ is the implied variance of market returns (S&P 500), and where $IV_{i,t,t+\Delta t}$ is the return variance of individual stocks.

The generalized lower bounds of Chabi-Yo, Dim, and Vilkov (2020) (hereinafter GLB) account for the entire risk-neutral distribution, implicitly considering all higher-order moments – it in turn captures the expected returns of investors who also care about higher moments in the portion unspanned by the variance.[17] The proxy by GLB is calculated as follows:

$$GLB_{i,t,t+\Delta t} = \max_{\theta \in \underline{\Theta}_{i,t}} \left\{ \mathbb{E}_t^* \left(\varphi_\theta \left[R_{i,t,t+\Delta t} \right] \right) / \mathbb{E}_t^* \left(\frac{\varphi_\theta \left[R_{i,t,t+\Delta t} \right]}{R_{i,t,t+\Delta t}} \right) - R_{f,t,t+\Delta t} \right\}, \tag{3}$$

where $\mathbb{E}_t^*$ denotes the risk-neutral expectation, where $\varphi_\theta(x) = x^{\theta+1}$, and where $\underline{\Theta}_{i,t}$ is the stock- and time-varying set identified from historical parameters as described in Proposition 2 in Chabi-Yo, Dim, and Vilkov (2020).[18]

We focus on the proxies provided by MW and GLB and consider the KT proxy for robustness (results are similar to those using the MW bounds). We emphasize any potential differences in results between these two proxies to obtain insights into climate-related higher-order risks, as well as whether and how the respective risk premiums are priced by market participants.

2.3.2 Option-Based Measures of Central Moments and Tail Risk Proxies

We make use of options data to estimate central moments of the return distribution and proxies for tail risk. While these "risk quantities" do not directly reflect expectations of risk in the real (physical) world, they efficiently aggregate the forward-looking consensus of market participants with respect to the future return distribution up to a given option maturity.[19] For example,

[17]Back, Crotty, and Kazempour (2020) test the validity and tightness of the MW and KT methods to find that in conditional settings, bounds based on second-order moments are not necessarily tight – that is, they provide a well-performing, but still biased, proxy for conditional expected returns. Chabi-Yo, Dim, and Vilkov (2020) find that the GLB is conditionally valid and is a tight proxy of expected excess returns. Grammig, Hanenberg, Schlag, and Sönksen (2020) compare several theory-based proxies with machine learning-based expected returns to demonstrate that option-implied bounds provide a superior expected return proxy for short horizons (of up to several months). Moreover, they show that the GLB approach typically outperforms the alternative methods.

[18]The data are available on https://doi.org/10.17605/OSF.IO/Z2486, see Vilkov (2020).

[19]This approach of using risk-neutral quantities follows the literature. The benefit of option-implied variables, compared to equivalents under the physical probability measure, is their forward-looking character. The cost includes a potential bias stemming from the risk premium effect (for discussions of related issues, see Vanden (2008), Chang, Christoffersen, Jacobs, and Vainberg (2012), Cremers, Halling, and Weinbaum (2012), DeMiguel, Plyakha, Uppal, and Vilkov (2013)).

the implied variance is a strong predictor of the future realized variance (Poon and Granger (2003)), the implied skewness allows for the quantification of the asymmetry of the risk-neutral distribution, and the implied volatility slope represents a heuristic proxy for the relative price of protection against tail risk (Kelly, Pástor, and Veronesi (2016)).

Higher-order central moments: Implied Variance, Skewness, Kurtosis. To measure implied variance (IV), we take the Martin (2017) variance swap rate $IV_{t,t+\Delta t}$ for a given maturity $t+\Delta t$, constructed from the prices of out-of-the-money (OTM) calls $C(t, t+\Delta, K)$ and puts $P(t, t+\Delta, K)$ with strike prices K observed at t.[20]

$$IV_{t,t+\Delta t} = \frac{2R_{f,t}}{S_t^2}\left[\int_0^{F_{t,t+\Delta t}} P(t, t+\Delta, K)dK + \int_{F_{t,t+\Delta t}}^{\infty} C(t, t+\Delta, K)dK\right], \tag{4}$$

where S_t and $F_{t,t+\Delta t}$ are the spot and forward prices of the underlying stock, and where $R_{f,t}$ is the gross risk-free rate. We use a similar approach for the implied skewness, $ISkew$, and for the implied kurtosis, $IKurt$, applying the formulas for the log returns provided in Bakshi, Kapadia, and Madan (2003). We approximate each integral in Equation (4) for IV using a finite sum of 500 option prices (we do likewise for similar integrals in the formulas for $ISkew$ and $IKurt$). As our data source, we use the Volatility Surface File of Ivy DB OptionMetrics, which contains option-implied volatilities for standard maturities and delta points.[21]

Implied Volatility Slope. We measure the steepness of the implied volatility slope on the left ($SlopeD$) and right ($SlopeU$) from the at-the-money (ATM) point. As in Kelly, Pástor, and Veronesi (2016), the measures are the slopes of functions relating implied volatilities of OTM options to their deltas. We estimate $SlopeD$ by regressing implied volatilities of puts with deltas between -0.1 and -0.5 on their deltas (and a constant). For $SlopeU$, we regress implied volatilities of calls with deltas between 0.1 and 0.5 on their deltas. An increase in the measures

[20] We use the simple return variance as the variance proxy because it is the primary ingredient for computing the expected excess returns (Martin and Wagner (2019)). Results based on the log return variance computed as in Bakshi, Kapadia, and Madan (2003) are similar.

[21] The matching of stock variables to options data is implemented through the historical CUSIP link of OptionMetrics. To prepare the Volatility Surface for computations, we select OTM options with absolute deltas strictly smaller than 0.5 for puts, and weakly smaller for calls, for the maturity of 30 days. We then interpolate the implied volatilities available for each maturity as a function of moneyness (strike over spot price) for the range between available moneyness points, and we then extrapolate by filling in the missing extreme data by the implied volatility values from the left and right boundaries to fill in the moneyness range of [1/3,3] with a total of 1,001 points. For the interpolations, we use a piece-wise cubic Hermite interpolating polynomial.

indicates that deeper OTM options become more expensive, reflecting a relatively higher cost of protection against tail risks. The measures are on average positive as far OTM options are typically more expensive (in terms of implied volatilities) than ATM options.

2.3.3 Option-Based Measures of Risk Premiums for Particular Risks

We calculate risk premiums for particular risks by comparing expected quantities under the physical and risk-neutral probability measures.[22]

Variance Risk Premium. The variance risk premium (VRP) allows us to evaluate the cost of protection against general variance risk (or uncertainty, as suggested in Bali and Zhou (2016)). VRP is computed as the difference between the risk-neutral expected and the past realized variances (the latter acting as a proxy for expected variance under the physical measure):

$$VRP_{t,t+\Delta t} = IV_{t,t+\Delta t} - RV_{t-\Delta t,t}, \tag{5}$$

where $RV_{t-\Delta t,t}$ is computed from daily simple returns over the rolling window $[t - \Delta t, t]$.

Upside and Downside Variance Risk Premium. We construct the downside ($VRPD$) and upside ($VRPU$) semi-variance risk premiums to predominantly quantify the compensation for downside and upside jumps (Kilic and Shaliastovich (2019), Feunou, Jahan-Parvar, and Okou (2018)). These measures are computed in a manner similar to the variance risk premium, but semi-variances are used in place of implied and realized variances. For $VRPD$, we use the implied downside semi-variance and the realized downside semi-variance. The implied downside semi-variance is computed using only the first component (OTM puts) in the simple variance swap rate formula (Equation (4)). The realized downside semi-variance is the variance of *negative* returns over a given time window. Similarly, for $VRPU$, we use the upside semi-variances.

Skewness Risk Premium. Following Feunou, Jahan-Parvar, and Okou (2018), we construct the risk premium for skewness (SRP) as the difference between the upside and downside semi-variance risk premiums: $SRP = VRPU - VRPD$.

[22] The theoretically sound definition of the finite-period risk premium is the expectation under the risk-neutral (Q) measure minus expectation under the physical (P) measure; for convenience, we follow an information tradition of computing the finite-period risk premium as the Q minus P expectation.

Variable	Mean	Std.	10%	25%	50%	75%	90%	Obs.
Market cap., mil USD	23965	50343	1953	4108	9420	21575	53034	121380
Climate Change Exposure Metrics								
$CCExposure$	941.766	2334.929	53.984	131.469	277.809	668.858	1838.931	121878
$CCExposure^{Ind}$	937.236	1691.387	222.928	277.619	433.918	862.426	1207.647	121331
$CCExposure^{Res}$	-0.000	1614.602	-663.072	-332.663	-144.502	74.219	617.928	121331
$CCExposure^{Opp}$	364.643	1097.871	0.206	15.434	81.155	221.835	667.882	121878
$CCExposur^{Reg}$	59.643	240.222	0.000	0.000	0.000	10.465	116.740	121878
$CCExposure^{Phy}$	12.452	68.529	0.000	0.000	0.000	0.088	22.905	121878
Betas for 4- and 5-factor Models								
$Market$	1.051	0.374	0.614	0.807	1.020	1.257	1.515	121219
$Size$ (SMB)	0.198	0.531	-0.344	-0.148	0.101	0.429	0.856	121219
$Value$ (HML)	0.127	0.770	-0.642	-0.295	0.040	0.469	1.001	121219
$Mom.$ (WML)	-0.065	0.552	-0.639	-0.308	-0.038	0.200	0.440	121219
$Prof.$ (RMW)	-0.011	0.835	-0.977	-0.366	0.086	0.451	0.810	121219
$Inv.$ (CMA)	0.110	0.963	-0.988	-0.333	0.183	0.651	1.100	121219
Expected Excess Return Proxies								
RET, *p.a.*	0.150	1.066	-1.087	-0.422	0.155	0.716	1.350	120650
MW, *p.a.*	0.063	0.079	0.008	0.019	0.039	0.075	0.141	118836
GLB, *p.a.*	0.081	0.087	0.022	0.033	0.054	0.094	0.159	117885
Option-based Risk Measures								
IV	0.143	0.151	0.040	0.059	0.095	0.163	0.289	118836
$ISkew$	-0.572	0.467	-1.116	-0.795	-0.542	-0.316	-0.080	118836
$IKurt$	4.772	1.904	3.263	3.548	4.070	5.224	7.476	118836
SlopeU	-0.101	0.255	-0.411	-0.135	-0.016	0.034	0.082	118836
SlopeD	0.299	0.285	0.078	0.138	0.215	0.355	0.620	118836
Option-based Risk Premiums								
VRP, *p.a.*	0.019	0.119	-0.056	0.001	0.026	0.057	0.107	118821
$VRPD$, *p.a.*	0.013	0.060	-0.026	0.004	0.017	0.035	0.059	118821
$VRPU$, *p.a.*	0.007	0.083	-0.042	-0.004	0.011	0.030	0.065	118821
SRP, *p.a.*	-0.006	0.090	-0.066	-0.025	-0.006	0.014	0.057	118821

Table 1: Summary Statistics. This table reports summary statistics at the firm-month level for our sample. The climate change exposure metrics are scaled up by 10^6. The sample covers the years 2003 to 2019 and includes stocks in the S&P 500.

