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Pricing Climate Change Exposure

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Abstract. We estimate the risk premium for firm-level climate change exposure among S&P 500 stocks and its time-series evolution between 2005 to 2020. Exposure reflects the attention paid by market participants in earnings calls to a firm's climate-related risks and opportunities. When extracted from realized returns, the unconditional risk premium is insignificant but exhibits a period with a positive risk premium before the financial crisis and a steady increase thereafter. Forward-looking expected return proxies deliver an unconditionally positive risk premium with maximum values of 0.5%–1% p.a., depending on the proxy, between 2011 and 2014. The risk premium has been lower since 2015, especially when the expected return proxy explicitly accounts for the higher opportunities and lower crash risks that characterize high-exposure stocks. This finding arises as the priced part of the risk premium primarily originates from uncertainty about climate-related upside opportunities. In the time series, the risk premium is negatively associated with green innovation; Big Three holdings; and environmental, social, and governance fund flows and positively associated with climate change adaptation programs.

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1. Introduction

Climate change presents huge challenges for financial markets. How should firm-level exposure to climate change be measured? Is there a risk premium for climate change exposure, and—if it exists—how does it evolve over time? Which underlying climate-related economic variables drive this risk premium? In light of these challenging questions, significant resources have recently been allocated to develop the area of climate finance in order 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 understand more fully how climate-related risks and opportunities affect stock returns.

This paper employs time-varying measures of how market participants perceive individual firms' exposures to climate change and examines whether these perceived exposures are priced in financial markets. The measures of climate change exposure build upon recent work by Sautner et al. (2023) (SvLVZ), who use quarterly earnings calls as a source to identify the attention paid by market participants to firms' climate-related risks and opportunities.[1] To measure a firm's climate change exposure, SvLVZ use the proportion of the conversation during an earnings call that is centered on climate change.[2]

Earnings calls are key corporate events in which financial analysts listen to management and ask firm officials about material current and future developments relevant to investing in the firm's stock. Therefore, a feature of the measures is that they reflect "soft" information originating from information exchanges between managers and analysts. This feature allows us to complement related work examining the asset pricing effects of "hard" information, such as carbon emissions or extreme local weather events. For example, Bolton and Kacperczyk (2021, 2023), Ilhan et al. (2021), Görgen et al. (2019), and In et al. (2019) examine how carbon emissions are priced in equity or option markets as either a firm characteristic or risk factor. Similarly, Hong et al. (2019), Addoum et al. (2020), and Kruttli et al. (2021) examine the asset pricing implications of extreme weather events.

Why should measured climate change exposure command a risk premium? The reason is that the effects of climate change on individual stocks are highly uncertain, and Barnett et al. (2020) demonstrate theoretically that this uncertainty should be priced. Climate change uncertainty arises because it is highly unclear how much temperatures will rise, how strongly emissions must be curbed to limit global warming, and how regulatory interventions will subsidize green (and tax brown) activities. Concerning technology, it is also difficult to predict whether innovations that facilitate the low-carbon transition will be successful (e.g., whether investments into carbon storage will succeed and to what extent battery technology will see breakthroughs). Similarly, low wind speeds in Europe in 2021 made clear to investors the risks of investing in wind farms (Thomas 2021) as has volcanic activity to investors in solar installations. These examples illustrate the uncertainties that make it difficult for investors to evaluate how individual stocks will be affected by climate change, and they imply that measured climate change exposure, which encapsulates all of these aspects, should be associated with a risk premium.

Broader societal trends toward environmental, social, and governance (ESG) and impact investing can also affect the risk premium for climate change exposure with some investors possibly investing in stocks exposed to climate change for nonpecuniary reasons (Zerbib 2022, Pastor et al. 2021, Pedersen et al. 2021). One consequence of this trend is that some investors may tolerate higher (tail) risks for holding high climate change exposure stocks. Some investors might also derive utility from investing in climate-related "lotteries," accepting low expected returns for a small chance of extreme successes of some green technologies. The resultant capital allocations affect returns and could lead to zero (or even a negative) risk premium for climate change exposure.