2.4 Summary Statistics

Table 1 reports summary statistics at the firm-month level. $CCExposure$ is quite volatile, and it is on average available for most of the sample observations (10th percentile is positive). $CCExposure^{Ind}$ is on average similar to the general measure, but less volatile, and $CCExposure^{Res}$ is on average zero (as expected). The topic-based exposure measures are more sparse than the general measure. The annualized realized excess return equals 15% per year on average, which compares to 6.3% and 8.1% for the MW and GLB proxies, respectively. Realized excess returns are far more noisy across time and firms (standard deviation of 106.6%) compared to the MW and GLB proxies (standard deviations of 7.9% and 8.7%, respectively).

3 Risk Premium for Climate Change Exposure

3.1 Risk Premium for Climate Change Exposure: Cross-Sectional Analysis

We first test whether $CCExposure$ is related to excess returns in the cross-section of stocks using the two-stage approach by Fama and MacBeth (1973). We employ realized excess returns (RET) as well as the MW- and GLB-based proxies for expected excess returns (in annual terms). $CCExposure$ reflects the perceived importance of climate-related topics in a firm's current and future activities. If these perceptions are priced by market participants, then we expect $CCExposure$ to be positively associated with excess returns; such a relationship would indicate that a high degree of attention to climate topics represents a priced risk from the perspective of investors. We also investigate whether any such risk premium is firm-specific ($CCExposure^{Res}$) or is instead driven by investor attitudes toward particular industries ($CCExposure^{Ind}$).

Table 2 reports the risk premiums for climate change exposure, controlling for the standard risk factors using 4- and 5-factor models. Columns 1 and 2 report estimates for realized excess returns (RET), Columns 3 and 4 for the MW proxy of expected returns, and Columns 5 and 6 for the GLB proxy. Panel A uses $CCExposure$ as the climate change metric, and Panel B uses $CCExposure^{Ind}$ and $CCExposure^{Res}$, respectively. The estimates for the *realized* excess return in Columns 1 and 2 deliver insignificant climate-related risk premiums, both in Panel A and in Panel B. These insignificant outcomes are not unexpected, given that the risk premiums for most standard risk factors in the two columns are also insignificant (with the exception of SMB). As explained above, these insignificant estimates likely reflect the large amounts of noise in realized excess returns in our short sample period.

To the contrary, $CCExposure$ is positively associated with *expected* excess returns. Considering in Columns 3 and 4 of Panel A the MW-based proxy, stocks are expected to deliver higher excess returns when $CCExposure$ is higher (t-stats of 2.9 and 3.0, respectively). Panel B shows that the industry- *and* the firm-level components of $CCExposure$ are priced. The findings in both panels convey an important message: higher climate change exposure – in other words, more conversations on climate-related topics in earnings calls – is associated with a higher risk premium, and firms do not simply inherit an industry-average premium for such exposure.

Expected Return	*RET*		*MW*		*GLB*	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total CCExposure Risk Premium						
Constant	0.1394	0.1290	0.0104	0.0105	0.0393	0.0394
	(4.38)	(4.92)	(2.38)	(3.48)	(5.03)	(5.78)
Market	-0.0056	0.0073	0.0386	0.0386	0.0365	0.0365
	(-0.14)	(0.20)	(4.16)	(4.52)	(5.33)	(4.77)
Size (*SMB*)	0.0381	0.0482	0.0499	0.0522	0.0152	0.0149
	(2.32)	(2.81)	(12.68)	(12.11)	(5.13)	(5.03)
Value (*HML*)	-0.0193	-0.0191	0.0036	0.0078	0.0052	0.0049
	(-1.24)	(-1.24)	(0.79)	(1.62)	(2.44)	(1.90)
Mom. (*WML*)	0.0103	–	-0.0248	–	-0.0076	–
	(0.36)	–	(-2.43)	–	(-1.13)	–
Prof. (*RMW*)	–	0.0085	–	-0.0203	–	-0.0067
	–	(0.62)	–	(-7.79)	–	(-4.89)
Inv. (*CMA*)	–	-0.0170	–	0.0018	–	-0.0002
	–	(-1.42)	–	(0.63)	–	(-0.20)
CCExposure	-0.2085	-0.0807	0.2239	0.2250	0.1615	0.1395
	(-0.48)	(-0.18)	(2.92)	(3.04)	(1.93)	(1.60)
Obs.	117632	117632	117972	117972	117362	117362
R^2	0.0005	0.0012	0.1999	0.2173	0.0439	0.0541
Panel B: Industry Decomposition of CCExposure Risk Premium						
Constant	0.1403	0.1293	0.0100	0.0100	0.0392	0.0394
	(4.50)	(4.98)	(2.31)	(3.36)	(5.04)	(5.82)
Market	-0.0063	0.0072	0.0391	0.0392	0.0365	0.0365
	(-0.16)	(0.21)	(4.16)	(4.60)	(5.31)	(4.74)
Size (*SMB*)	0.0368	0.0464	0.0500	0.0522	0.0154	0.0150
	(2.22)	(2.72)	(12.20)	(12.01)	(5.09)	(4.97)
Value (*HML*)	-0.0186	-0.0188	0.0035	0.0076	0.0052	0.0049
	(-1.14)	(-1.11)	(0.74)	(1.57)	(2.44)	(1.91)
Mom. (*WML*)	0.0103	–	-0.0245	–	-0.0076	–
	(0.38)	–	(-2.37)	–	(-1.14)	–
Prof. (*RMW*)	–	0.0088	–	-0.0202	–	-0.0068
	–	(0.65)	–	(-7.75)	–	(-4.90)
Inv. (*CMA*)	–	-0.0168	–	0.0017	–	-0.0002
	–	(-1.47)	–	(0.59)	–	(-0.15)
$CCExposure^{Ind}$	-0.3944	-0.2812	0.1900	0.2124	0.1230	0.0905
	(-0.74)	(-0.51)	(2.44)	(2.75)	(1.83)	(1.24)
$CCExposure^{Res}$	0.1023	0.1429	0.1339	0.1131	0.1089	0.1099
	(0.34)	(0.47)	(2.67)	(2.12)	(1.94)	(1.96)
Obs.	117093	117093	117426	117426	116823	116823
R^2	0.0005	0.0012	0.2005	0.2181	0.0442	0.0544

Table 2: Risk Premium for Climate Change Exposure: Cross-Sectional Analysis. This table reports the results of the Fama-MacBeth regressions at the firm-month level. We report in Panel A the risk premium estimates for firm-specific climate change exposure (*CCExposure*) and in Panel B for the exposure measure's two components, industry average climate change exposure ($CCExposure^{Ind}$) and the residual ($CCExposure^{Res}$). All risk premiums are reported after controlling for 4- and 5-factor models (in decimals p.a.). As proxies for expected excess returns, we use in Columns 1 and 2 the realized excess returns (*RET*), in Columns 3 and 4 the forward-looking proxy by Martin and Wagner (2019) (*MW*), and in Columns 5 and 6 the forward-looking proxy by Chabi-Yo, Dim, and Vilkov (2020) (*GLB*). t-statistics based on Newey and West (1987) standard errors are reported in parentheses. The sample covers the years 2003 to 2019 and includes stocks in the S&P 500.

We obtain a more nuanced picture when we consider in Columns 5 and 6 the *GLB* proxy. In Panel A, the magnitude of the climate risk premium decreases when compared to the *MW* proxy:

the coefficients for $CCExposure$ decline by 25% to 40%, and the t-stats drop to 1.93 and 1.60, respectively. When we split $CCExposure$ in Panel B into its industry and residual components, both exposure measures have similar coefficients, but the risk premium for $CCExposure^{Res}$ is slightly more significant (t-stats of 1.94 and 1.96 vs. 1.83 and 1.24, respectively).

The differences between the MW- and GLB-based risk premiums raise the question of which climate-related factors cause the two premiums to deviate? Recall that a difference between the two proxies stems from differences in (model-implied) investor risk attitudes. While the MW proxy is based on preferences that do not consider higher-order risks unspanned by a stock's variance, the GLB proxy reflects more general risk preferences (inasmuch as it also considers the role of unspanned higher-order risks). The divergence in results may hence be explained by two (non-mutually exclusive) mechanisms. First, investors allocate relatively high upside potential (right tail) and relatively low crash risk (left tail) to firms with high climate change exposure. This conclusion emerges because, compared to the MW proxy, the GLB proxy increases more strongly in the left tail and decreases more strongly in the right tail. This causes firms with high climate-related opportunities and low crash risk to earn smaller expected returns for the GLB proxy.[23] Second, the prices of left- and right-tail risks are misaligned – that is, either left-tail events are underpriced or the right-tail potential is overpriced by the market.[24]

We pursue three directions to better understand these mechanisms: (i) we analyze the dynamics of the conditional risk premiums; (ii) we directly examine the link between $CCExposure$ and higher-order risks and their respective risk premiums; and (iii) we decompose $CCExposure$ into its topic-based components.

Before turning to these tests, we note that the MW- and GLB-based estimates exhibit meaningful risk premiums for the standard risk factors. Unlike Columns 1 and 2, there is significant compensation for market, size, and profitability exposure (consistent with Martin and Wagner (2019), Kadan and Tang (2020), Chabi-Yo, Dim, and Vilkov (2020)). The same

[23]We provide evidence corroborating this interpretation below, where we split exposure into its opportunity, regulatory, and physical shock components.

[24]OA Table 5 re-runs the risk premium estimations using the ISS Carbon Risk Rating ($ISS\ CRR$), which assesses the carbon-related performance of firms. It takes values between 1 (poor performance) and 4 (excellent performance). The rating data is available only for a subset of S&P 500 firms and for the years 2015 to 2018. The ISS rating relates positively to the realized risk premium and negatively to the MW-based expected risk premium, and it is unrelated to the GLB proxy. The effects of $CCExposure$ are unchanged when controlling for the ISS rating (the insignificant effect of the GLB-based risk premium is consistent with the next subsection).

holds for the negative momentum risk premium. The insignificant CMA risk premium may be due to our sample period. Overall, these estimates corroborate that option-implied risk premiums in our context are more appropriate than are realized return proxies.

3.2 Risk Premium for Climate Change Exposure: Time-Series Dynamics

Climate-related risk premiums may vary over time. SvLVZ demonstrate that $CCExposure$ fluctuates over time due to changes in investor attention to climate change, and that climate topics can temporarily be crowded out by other topics (e.g., COVID-19). Figure 1, Panel A, therefore depicts the time-series evolution of the MW- and GLB-based risk premiums for $CCExposure$. We provide two versions of the risk premiums' time-series: a raw estimate, and a trend obtained by applying the STL decomposition of the series into additive seasonal, trend, and residual components (Cleveland, Cleveland, McRae, and Terpenning (1990)). As before, we extract the risk premiums jointly with factor model risk premiums using the Fama-MacBeth procedure.

Figure 1 shows that Table 2 mask important time-series heterogeneity. Before 2010, the MW and GLB risk premium for $CCExposure$ fluctuate around zero. Starting in 2010, however, both premiums turn positive, with the MW premium gradually rising to about 0.5% in 2012, and remaining at this level thereafter (until 2019). Somewhat differently, the GLB premium experiences a faster increase to 0.75% between 2012 and 2014 but then reverts back to a level of around zero by 2015, remaining at this level thereafter.

What can we learn from these diverging dynamics? If higher-order risks are not explicitly considered in the risk premium proxy, then climate change exposure is priced since 2010. If instead all risks encoded in the return distribution are considered, then climate-related exposure was priced only between 2010 and 2014. These differences signify the importance of understanding how $CCExposure$ is linked to the pricing of higher-order risks, notably the left and right tails, and how the pricing of these risks evolves over time.

Before turning to this analysis, we consider the dynamics of the *realized* risk premium. Figure 1, Panel B, shows that the insignificant overall effect for the realized premium masks that before the financial crisis, the compensation for climate exposure trended upwards. This increase was abruptly ended with a sharp decline with the financial crisis in 2008. The realized premium

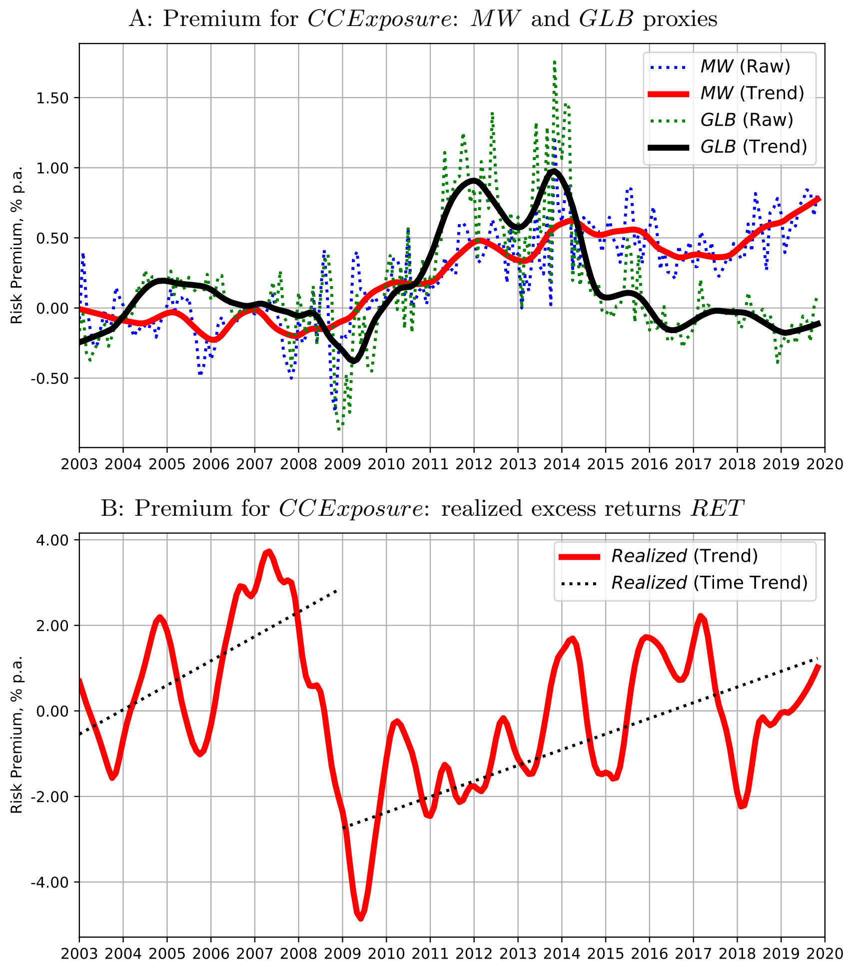

Figure 1: Risk Premium for Climate Change Exposure: Time-Series Dynamics. This figure shows the time series of the risk premium for $CCExposure$, estimated in Panel A from the expected excess return proxies of MW and GLB, and in Panel B from realized excess returns (risk premium in % p.a.). Risk premiums are obtained jointly with the 5-factor model premiums using the Fama-MacBeth procedure. Panel A provides two series: *Raw* reflects the raw estimate of the risk premium, while *Trend* captures the trend of the risk premium based on a decomposition of the raw estimate into additive seasonal, trend and residual components using the STL decomposition (Cleveland, Cleveland, McRae, and Terpenning (1990)). Panel B contains the trend component from the STL decomposition and a simple time trend, separately fitted for 2003–2008 and 2009–2019. The sample covers the years 2003 to 2019 and includes stocks in the S&P 500.

even became negative, indicating an excessive sell-off by investors becoming increasingly worried about the prospects of uncertain and quite long-term climate-related bets. The crisis-related drop was then followed by a secular upward trend in the realized premium until the end of the sample period. The initial trend, and the subsequent recovery after the financial crisis, indicate that the realized compensation for climate change exposure was non-zero for a substantial time.

The climate-related risk premiums around the financial crisis in both panels is consistent with two mechanisms: a crowding out of stocks with high climate change exposure during the financial crisis (as evidenced from the realized premium dynamics in Panel B); or a higher importance attributed by market participants to elevated risk regimes, broadly defined and covering any potential tail risk sources, after the financial crisis (Gennaioli, Shleifer, and Vishny (2015)).

4 Climate Change Exposure and Financial Risks

4.1 Unconditional Link: Central Moments and Tail Risks

The diverging dynamics of the expected return proxies reveal that the pricing of climate change exposure depends on which investor risk preferences are captured. To better understand the role of these risk preferences, we examine in Table 3 the relationship between $CCExposure$ and different proxies that contain information about the return distribution: the second (IV), third ($ISkew$), and fourth ($IKurt$) central risk-neutral moments, and two heuristic variables quantifying the relative expensiveness of the left ($SlopeD$) and right ($SlopeU$) tails. Panel A relates these "risk quantities" to $CCExposure$, and Panel B to $CCExposure^{Ind}$ and $CCExposure^{Res}$. To diminish the effects of general market conditions, we standardize the risk quantities and the exposure measures at each point in time to have zero means and standard deviations of one. We account for the betas of the underlying returns with respect to the risk factors of the 4- and 5-factor models.[25] We further include time and industry fixed effects.

Table 3 documents that climate change exposure affects risk quantities, in particular tail risks. In Panel A, Columns 3 and 4, $CCExposure$ is significantly associated with a relatively more negative skewed distribution ($ISkew$), and in Columns 5 and 6 with fatter tails ($IKurt$). The negative coefficients for $SlopeU$ in Columns 9 and 10 indicate that upside potential becomes cheaper when $CCExposure$ increases, while the positive coefficients on $SlopeD$ in Columns 7 and 8 reflect the increasing costs of left-tail protection when $CCExposure$ is higher. Hence, we observe cheaper upside tail exposure and more expensive downside tail exposure for firms with higher values of $CCExposure$. This finding echoes the results in Ilhan, Sautner, and Vilkov (2021), who document more expensive tail protection for firms with higher carbon intensities;

[25]Results change only slightly if we use individual stock characteristics (market beta, size, book-to-market ratio, 12-month momentum, profitability, and investments) instead of factor betas (the IV effect becomes insignificant). We use factor betas, as the characteristics are observed less frequently than required for monthly return estimations.