These diverse views illustrate that the risk premium for climate change exposure is conceptually ambiguous. They also signify that the risk premium is likely to change over time as it remains unclear what the eventual equilibrium will resemble. One implication is that any estimation over a relatively short sample period presents the challenge that the pricing effects may not yet reflect the long-term equilibrium (but rather the path toward it). At the same time, the sign of the unconditional risk premium—if it exists—as well as its time-series dynamics raise interesting empirical questions. Documenting these important financial quantities can help guide the economic modeling of the dynamics toward the long-term equilibrium and improve our understanding of how climate change affects financial markets.

We answer four questions using the sample of S&P 500 stocks between 2002 and 2020: First, what is the relationship between measured climate change exposure—that is, the attention that market participants devote to climate-related topics during earnings calls—and realized and expected returns? Second, how does compensation for measured climate change exposure evolve for both realized and expected returns? Third, unconditionally and dynamically, what climate-related risk quantities are associated with measured climate change exposure? Fourth, which climate-related economic factors drive the compensation for climate change exposure?

We begin by establishing new empirical facts: Unconditionally, that is, across the full sample, the *realized* risk premium for measured climate change exposure is indistinguishable from zero. However, we document that the investors who buy stocks with higher climate change exposure expect to earn a risk premium ex ante. We identify the *expected* risk premium using two approaches that exploit option-implied information and differ in the assumed investor preferences used to derive the risk premium estimates. The risk premium based on the expected return proxy by Martin and Wagner (2019) (*MW*) assumes that variance is the sufficient risk statistic for investors—that is, a stock's risk premium is based on the second moments of the returns of the market index and the stocks in the index. Somewhat differently, Chabi-Yo et al. (2023) (*GLB*) assume that investors also consider extreme risks and opportunities, so their approach explicitly accounts for returns' higher order moments in the risk premium estimation. Hence, both approaches use different, though overlapping, pieces of information from the options market to estimate expected returns. Across all sample years, a one-standard-deviation shock to climate change exposure increases the *MW*-based risk premium by 0.09% p.a. (t-statistic of 2.88) and the *GLB*-based risk premium by 0.18% p.a. (t-statistic of 3.12). We demonstrate that these modest unconditional risk premiums mask large positive risk premium estimates during parts of the sample period.

When considering SvLVZ's decomposition of climate change exposure into opportunity, regulatory, and physical shocks, the positive unconditional risk premium for both forward-looking proxies originates mostly from the opportunity component. There is also a positive risk premium for regulatory shocks, but it is much smaller in magnitude.[3] All risk premium estimations apply the Fama–MacBeth methodology and control for a six-factor model and a series of stock characteristics. We select as stock characteristics known return predictors and variables possibly correlated with climate change exposure (e.g., carbon emissions or oil price betas).[4]

When turning to the time-series dynamics, we observe that the realized compensation for climate change exposure was positive (around 1% p.a.) before 2008. This period ended with a sharp decline in the risk premium during the financial crisis (2008–2009) when the realized premium became negative. This drop probably reflects an excessive sell-off by investors worried about the prospects of uncertain and long-term climate-related investments and a crowding out of climate-related concerns during the financial crisis.[5] The crisis-related drop was followed by a secular upward trend in the realized premium until the end of the sample period.

The patterns for the two proxies for expected returns look different compared with the realized premium and exhibit some subtle differences relative to each other. For both proxies, the risk premium fluctuates around zero before 2011. From 2011 onward, both premiums turn positive with the *MW*-based premium gradually rising to about 0.5% p.a. in 2012 and the *GLB*-based premium experiencing an even faster increase to about 1% p.a. between 2012 and 2014. Since 2015, both premiums revert to almost zero, but the *MW* proxy stays at a slightly higher level.