Risk Metric	IV		$ISkew$		$IKurt$		$SlopeD$		$SlopeU$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Total $CCExposure$										
$Constant$	-0.8173	-0.8653	-0.2633	-0.2374	0.5766	0.5833	0.0855	0.0560	-0.3125	-0.3305
	(-11.31)	(-13.37)	(-6.89)	(-5.56)	(9.23)	(9.36)	(2.01)	(1.23)	(-7.09)	(-8.29)
$Market$	0.6305	0.6733	0.2151	0.1928	-0.5468	-0.5542	-0.1134	-0.0886	0.3403	0.3579
	(9.61)	(11.64)	(5.86)	(4.86)	(-9.12)	(-9.36)	(-2.73)	(-2.00)	(7.86)	(9.04)
$Size\ (SMB)$	0.8718	0.8092	0.2391	0.2100	-0.0666	-0.0239	0.1442	0.1768	-0.2140	-0.2356
	(11.53)	(11.96)	(11.24)	(10.00)	(-2.24)	(-0.81)	(4.87)	(6.59)	(-5.78)	(-6.94)
$Value\ (HML)$	0.0262	0.0683	-0.0241	-0.0208	0.0593	0.0029	0.0569	0.0315	-0.0478	0.0122
	(0.40)	(1.22)	(-1.04)	(-1.43)	(1.33)	(0.10)	(2.37)	(1.11)	(-1.62)	(0.49)
$Mom.\ (WML)$	-0.1841	–	-0.0310	–	0.0383	–	-0.0283	–	-0.0049	–
	(-2.99)	–	(-1.49)	–	(1.36)	–	(-1.17)	–	(-0.28)	–
$Prof.\ (RMW)$	–	-0.3107	–	-0.1167	–	0.1322	–	0.0361	–	-0.0282
	–	(-6.71)	–	(-6.99)	–	(6.09)	–	(2.06)	–	(-2.26)
$Inv.\ (CMA)$	–	-0.00003	–	-0.0195	–	0.0473	–	0.0087	–	-0.0350
	–	(-0.00)	–	(-1.97)	–	(3.40)	–	(0.80)	–	(-2.46)
$CCExposure$	0.0300	0.0338	-0.0360	-0.0340	0.0881	0.0867	0.0806	0.0796	-0.0712	-0.0713
	(1.71)	(2.19)	(-3.83)	(-3.44)	(8.22)	(7.30)	(9.85)	(10.37)	(-9.55)	(-9.41)
Obs.	117093	117093	117093	117093	117093	117093	117093	117093	117093	117093
R^2	0.3005	0.3201	0.0308	0.0319	0.0949	0.0992	0.0174	0.0164	0.0398	0.0404
Panel B: Industry Decomposition of $CCExposure$										
$Constant$	-0.8168	-0.8651	-0.2637	-0.2377	0.5767	0.5835	0.0859	0.0564	-0.3124	-0.3306
	(-11.31)	(-13.35)	(-6.91)	(-5.58)	(9.21)	(9.36)	(2.02)	(1.24)	(-7.11)	(-8.34)
$Market$	0.6300	0.6730	0.2154	0.1930	-0.5474	-0.5549	-0.1141	-0.0893	0.3408	0.3586
	(9.59)	(11.60)	(5.89)	(4.88)	(-9.10)	(-9.36)	(-2.75)	(-2.02)	(7.88)	(9.09)
$Size\ (SMB)$	0.8721	0.8092	0.2397	0.2105	-0.0651	-0.0225	0.1449	0.1773	-0.2157	-0.2371
	(11.58)	(12.00)	(11.31)	(10.04)	(-2.16)	(-0.76)	(4.86)	(6.58)	(-5.82)	(-7.00)
$Value\ (HML)$	0.0263	0.0685	-0.0247	-0.0215	0.0589	0.0024	0.0570	0.0316	-0.0472	0.0130
	(0.40)	(1.22)	(-1.06)	(-1.49)	(1.32)	(0.08)	(2.37)	(1.11)	(-1.60)	(0.52)
$Mom.\ (WML)$	-0.1841	–	-0.0312	–	0.0378	–	-0.0285	–	-0.0043	–
	(-2.99)	–	(-1.51)	–	(1.33)	–	(-1.18)	–	(-0.24)	–
$Prof.\ (RMW)$	–	-0.3107	–	-0.1170	–	0.1313	–	0.0358	–	-0.0273
	–	(-6.71)	–	(-7.06)	–	(6.00)	–	(2.02)	–	(-2.16)
$Inv.\ (CMA)$	–	-0.00001	–	-0.0195	–	0.0474	–	0.0088	–	-0.0351
	–	(-0.00)	–	(-1.98)	–	(3.39)	–	(0.81)	–	(-2.47)
$CCExposure^{Ind}$	0.0296	0.0218	-0.0057	-0.0035	0.1047	0.1042	0.0753	0.0688	-0.0995	-0.0993
	(0.82)	(0.59)	(-0.44)	(-0.33)	(7.14)	(7.14)	(5.88)	(5.31)	(-10.92)	(-10.34)
$CCExposure^{Res}$	0.0178	0.0229	-0.0258	-0.0242	0.0571	0.0555	0.0525	0.0525	-0.0447	-0.0447
	(1.30)	(2.05)	(-4.04)	(-3.50)	(7.58)	(6.47)	(8.41)	(9.26)	(-8.10)	(-7.85)
Obs.	117093	117093	117093	117093	117093	117093	117093	117093	117093	117093
R^2	0.3003	0.3201	0.0309	0.0320	0.0999	0.1041	0.0178	0.0167	0.0447	0.0451

Table 3: Unconditional Link: Climate Change Exposure vs. Central Moments and Tail Risks. This table reports results of panel regressions at the firm-month level. We report in Panel A regressions relating option-implied risk quantities (variance, skewness, kurtosis, up and down slope) to firm-specific climate change exposure ($CCExposure$). Panel B splits the exposure measure into its two components, industry average climate change exposure ($CCExposure^{Ind}$) and the residual ($CCExposure^{Res}$). The regressions control for the 4- and 5-factor model betas. We include fixed effects at the time (month-year) and industry (SIC2 code) level. Variables (except for factor betas) are standardized at each point in time to have zero means and standard deviations of one. t-statistics based on standard errors clustered by time and industry are reported in parentheses. The sample covers the years 2003 to 2019 and includes stocks in the S&P 500.

however, their analysis only captures carbon risks, while we examine climate change exposure more broadly. When we bifurcate $CCExposure$ in Panel B into its industry and residual components, the effects for IV and $ISkew$ are fully driven by $CCExposure^{Res}$, while the other risk quantities are similarly affected by the industry and residual components.

4.2 Conditional Link: Risk Premiums versus Financial Risks' Sensitivities

To understand how the MW- and GLB-based risk premiums are linked to the particular risks associated by investors with $CCExposure$. Formally, we regress the time-series values of the risk premiums for $CCExposure$ (RP_t, estimated in the first stage of the Fama-MacBeth procedure) on the time-series values of the cross-sectional sensitivities ($Sens_t$) of the risk quantities to $CCExposure$. The risk sensitivities are computed each month as slopes from regressing a particular risk quantity on $CCExposure$, controlling for the 5-factor model.[26] That is, we are interested in the γ coefficients of the following regressions:

$$RP_{cc,proxy,t} = \alpha + \sum_{risk} \gamma_{cc,risk} \times Sens_{risk,cc,t} + \varepsilon, \tag{6}$$

where our climate change metric is $cc \in (CCExposure)$, the expected return proxy is $proxy \in (MW, GLB)$, and $risk$ is a risk quantity from $(IV, ISkew, IKurt)$ or $(IV, SlopeD, SlopeU)$.[27] Results are reported in Table 4, with the MW premium in Columns 1 and 2, and the GLB premium in Columns 3 and 4. To understand the drivers of the wedge between the two risk premiums, we include in Columns 5 and 6 the risk premium difference (MW minus GLB).

Table 4 provides two insights. First, the MW-based premium in Columns 1 and 2 is explained almost perfectly by the sensitivities of the risk quantities, with adjusted R^2's of about 90%. This effect primarily originates from $Sens_{cc,IV}$. In fact, if we remove all variables except $Sens_{cc,IV}$, the adjusted R^2 is largely unchanged (it goes down to 83%). This confirms that the MW premium is based on second-order moments, and hence is most suitable for investors who do not care about higher-order risks unspanned by variance. In Columns 3 and 4, the GLB regressions exhibit a much lower adjusted R^2 (only around 30%). If we only keep $Sens_{cc,IV}$, the regression fit is diminished by about one fourth only (to an R^2 of 25.96%). Thus, tails and higher-order

[26]Effectively, the sensitivities are the coefficients obtained in the first stage of the Fama-MacBeth procedure applied to the risk quantities as the dependent variables, and $CCExposure$ (and factor-model controls) as the independent variables.

[27]We split the risk quantities into two sets to avoid multicollinearity; the sensitivities of asymmetry $ISkew$ and tail fatness $IKurt$ measures are highly correlated with the sensitivities of the slope measures $SlopeD$ and $SlopeU$.

Risk Premium	RP_{MW}		RP_{GLB}		$RP_{MW} - RP_{GLB}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Constant$	0.0340	0.0051	-0.1997	-0.1567	0.2337	0.1618
	(2.14)	(0.27)	(-4.10)	(-2.59)	(4.30)	(2.38)
$Sens_{cc,IV}$	5.5048	5.4781	3.1422	4.0856	2.3626	1.3925
	(37.18)	(37.90)	(6.91)	(8.95)	(4.66)	(2.71)
$Sens_{cc,ISkew}$	–	0.0561	–	0.4453	–	-0.3892
	–	(0.49)	–	(1.24)	–	(-0.96)
$Sens_{cc,IKurt}$	–	-0.0126	–	1.1804	–	-1.1931
	–	(-0.10)	–	(2.84)	–	(-2.56)
$Sens_{cc,SlopeD}$	-0.0625	–	0.9445	–	-1.0070	–
	(-0.47)	–	(2.33)	–	(-2.23)	–
$Sens_{cc,SlopeU}$	0.2705	–	-1.3260	–	1.5965	–
	(1.94)	–	(-3.10)	–	(3.34)	–
Obs.	203	203	203	203	203	203
Adj. R^2	0.8937	0.8907	0.3399	0.2820	0.1684	0.0814

Table 4: Conditional Link: Risk Premiums versus Financial Risk Sensitivities. This table reports results of time-series regressions at the monthly level. We report the slope coefficients ($\gamma_{cc,risk}$) from regressing the time-series estimates of the risk premiums for $CCExposure$ on the time-series estimates of the cross-sectional sensitivities ($Sens_{cc,risk}$) of different risk quantities to $CCExposure$. The specification is given in Equation (6). t-statistics are in parentheses. The sample covers the years 2003 to 2019 and includes stocks in the S&P 500.

risk sensitivities play a much more important role for the risk premium of investors considering the full shape of the return distribution; it is therefore unsurprising that the IV sensitivity significantly contributes to the risk-premium difference in Columns 5 and 6.

Second, beyond IV, the other significant risk sensitivities that explain the risk premium estimates differently are (i) $Sens_{cc,SlopeD}$, sensitivity of left tail protection to $CCExposure$; (ii) $Sens_{cc,SlopeU}$, the same sensitivity for the upside potential; and (iii) $Sens_{cc,IKurt}$, which reveals the effects of how fat the tails are. These estimates allow us to make several observations. When the sensitivity of the tail protection cost ($Sens_{cc,SlopeD}$) decreases, then the GLB premium decreases, but the MW premium is unchanged (Columns 1 and 3); as a result, the MW-GLB gap in Column 5 is positively affected. When $Sens_{cc,SlopeU}$ increases, the two premiums change in opposite directions (Columns 1 and 3), with the difference between the the risk premiums again positively affected (i.e., increasing for a positive gap, and becoming narrower for a negative gap) (Columns 5). The picture for $Sens_{cc,IKurt}$ in Columns 2, 4, and 6 is similar to $Sens_{cc,SlopeD}$. A conclusion is that the increasingly positive gap between the two premiums from 2015 onward can be explained by a larger upside potential, and/or smaller left tail risk, for stocks with high climate change exposure.

4.3 Conditional Link: Climate Change Exposure, Risks, and Period Effects

Our evidence suggests that any relationship between $CCExposure$ and risk quantities is likely to be time dependent. We follow this intuition by estimating in Table 5 the relationship between $CCExposure$ and higher-order moments and tail risks, thereby explicitly accounting for time dependencies. To capture the regimes that emerged from Figure 1, we interact the risk quantities with two time-period dummies, which capture our prior observation that (i) from 2010 onward, the risk premium for $CCExposure$ increased for the MW and the GLB proxy ($D_{2010-2014}$); and (ii) from 2015 onward, the GLB premium disappeared ($D_{2015-2019}$). Results for $CCExposure$ are in Columns 1 and 2, and for $CCExposure^{Ind}$ and $CCExposure^{Res}$ in Columns 3 to 6.

The estimates reveal three insights: First, between 2010 and 2014, the positive association between $CCExposure$ and IV is much stronger compared to the base period before 2010. We find the same pattern for $SlopeD$. These results, coupled with those in Table 4, explain why $CCExposure$ exhibits a non-zero risk premium after 2009. Second, the MW-GLB wedge since 2015 can be attributed to the perception of tail risks. Specifically, the $D_{2015-2019}$ interactions show that higher tail fatness ($IKurt$) is associated with lower values of $CCExposure$ since 2015, while the relative costs for obtaining exposure to both tails ($SlopeU$ and $SlopeD$) increases in $CCExposure$. In terms of magnitude, the right tail effect is about twice as strong as the left tail effect. This means that since 2015, investors associate disproportionately higher growth opportunities with $CCExposure$ (relative to the left tail risks). These forces contribute to the growth in the MW-GLB gap, and they indicate that since 2015, investors who take all risks and opportunities into account do not expect a risk premium from stocks with high $CCExposure$. To the contrary, investors who care primarily about variance continue to expect a positive risk premium (they do not consider the trade-off between opportunities and tail risks). Third, in most cases, the risk quantities are related in similar ways to the industry and residual exposure components. Yet, in some cases, discrepancies arise. In Columns 1 and 2 of $CCExposure$, IV x $D_{2010-2014}$ is positive – that is, between 2010 and 2014, stocks with a high overall exposure had relatively higher volatility. However, for the same years, industries with high exposure exhibited lower IVs, implying that the total effect is driven by the residual component. For the same period, $SlopeU$ and $SlopeD$ are insignificantly related to overall exposure. Yet, the variables

Climate Exposure	$CCExposure$		$CCExposure^{Ind}$		$CCExposure^{Res}$	
	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.0229	-0.0016	0.0306	0.0041	0.0041	-0.0016
	(1.65)	(-0.11)	(1.72)	(0.24)	(0.53)	(-0.19)
$ISkew$	0.0667	–	0.0576	–	0.0361	–
	(5.42)	–	(4.12)	–	(5.62)	–
$IKurt$	0.1606	–	0.1610	–	0.0599	–
	(12.64)	–	(11.66)	–	(7.15)	–
$SlopeD$	–	0.0191	–	0.0159	–	0.0073
	–	(1.88)	–	(1.47)	–	(0.97)
$SlopeU$	–	-0.1081	–	-0.1116	–	-0.0365
	–	(-8.89)	–	(-8.40)	–	(-4.63)
$IV \times D_{2010-2014}$	0.0546	0.0354	-0.0292	-0.0363	0.0998	0.0765
	(2.77)	(1.96)	(-1.47)	(-2.07)	(7.18)	(6.11)
$ISkew \times D_{2010-2014}$	-0.0565	–	0.0147	–	-0.0950	–
	(-2.94)	–	(0.76)	–	(-6.19)	–
$IKurt \times D_{2010-2014}$	-0.0061	–	0.0301	–	-0.0295	–
	(-0.40)	–	(1.99)	–	(-1.86)	–
$SlopeD \times D_{2010-2014}$	–	0.0404	–	-0.0010	–	0.0598
	–	(1.82)	–	(-0.06)	–	(3.10)
$SlopeU \times D_{2010-2014}$	–	0.0123	–	-0.0256	–	0.0342
	–	(0.67)	–	(-1.60)	–	(2.03)
$IV \times D_{2015-2019}$	0.0241	0.0188	0.0505	0.0540	-0.0204	-0.0338
	(1.59)	(1.44)	(2.10)	(2.60)	(-2.44)	(-3.81)
$ISkew \times D_{2015-2019}$	-0.0888	–	-0.0664	–	-0.0589	–
	(-5.88)	–	(-3.99)	–	(-6.17)	–
$IKurt \times D_{2015-2019}$	-0.0505	–	-0.0651	–	-0.0009	–
	(-3.15)	–	(-4.73)	–	(-0.05)	–
$SlopeD \times D_{2015-2019}$	–	0.0451	–	0.0322	–	0.0353
	–	(2.94)	–	(2.24)	–	(2.54)
$SlopeU \times D_{2015-2019}$	–	0.0792	–	0.0819	–	0.0257
	–	(5.21)	–	(5.03)	–	(1.98)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
5-Factor Betas	Yes	Yes	Yes	Yes	Yes	Yes
Period Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	117093	117093	119218	119218	117093	117093
R^2	0.0548	0.0485	0.0709	0.0639	0.0084	0.0067

Table 5: Conditional Link: Climate Change Exposure and Financial Risks. This table reports the results of panel regressions at the firm-month level. We report regressions, explaining in Columns 1 and 2 firm-specific climate change exposure ($CCExposure$), in Columns 3 and 4 industry average climate change exposure ($CCExposure^{Ind}$), and in Columns 5 and 6 the residual ($CCExposure^{Res}$). The regressions include risk quantities (variance, skewness, kurtosis, up and down slope), time-period dummies, and interactions between the risk quantities and the time-period dummies. We also control for the 5-factor model based on stock returns. All variables (except for the factor betas) are standardized at each point in time to have zero means and standard deviations of one. t-statistics are based on standard errors robust to heteroskedasticity, serial correlation and spatial correlation (Driscoll and Kraay (1998)). The sample covers the years 2003 to 2019 and includes stocks in the S&P 500.

have a positive and significant effect on residual exposure, and a negative and insignificant one on the industry metric. The picture partially reverses after 2015: Now, volatility has a stronger effect on the industry metric, while the opposite holds for the residual measure. For the tail variables, we find positive effects between 2015 and 2019 for both components.

We offer two non-mutually exclusive explanations for what happened after 2015. First, 2015 was the year of the Paris Agreement, and markets may have started to update their views on the likelihood of climate-related investment opportunities eventually succeeding. This may have led to lower downside crash risk and higher upside potential for firms with high $CCExposure$ (we document below that significant components of the risk premium originate from opportunity shocks). Second, Azar, Duro, Kadach, and Ormazabal (2021) document that since 2015, there has been increased shareholder engagement by the Big Three with the objective to reduce firms' carbon emissions. This engagement lowered carbon emissions, which in turn plausibly reduced downside tail risks of firms with high $CCExposure$, at least to the extent that this is captured in overall climate change exposure.

4.4 Climate Change Exposure and Risk Premiums for Higher-Order Risks

Table 6 relates $CCExposure$ to the risk premium for higher-order risks: the variance risk premium; the upside and downside semi-variance risk premiums; and the skewness risk premium.[28] Documenting a link between climate change exposure and these risk premiums is important, because these relationships indicate how these risks are priced in options markets. As before, we consider total climate change exposure in Panel A and its two components in Panel B.

In Panel A, Columns 1 and 2, $CCExposure$ is positively related to the compensation for variance risk (t-stats of 2.82 and 3.45). Further, Columns 3 and 5 indicates that $CCExposure$ affects the risk premium for downside jump risk ($VRPD$) 60% more strongly than the premium

[28] These variables have been shown to explain some portion of the equity risk premium. Most models developed to date link the risk premiums embedded in options to the equity risk premium at the aggregate market level; we instead work with the cross-section of stocks. For example, Bollerslev, Tauchen, and Zhou (2009) develop a model in which the equity and variance risk premiums on the market level share a common component arising from the volatility of volatility. Similarly, models exist that link equity risk premium and premiums for jumps and tail risks (Bollerslev and Todorov (2011), Bollerslev, Todorov, and Xu (2015), Kilic and Shaliastovich (2019)).