What can we learn from these diverging time-series patterns? One conclusion is that climate change exposure has subtle effects: the associated risk premiums evolve nonmonotone depending on which investor risk preferences are assumed in the estimation.[6] A second conclusion is that a better understanding is needed of how climate change exposure maps into risk quantities (including those beyond the second moment) and how time variations of such mappings affect the conditional risk premiums. Indeed, comparing the *MW* and *GLB* proxies provides economic insights because each captures distinct investor preferences about risk quantities.

We demonstrate this point by documenting that the dynamics of the two risk premiums based on conditional expected returns can be attributed to how investors map climate change exposure into different risk quantities. Between 2011 and 2014, investors perceived high-exposure stocks as highly volatile and with elevated downside crash risk, whereas beginning in 2015, investors started to associate smaller variance, relatively lower downside crash risk, and somewhat higher upside opportunities with such stocks. Whereas the lower variance of high-exposure stocks decreases the risk premium for both proxies, the reallocation of the likelihood of left versus right tail events further reduces the required compensation for climate change exposure among investors with preferences over higher order risks (as reflected in the *GLB* proxy). We capture these effects of the return distribution as our measures of climate change exposure identify upside and downside shocks. Importantly, the documented effects reflect that large parts of the expected risk premium as well as the risks associated with climate change exposure originate from climate-related opportunity shocks. As such opportunities are uncertain, leading to either very high or very low payoffs, they cause investors to demand a risk premium.[7]

We consider several climate-related economic channels to understand better the effects of the risk quantities. Using monthly time-series regressions, we relate the risk premium estimates to aggregate institutional and market factors plausibly associated with climate change exposure. We provide several new results regarding the drivers of the forward-looking risk premiums. First, more successful developments of green technologies, as reflected in more green patenting, decrease the risk premium. This effect is plausible because the successful development of climate-related technologies reduces the (downside) risks of the opportunities that high-exposure stocks have. Second, the compensation for high-exposure stocks increases in the proportion of climate change exposure in the S&P 500 coming from stocks headquartered in U.S. states that adopt climate change adaptation plans. State-led adaptation plans increase the likelihood of new regulations in the climate sphere, making the prospects of high-exposure stocks riskier.[8]

Third, flows into ESG funds decrease the risk premium. As opportunities strongly drive the risk premium for climate change exposure, this finding reflects the expectation that price pressure by funds seeking to invest in high-opportunity stocks pushes up stock prices, thus reducing the conditional risk premium.[9] Fourth, the oil price positively relates to the risk premium, probably because high oil prices incentivize legacy investment in traditional oil and gas activities (Acemoglu et al. 2020), making nontraditional investments in green technologies riskier. With our risk premium originating mostly from climate-related opportunities, high oil prices thereby increase the risk premium for high-exposure stocks.

Fifth, higher aggregate holdings of the "Big Three" (Vanguard, Blackrock, and StateStreet) in the S&P 500, weighted by climate change exposure, decrease the risk premium. This finding aligns with Azar et al. (2021), who document that increased shareholder engagement by the Big Three has led to stock-level reductions in carbon emissions. As emission reductions reduce risk, especially downside tail risk (Ilhan et al. 2021), higher exposure–weighted holdings by the Big Three reduce the risk premium. This result is stronger for the *GLB* proxy, corroborating the idea that this risk premium channel goes through tail risk (in addition to volatility).

Overall, our paper addresses two challenges identified by Giglio et al. (2021) in the analysis of how climate change affects asset prices. The first challenge lies in the need to obtain firm-level exposure measures, which (i) distinguish between physical and regulatory climate risks and (ii) capture climate-related upside and downside potential. The second challenge is that climate change exposure data are usually available for a short period and, importantly, that changes in investors' attention to climate topics can occur during that short period.