Risk Premium	*VRP*		*VRPD*		*VRPU*		*SRP*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Total CCExposure								
Constant	0.1111	0.1146	0.0941	0.0531	0.0709	0.1079	0.0104	0.0643
	(2.35)	(2.33)	(1.95)	(1.19)	(1.68)	(2.36)	(0.33)	(2.06)
Market	-0.1481	-0.1477	-0.1314	-0.0886	-0.1041	-0.1371	-0.0164	-0.0683
	(-3.46)	(-3.38)	(-3.01)	(-2.23)	(-2.74)	(-3.38)	(-0.56)	(-2.46)
Size (SMB)	0.2316	0.1969	0.2224	0.2046	0.2125	0.1801	0.0551	0.0404
	(5.46)	(4.65)	(5.66)	(5.58)	(5.29)	(4.39)	(2.08)	(1.53)
Value (HML)	0.0116	-0.0108	-0.0017	-0.0131	0.0119	-0.0127	0.0047	-0.0089
	(0.57)	(-0.45)	(-0.08)	(-0.61)	(0.64)	(-0.54)	(0.31)	(-0.46)
Mom. (WML)	-0.0214	–	-0.0472	–	-0.0013	–	0.0287	–
	(-1.00)	–	(-2.17)	–	(-0.06)	–	(1.37)	–
Prof. (RMW)	–	-0.0345	–	-0.0389	–	-0.0327	–	-0.0097
	–	(-2.04)	–	(-2.31)	–	(-2.04)	–	(-0.77)
Inv. (CMA)	–	0.0441	–	0.0203	–	0.0416	–	0.0209
	–	(3.57)	–	(1.78)	–	(3.21)	–	(1.83)
CCExposure	0.0249	0.0255	0.0269	0.0279	0.0165	0.0167	-0.0033	-0.0034
	(2.82)	(3.45)	(5.61)	(6.01)	(1.58)	(2.01)	(-0.48)	(-0.69)
Obs.	117093	117093	117093	117093	117093	117093	117093	117093
R^2	0.0124	0.0119	0.0117	0.0097	0.0092	0.0098	0.0004	0.0010
Panel B: Industry Decomposition of CCExposure								
Constant	0.1112	0.1147	0.0943	0.0532	0.0709	0.1080	0.0103	0.0642
	(2.35)	(2.34)	(1.96)	(1.20)	(1.68)	(2.37)	(0.32)	(2.06)
Market	-0.1483	-0.1479	-0.1317	-0.0888	-0.1042	-0.1373	-0.0163	-0.0683
	(-3.47)	(-3.39)	(-3.02)	(-2.24)	(-2.74)	(-3.38)	(-0.56)	(-2.46)
Size (SMB)	0.2318	0.1971	0.2224	0.2046	0.2127	0.1803	0.0554	0.0406
	(5.47)	(4.66)	(5.66)	(5.59)	(5.31)	(4.41)	(2.09)	(1.54)
Value (HML)	0.0117	-0.0108	-0.0015	-0.0129	0.0119	-0.0128	0.0045	-0.0091
	(0.57)	(-0.45)	(-0.07)	(-0.60)	(0.64)	(-0.55)	(0.29)	(-0.48)
Mom. (WML)	-0.0215	–	-0.0472	–	-0.0014	–	0.0286	–
	(-1.00)	–	(-2.17)	–	(-0.06)	–	(1.37)	–
Prof. (RMW)	–	-0.0347	–	-0.0389	–	-0.0329	–	-0.0099
	–	(-2.05)	–	(-2.31)	–	(-2.05)	–	(-0.78)
Inv. (CMA)	–	0.0441	–	0.0203	–	0.0416	–	0.0209
	–	(3.57)	–	(1.78)	–	(3.22)	–	(1.84)
$CCExposure^{Ind}$	0.0231	0.0240	0.0182	0.0179	0.0179	0.0192	0.0045	0.0064
	(2.46)	(3.70)	(2.48)	(2.60)	(1.54)	(2.66)	(0.67)	(1.48)
$CCExposure^{Res}$	0.0164	0.0167	0.0180	0.0189	0.0108	0.0108	-0.0025	-0.0029
	(2.73)	(3.25)	(5.14)	(5.69)	(1.52)	(1.87)	(-0.51)	(-0.78)
Obs.	117093	117093	117093	117093	117093	117093	117093	117093
R^2	0.0125	0.0119	0.0117	0.0097	0.0093	0.0099	0.0006	0.0011

Table 6: Climate Change Exposure and Risk Premiums for Higher-Order Risks. This table reports results of panel regressions at the firm-month level. We report in Panel A regressions relating the risk premiums for the variance, downside and upside variances, and skewness with firm-specific climate change exposure (*CCExposure*). Panel B splits the exposure measure into its two components, the industry average climate change exposure ($CCExposure^{Ind}$) and the residual ($CCExposure^{Res}$). The regressions control for the 4- and 5-factor model betas. We include fixed effects at the time (month-year) and industry (SIC2 code) level. Variables (except for factor betas) are standardized at each point in time to have zero means and standard deviations of one. t-statistics based on standard errors clustered by time and industry are reported in parentheses. The sample covers the years 2003 to 2019 and includes stocks in the S&P 500.

for upside exposure ($VRPU$) (t-stat of 6.01 vs. 2.01).[29] In Columns 7 and 8, the skewness risk premium (SRP) does not reveal a prevailing effect on downside vs. upside protection costs across different levels of $CCExposure$. Finally, in Panel B, both components of $CCExposure$ contribute equally to the higher-order risk premiums. Hence, selling (total, upside, and downside) volatility for stocks with high $CCExposure$ promises compensation, and we can conclude that climate change exposure is priced in options markets. It should be noted that the average effects are modest, and, taking transaction costs into consideration, hardly tradeable. However, through the link to the return risk premium, the premiums paid for downside and upside semi-variances contribute to the expected returns, with the former premium likely dominating.

Considering all evidence, climate change exposure affects both general risk and the tail regions of the return distribution. The compensation paid for stocks with high exposure reflects climate-related effects on general uncertainty and on both tails, with the left-tail hedge price being larger than the price for right-tail opportunities. A time-varying attribution of different left- and right-tail risks to firm-specific exposure can potentially explain the gap in the exposure pricing by different investor types. The importance of the tail regions in the pricing of climate change exposure is consistent with Ilhan, Sautner, and Vilkov (2021).

5 Taxonomy of Climate Change Risk Premiums

5.1 Risk Premium for Climate Change Topics: Cross-Sectional Analysis

We next explore how investors consider exposure to climate-related opportunity, regulatory, and physical shocks in forming return expectations. Toward this end, Table 7 repeats the risk premium analysis from above, but uses exposure to opportunity, regulatory and physical shocks. Columns 1 and 2 report results for realized excess returns, Columns 3 and 4 for MW-based expected excess returns, and Columns 5 and 6 for the GLB proxy.[30]

[29] Because our variables are standardized in the cross-section at each point in time, we can directly infer the magnitude of the effects from the coefficients. A one-sigma change in $CCExposure$ relates to 2.79% of a one-sigma change in $VRPD$, but to only 1.67% of a one-sigma change in the $VRPU$.

[30] As in Table 2, we control for the 4- and 5-factor models and standardize the climate change metrics to have zero means and 0.01 standard deviations (such that the risk premium estimates are specified in percentages *per annum*). We do not split the metrics further into industry and residual components, because, as we discovered earlier, both components contribute about equally to the $CCExposure$ risk premium.

Expected Return	*RET*		*MW*		*GLB*	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1392	0.1291	0.0103	0.0104	0.0394	0.0395
	(4.37)	(5.15)	(2.31)	(3.42)	(5.06)	(5.83)
Market	-0.0052	0.0072	0.0387	0.0387	0.0363	0.0364
	(-0.13)	(0.21)	(4.08)	(4.52)	(5.29)	(4.73)
Size (*SMB*)	0.0378	0.0478	0.0499	0.0522	0.0153	0.0149
	(2.31)	(2.78)	(12.32)	(12.09)	(5.16)	(5.05)
Value (*HML*)	-0.0192	-0.0188	0.0036	0.0078	0.0052	0.0050
	(-1.23)	(-1.10)	(0.76)	(1.61)	(2.46)	(1.91)
Mom. (*WML*)	0.0114	–	-0.0248	–	-0.0076	–
	(0.40)	–	(-2.38)	–	(-1.12)	–
Prof. (*RMW*)	–	0.0081	–	-0.0202	–	-0.0067
	–	(0.61)	–	(-7.76)	–	(-4.88)
Inv. (*CMA*)	–	-0.0168	–	0.0018	–	-0.0002
	–	(-1.49)	–	(0.64)	–	(-0.18)
$CCExposure^{Opp}$	-0.0594	0.0414	0.1635	0.1629	0.1281	0.1159
	(-0.14)	(0.09)	(3.02)	(2.91)	(2.22)	(1.94)
$CCExposur^{Reg}$	-0.0841	-0.0379	0.0883	0.0919	0.0443	0.0345
	(-0.25)	(-0.12)	(1.64)	(1.96)	(1.13)	(0.86)
$CCExposure^{Phy}$	-0.1183	-0.1465	-0.0689	-0.0760	-0.0081	-0.0126
	(-0.45)	(-0.56)	(-2.29)	(-2.54)	(-0.55)	(-0.79)
Obs.	117632	117632	117972	117972	117362	117362
R^2	0.0005	0.0012	0.2002	0.2177	0.0439	0.0540

Table 7: Risk Premium for Climate Change Topics: Cross-Sectional Analysis. This table reports the results of the Fama-MacBeth regressions at the firm-month level. We report the risk premiums for topic-based climate exposure ($CCExposure^{Opp}$, $CCExposure^{Reg}$, $CCExposure^{Phy}$). All risk premiums are reported in % p.a., after controlling for 4- and 5-factor models. As proxies for expected excess returns, we use in Columns 1 and 2 the realized excess returns (RET), in Columns 3 and 4 the forward-looking proxy by Martin and Wagner (2019) (MW), and in Columns 5 and 6 the forward-looking proxy by Chabi-Yo, Dim, and Vilkov (2020) (GLB). t-statistics based on Newey and West (1987) standard errors are reported in parentheses. The sample covers the years 2003 to 2019 and includes stocks in the S&P 500.