We offer a solution to both challenges. First, we use firm-level exposure measures to quantify investor attention to climate-related topics. We split exposure into opportunity, regulatory, and physical shocks and trace the financial market effects of these facets. Second, instead of relying solely on a noisy measure of realized returns, we use conditional forward-looking proxies of expected returns. Such proxies work well as unbiased predictors of unconditional expected excess returns, and they can serve as conditional predictors under most economic conditions (Back et al. 2022). Different expected return proxies enable us to disentangle the effects of second order (variance) risks from those of tail and higher order risks not spanned by the variance.

Our exposure measures capture the current attention of investors to those climate topics relevant to their investment decisions. As a result, the measures vary within firm and reflect 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 at any point in time it reflects the current mapping by market participants from information flows in earnings calls into returns.[10]

These features might help the development of climate finance models. For example, the diminishing risk premium for climate change exposure for some investors since 2015 can be linked to the ESG–capital asset pricing model (CAPM) framework of Pedersen et al. (2021) and the increasing awareness of climate topics among investors. The positive unconditional risk premium lends support to models with "uncertainty about the path of climate change" (Giglio et al. 2021, p. 18), in which high exposure to climate change commands a risk premium.[11] We show that a decreasing conditional risk premium for high-exposure stocks related to their higher opportunities implies that theoretical models also need to account for a dynamic component linking exposure to growth opportunities.

2. Data and Variable Measurement

2.1. Firm-Level Climate Change Exposure

2.1.1. Variable Measurement. We capture a stock's climate change exposure using a series of measures developed by SvLVZ from transcripts of quarterly earnings calls. Earnings calls allow market participants to listen to management and inquire about material current and future developments (Hollander et al. 2010). Earnings calls provide a forum for market participants to query firms' exposures to various risks and opportunities, including climate change. The SvLVZ measures capture the proportions of these earnings calls that are devoted to talking about climate change. We focus on S&P 500 stocks from January 2005 to December 2020 to ensure that data quality requirements are met for our expected return and risk measures.[12]

To measure climate change exposure, SvLVZ identify when the discussion between analysts and management turns to climate change. To pinpoint such discussions, the algorithm determines the salient word combinations that are used in talks about climate change. This step is not obvious to implement as the language used in earnings calls is tailored to firms' specific business models and ecosystems. For this purpose, SvLVZ adapt the keyword discovery algorithm by King et al. (2017) to produce a set of bigrams $\mathbb{C}$ that are unique to climate change discussions. Furthermore, SvLVZ separate three categories of bigram topics related to climate-related opportunity, regulatory, and physical shocks ($\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, and $\mathbb{C}^{Phy}$, respectively). Based on these bigram sets, SvLVZ construct four metrics to quantify, for each quarter, a firm's exposure to climate change. These metrics capture how frequently a set of climate change bigrams appears in a transcript scaled by the length of the transcript:

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

where $b = 1, \ldots B_{i,t}$ are the bigrams appearing in the transcript of firm i in quarter t, where $1[\cdot]$ is the indicator function and $\mathbb{C}$ is a set of climate change bigrams ($\mathbb{C}$, $\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, or $\mathbb{C}^{Phy}$). The overall measure is labeled as *CCExposure* and the three topic-based measures as $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$, respectively.[13]

Some of our tests examine whether the risk premium for climate change exposure is stock-specific or driven by investor attitudes toward particular industries. To this end, we compute a measure of industry-level exposure, $CCExposure^{Ind}$, by averaging *CCExposure* across all stocks in an industry at a point in time (based on two-digit Standard Industrial Classification (SIC) codes). For each stock, we calculate the "pure" stock-specific component $CCExposure^{Res}$ as $CCExposure - CCExposure^{Ind}$.