Columns 1 and 2 continue to show insignificant realized risk premiums for all three exposure topics. Columns 3 and 4 show that the MW premium for $CCExposure$ is largely driven by exposure to climate-related *opportunities*. Results are similar in Columns 5 and 6 when we use the GLB proxy (but with lower significance levels). For the MW proxy, we also observe in Columns 3 and 4 that exposure to regulatory shocks is associated with a risk premium on top of the premium for opportunity shocks (albeit two times smaller). The effect for the GLB-based premium is also positive but insignificant. Exposure to physical shocks is negatively priced for the MW premium, but the effect is insignificant for the GLB proxy.

What explains these results? Given the properties of the MW and GLB premiums, and their sensitivities to the tail and high-order risks, climate-related opportunities seem to be associated with higher risks in the form of higher expected volatility. Regulatory shocks are also related to higher volatility, but to a lesser extent. The negative price of risk for physical shocks is surprising, but can potentially be explained by two points: First, climate-related physical damage is not abstract and can be quantified in many cases, at least over the short horizon.[31] Second, the insignificant GLB premiums indicate that investors who take left-tail risks and right-tail potential into account do not price physical shocks. The discrepancy with the MW premiums should then stem from variance-reliant investors.

5.2 Risk Premium for Climate Change Topics: Time-Series Analysis

Figure 2 presents the time series of the risk premiums for the three topic measures; we again plot the additive trend extracted from the time-series estimates using the STL decomposition. The MW premiums are reported in Panel A, and the GLB premiums in Panel B.

Across both panels, the picture for $CCExposure^{Opp}$ is similar to the one for $CCExposure$ in Figure 1, although the topic-based trends are more noisy. For the MW proxy, the risk premium is positive between 2010 and 2019. Until 2015, the pattern is similar for the GLB proxy, but the risk premium then declines to zero. The discrepancy between the two premiums in the last five years stems from the different treatment of the tails, as discussed earlier. Evidently, in more recent years, when investors pay a great deal of attention to climate-related opportunity topics, they then assign higher right and less extreme left tail to such firms. Such a reallocation of probabilities in the expected distribution leads to the elimination of the risk premium in the eyes of investors taking higher-order risks into account. The $CCExposure^{Reg}$ risk premium is mostly negative for the MW approach and is close to zero for the GLB approach; as discussed earlier, the difference originates from the differential treatment of the tails in the two proxies.

[31] It is easier for firms to secure protection against physical climate shocks in the form of insurance; the necessary insurance costs reduce the profitability and the expected returns, while at the same time keeping risks under control. The report on climate-related physical impact in Economist (2020) cites studies quantifying physical climate impact on firm value and concludes that "As its impact becomes clearer, companies have to take climate change more seriously." The same report, using Swiss Re data, shows that worldwide weather-related losses have been increasing over the last 30 years, but a higher proportion of these losses was insured in the last 10-15 years compared to the earlier periods. Hence, firms have to spend more on safer infrastructure and business resilience, inevitably reducing the margins and future returns.

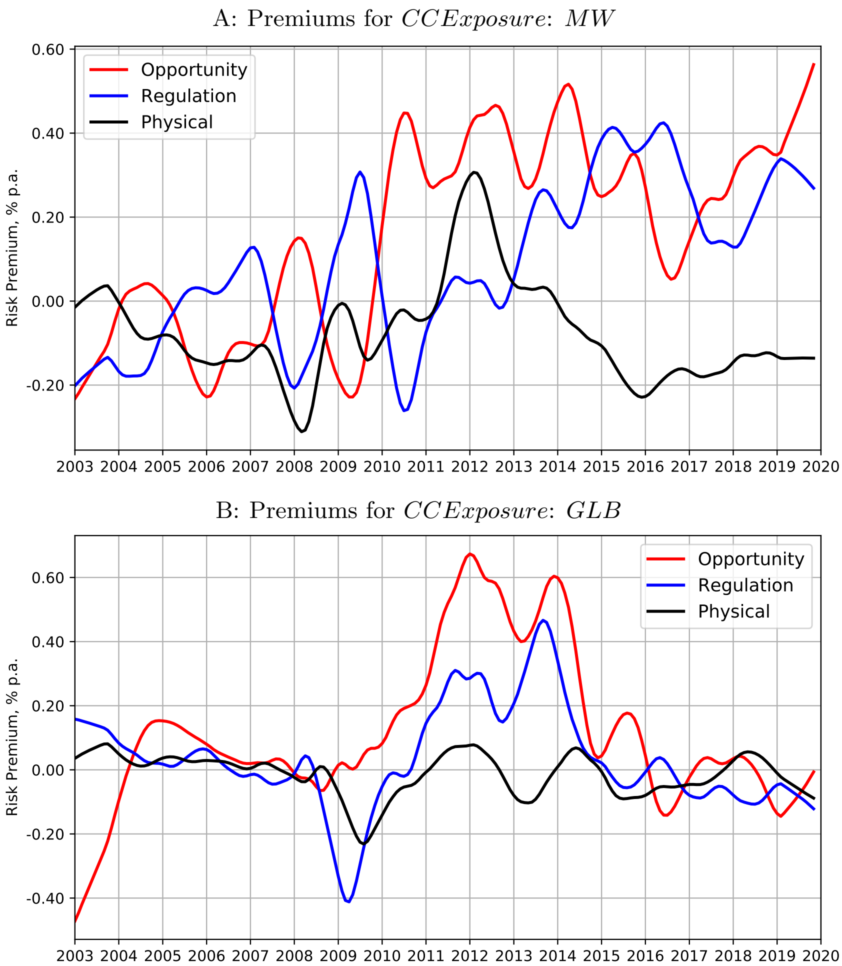

Figure 2: Risk Premium for Climate Change Topics: Time-Series Dynamics. This figure shows the trend component (from an STL decomposition of Cleveland, Cleveland, McRae, and Terpenning (1990)) of the time series of the risk premiums for topic-based climate change exposure (opportunity, regulatory, and physical exposure), obtained jointly with 5-factor model premiums in the first stage of the Fama-MacBeth regressions using the MW- and the GLB-based proxies for expected excess returns. The sample covers the years 2003 to 2019 and includes stocks in the S&P 500.

6 Conclusion

We demonstrate that firm-level climate change exposure is related to stock returns and risk quantities. Instead of relying on carbon emissions or ESG scores, we employ a measure recently introduced by SvLVZ, which captures climate-related upside and downside aspects. Unconditionally, the *realized* risk premium for climate change exposure is indistinguishable from zero. To the contrary, investors who buy stocks with higher climate change exposure *expect* to earn a risk premium; we document this result using the expected return models of Martin and Wagner (2019) and Chabi-Yo, Dim, and Vilkov (2020).

These unconditional effects mask high time-series heterogeneity. Realized compensation for climate change exposure rises steadily, from zero in 2003 to 2% just before the financial crisis. It then declines sharply between 2007 and 2009, only to resume its upward trend until 2019. The time-series patterns for the expected premiums look different, relative to the realized premium, and also relative to each other. For investors using variance as the sufficient risk statistic (Martin and Wagner (2019)), the expected risk premium increases from zero to 0.5% in 2012, and it then plateaus around this level for the next decade. Until 2015, this pattern is similar if we construct the risk premium for investors also considering extreme risks and opportunities (Chabi-Yo, Dim, and Vilkov (2020)). However, we observe a divergence after 2015: When we infer risk premiums under such investor preferences, there is a secular decline in the premium to zero in 2019.

The heterogeneity in the results depending on investor risk preferences prompts us to explore how climate change exposure affects higher-order moments and tail risks. The dynamics of the two expected risk premiums originate from how investors map climate exposure into variance and higher-order risks. Since 2015, investors began to associate relatively smaller crash risks and higher opportunities with climate exposure. This reduced the required compensation in the eyes of investors with preferences that take higher-order risks into account. We capture these subtle effects as our measure of exposure reflects upside and downside aspects. Large components of the expected premiums, and of the risks associated with climate change exposure, originate from climate-related opportunities. While a higher risk in the form of a higher expected variance implies a higher risk premium for firms with better opportunities, the expected premiums can be reduced to zero if one takes into account that higher exposure also means better growth potential and smaller crash risk.

Our results confirm that the exposure measure by SvLVZ reveals investors' attitudes toward the risks and opportunities related to climate change, as well as their expectations of equity returns and risks. The dynamics of the risk premium link to the nascent theoretical literature on climate finance, and they may well inspire further theoretical work, taking into account potential changes in investors' attitudes toward climate topics and ESG awareness.

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Online Appendix

to

"Pricing Climate Change Exposure"

Bigram	Frequency	Bigram	Frequency	Bigram	Frequency
renewable energy	12406	coastal area	738	snow ice	481
electric vehicle	6732	energy star	737	electrical energy	480
clean energy	4815	scale solar	708	electric hybrid	476
new energy	3751	major design	696	solar installation	474
wind power	3673	transmission grid	692	connect grid	474
wind energy	3611	energy plant	678	driver assistance	473
energy efficient	3588	global warm	671	reach gigawatt	471
climate change	2709	motor control	661	provide clean	466
greenhouse gas	2341	battery electric	659	reinvestment act	460
solar energy	2153	clean water	648	invest energy	454
clean air	2019	combine heat	645	green build	453
air quality	1959	need energy	602	sector energy	452
reduce emission	1567	future energy	581	california department	449
water resource	1336	use water	564	plant use	447
energy need	1291	environmental concern	560	friendly product	447
carbon emission	1273	include megawatt	557	energy initiative	444
carbon dioxide	1247	build owner	557	issue rfp	443
carbon footprint	1180	electric grid	551	transmission capacity	442
gas emission	1166	energy team	544	close megawatt	441
energy environment	1145	world energy	544	market solar	437
wind resource	1065	energy application	544	business air	437
air pollution	1063	wind capacity	541	construction megawatt	435
reduce carbon	1004	transmission infrastructure	540	rooftop solar	434
president obama	980	population center	532	application power	431
battery power	969	energy reform	523	forest land	426
clean power	955	charge station	523	grid power	421
energy regulatory	921	wind park	522	advance driver	419
plug hybrid	890	produce power	521	northern pass	418
obama administration	886	environmental footprint	519	nox emission	418
build power	849	source power	512	wind facility	418
world population	838	pass house	512	energy component	417
heat power	835	gas vehicle	511	vehicle application	415
light bulb	808	plant power	500	emission trade	412
carbon capture	804				

OA Table 1: Top-100 Bigrams Captured by Climate Change Exposure (*CCExposure*). This table reports the top-100 bigrams associated with *CCExposure*, which measures the relative frequency with which bigrams related to climate change occur in the transcripts of earnings conference calls.

Bigrams	Exposure	Bigrams	Exposure	Bigrams	Exposure
renewable energy	12406	gas clean	289	energy target	223
electric vehicle	6732	vehicle lot	287	term electric	221
clean energy	4815	vehicle place	286	power world	220
new energy	3751	meet energy	286	vehicle small	216
wind power	3673	vehicle type	281	renewable electricity	216
wind energy	3611	vehicle future	276	wave power	214
solar energy	2153	energy commitment	276	carbon neutral	213
plug hybrid	890	electronic consumer	275	auction new	211
heat power	835	expand energy	269	cost renewable	210
renewable resource	800	gigawatt install	266	vehicle talk	210
solar farm	753	bus truck	264	vehicle offer	210
battery electric	659	ton waste	263	customer clean	210
electric hybrid	476	energy research	258	power solar	209
reinvestment act	460	focus renewable	257	vehicle opportunity	208
issue rfp	443	pure electric	256	community solar	208
construction megawatt	435	ev charge	255	energy goal	207
rooftop solar	434	grid technology	249	vehicle hybrid	207
grid power	421	geothermal power	249	invest renewable	207
recovery reinvestment	395	type energy	246	incorporate advance	206
solar generation	394	solar program	245	talk solar	203
energy standard	384	vehicle development	243	ton carbon	202
sustainable energy	376	energy important	243	small hydro	202
vehicle charge	374	install solar	242	base solar	202
guangdong province	360	vehicle battery	242	target gigawatt	201
hybrid car	341	energy vehicle	242	charge network	201
charge infrastructure	323	energy bring	240	capacity generation	201
micro grid	322	vehicle space	233	vehicle add	200
grid connect	319	opportunity clean	231	vehicle infrastructure	200
clean efficient	308	demand wind	227	solar array	198
carbon free	306	vehicle good	226	energy auction	198
hybrid technology	306	medical electronic	226	product hybrid	192
generation renewable	303	incremental content	224	product solar	192
energy wind	295	supply industrial	223	exist wind	192
battery charge	290				

OA Table 2: Top-100 Bigrams Captured by Opportunity Climate Change Exposure ($CCExposure^{Opp}$). This table reports the top-100 bigrams associated with $CCExposure^{Opp}$, which measures the relative frequency with which bigrams that capture opportunity shocks related to climate change occur in the transcripts of earnings conference calls.

Bigrams	Exposure	Bigrams	Exposure	Bigrams	Exposure
greenhouse gas	2341	issue air	157	comply environmental	114
reduce emission	1567	promote energy	153	glacier hill	111
carbon emission	1273	emission free	152	hill wind	110
carbon dioxide	1247	implement energy	151	nox sox	110
gas emission	1166	recovery pollution	149	tax australia	106
air pollution	1063	control regulation	146	way comply	105
reduce carbon	1004	florida department	144	emission intensity	103
energy regulatory	921	commission license	141	oxide emission	101
carbon tax	792	gas regulation	140	emission improve	101
carbon price	760	appeal district	139	emission increase	100
environmental standard	496	source electricity	139	install low	99
nox emission	418	effective energy	138	commission public	97
emission trade	412	nitrous oxide	138	castle peak	97
dioxide emission	396	impact clean	134	capture carbon	97
epa regulation	370	think carbon	134	wait commission	96
energy independence	350	global climate	132	emission compare	92
carbon reduction	338	produce carbon	128	clean electricity	92
know clean	276	clean job	126	high hydrocarbon	92
standard requirement	268	efficient natural	124	emission come	88
development renewable	267	emission monitor	124	weight fuel	87
carbon market	259	emission issue	123	stability reserve	87
trade scheme	232	quality permit	122	quality regulation	86
deliver clean	228	product carbon	122	request public	86
mercury emission	220	china air	122	additive process	86
reduce air	218	reduce sulfur	121	gas carbon	84
save technology	193	available control	121	epa requirement	83
talk clean	190	emission rate	119	liter diesel	83
energy alternative	188	regulation low	118	meet reduction	81
place energy	176	capture sequestration	118	talk climate	81
reduce nox	175	nation energy	117	expect carbon	80
air resource	169	emission year	115	emission ton	80
target energy	166	efficient combine	115	ambient air	80
change climate	163	carbon economy	114	know carbon	79
impact climate	163				

OA Table 3: Top-100 Bigrams Captured by Regulatory Climate Change Exposure ($CCExposure^{Reg}$)**.** This table reports the top-100 bigrams associated with $CCExposure^{Reg}$, which measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of earnings conference calls.

Bigrams	Exposure	Bigrams	Exposure	Bigrams	Exposure
coastal area	738	ice product	198	especially coastal	58
global warm	671	security energy	194	sewer overflow	52
snow ice	481	water act	182	combine sewer	52
friendly product	447	management district	174	area coastal	52
forest land	426	weather snow	154	large desalination	50
area florida	367	service reliable	148	plant algeria	50
sea level	365	management water	138	warm product	47
provide water	364	ability party	134	solution act	47
nickel metal	362	ice control	128	fluorine product	47
supply water	297	inland area	127	area inland	43
storm water	262	non coastal	115	fight global	41
heavy snow	252	storm january	105	sell forest	39
air water	251	sale forest	93	exposure coastal	34
natural hazard	227	value forest	80	city coastal	34
sea water	218	land forest	79	marina east	28
warm climate	213	particularly coastal	66	day desalination	23
water discharge	211	golf ground	58		

OA Table 4: Top-100 Bigrams Captured by Physical Climate Change Exposure ($CCExposure^{Phy}$). This table reports the top-100 bigrams associated with $CCExposure^{Phy}$, which measures the relative frequency with which bigrams that capture physcial shocks related to climate change occur in the transcripts of earnings conference calls.

Expected Return	*RET* (1)	*RET* (2)	*RET* (3)	*MW* (4)	*MW* (5)	*MW* (6)	*GLB* (7)	*GLB* (8)	*GLB* (9)
Constant	0.4104	0.4134	0.4130	0.0113	0.0141	0.0101	0.0296	0.0283	0.0283
	(31.22)	(37.41)	(33.57)	(2.87)	(2.78)	(2.51)	(4.61)	(3.84)	(3.98)
Market	0.0132	0.0104	0.0108	0.0227	0.0196	0.0238	0.0236	0.0248	0.0249
	(1.21)	(1.06)	(1.05)	(7.52)	(4.48)	(6.92)	(12.01)	(12.18)	(12.13)
Size (*SMB*)	-0.0045	-0.0028	-0.0021	0.0629	0.0601	0.0618	0.0096	0.0080	0.0081
	(-0.77)	(-0.41)	(-0.30)	(32.95)	(23.67)	(31.52)	(3.52)	(3.00)	(2.88)
Value (*HML*)	-0.0091	-0.0080	-0.0085	-0.0074	-0.0068	-0.0075	0.0011	0.0010	0.0009
	(-0.47)	(-0.41)	(-0.44)	(-9.30)	(-6.06)	(-9.30)	(0.83)	(0.58)	(0.51)
Prof. (*RMW*)	-0.0011	-0.0019	-0.0020	-0.0151	-0.0145	-0.0146	-0.0055	-0.0048	-0.0049
	(-0.20)	(-0.32)	(-0.34)	(-8.63)	(-8.03)	(-8.94)	(-4.48)	(-3.10)	(-3.06)
Inv. (*CMA*)	-0.0130	-0.0132	-0.0140	0.0026	0.0040	0.0029	-0.0023	-0.0020	-0.0021
	(-0.83)	(-0.85)	(-0.90)	(1.35)	(2.27)	(1.62)	(-1.20)	(-0.93)	(-1.02)
CCExposure	0.1208	–	0.1208	0.5212	–	0.5261	0.0130	–	0.0226
	(0.90)	–	(0.93)	(10.22)	–	(9.91)	(0.29)	–	(0.49)
ISS CRR	–	0.4508	0.4515	–	-0.1714	-0.1947	–	-0.2392	-0.2402
	–	(1.64)	(1.67)	–	(-1.96)	(-2.64)	–	(-7.65)	(-7.29)
Obs.	1914	1914	1914	1914	1914	1914	1914	1914	1914
R^2	0.0136	0.0168	0.0174	0.4519	0.4365	0.4543	0.1354	0.1389	0.1391

OA Table 5: Risk Premium for Carbon Risk Rating (ISS CRR): Cross-Sectional Analysis for 2015-2018. This table reports results of Fama-MacBeth regressions at the firm-year level for the years from 2015 to 2018. We report the risk premium estimates for the ISS ESG Carbon Risk Rating (*ISS CRR*) and for firm-specific climate change exposure (*CCExposure*), controlling for the 5-factor exposures (risk premiums in decimals p.a.). *CCExposure* and *ISS CRR* are standardized each period to have zero mean and standard deviation of 0.01 (hence, the risk premium estimates are in percentage terms). As proxies for expected excess returns we use in Columns 1 and 2 the realized excess returns (*RET*), in Columns 3 and 4 the forward-looking proxy by Martin and Wagner (2019) (*MW*), and in Columns 5 and 6 the forward-looking proxy by Chabi-Yo, Dim, and Vilkov (2020) (*GLB*). t-statistics based on Newey and West (1987) standard errors are reported in parentheses. The sample covers the years 2003 to 2019 and includes stocks in the S&P 500.