To further probe the pricing effects of climate change exposure, we use a measure that reflects the negative tone or sentiment of the climate change discussions. $CCSentiment^{Neg}$ counts the number of climate change bigrams after conditioning on the presence of negative tone words in the sentence in which a bigram is used. We use the negative tone words in Loughran and McDonald (2011) and normalize the count again by the number of bigrams in the call:

$$CCSentiment^{Neg}_{i,t} = \frac{1}{B_{i,t}} \sum_{b}^{B_{i,t}} \{(1[b \in \mathbb{C}]) \times \sum_{b}^{b \in S} \mathcal{T}_{Neg}(b)\}, \tag{2}$$

where S represents the sentence containing bigrams $b = 0, 1, \ldots, B_{i,t}$ and $\mathcal{T}_{Neg}(b)$ assigns sentiment to each bigram b ($\mathcal{T}_{Neg}(b) = 1$ if the sentiment word used in the neighborhood of b has a negative tone).

To demonstrate that the SvLVZ algorithm can be tailored to specific applications, we purpose-develop in this paper a measure of litigation exposure ($CCExposure^{Ltg}$), which counts how frequently climate change bigrams appear in the same sentence as litigation keywords:

$$CCExposure^{Ltg}_{i,t} = \frac{1}{B_{i,t}} \sum_{b}^{B_{i,t}} \{(1[b \in \mathbb{C}]) \times \sum_{b}^{b \in S} \mathcal{T}_{Ltg}(b)\}, \quad (3)$$

where S represents the sentence containing bigrams $b = 0, 1, \ldots, B_{i,t}$ and $\mathcal{T}_{Ltg}(b)$ is an indicator function for a litigation keyword appearing in the same sentence as b. We use a total of 21 litigation keywords, including "litigation," "lawsuit," "sued," or "class action."

2.1.2. Variable Transformation: Time Structure and Matching Procedure.

Two data features require the transformation of the exposure measures before matching them with the expected return proxies. First, the exposure measures are observed quarterly, whereas the returns are measured monthly. Second, when specific climate topics are discussed in an earnings call, subsequent calls may not immediately inspire interest in the same topic again.[14] Beyond these considerations, we need to match the data without introducing look-ahead bias; the exposure measures must be observable when constructing the return proxies.

We address these data features by processing the exposure measures in two steps. In the first step, we match the month of a transcript's date with the end-of-month date in the Center for Research in Security Prices (CRSP) Monthly Stock File and record to that date the exposure measure from SvLVZ (we initially set the exposure values for the other months in the same calendar quarter to zero). This practice eliminates look-ahead bias by ensuring that the information from the earnings call is available before the stock data date. In the second step, we exponentially smooth monthly observations of the exposure measures using a half-life of three months. We replace each exposure measure $x_{i,t}$ with its exponentially weighted moving average $y_{i,t}$:

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

where the decay α is related to half-life τ as $\alpha = 1 - \exp(-\ln(2)/\tau)$. We normalize the measures for each month using $\frac{y}{100\sigma_y}$, where σ_y is the cross-sectional standard deviation of y in a given month, to obtain the respective risk premiums directly in percentages.

2.2. Realized and Expected Returns

Our tests use three proxies for expected excess returns. The first proxy, the realized excess return (*RET*), is computed as the next-month realized return minus the one-month Treasury bill rate for the corresponding period. A concern with this proxy is that it may not work well in producing reasonable risk premiums because of our short sample period and the infrequently observed exposure measures.[15] To address this estimation challenge, we construct two expected excess return proxies from forward-looking, option-implied quantities. These proxies follow recent work by Martin and Wagner (2019) and Chabi-Yo et al. (2023).[16]

Martin and Wagner (2019) (*MW*) derive their proxy as lower bounds $\mathcal{LB}_t$ for the conditional expected excess return, that is, as $E_t[R_{t+1}] - R_{f,t} \geq \mathcal{LB}_t$ (Kadan and Tang 2020 use a similar approach). Whereas the derivations make a statement about the lowest estimate of the conditional expected return and not about the expected excess return itself, one can test whether the bound is valid (expected excess returns are not lower than the bound) and tight (the bound is an unbiased predictor of the expected excess return). The *MW* bounds are based on the second order, risk-neutral moments of the return distribution and, thus, do not consider the effects of tail risks and asymmetry in the return distribution (beyond the portions spanned by the variances of individual stocks and the market index). Hence, these bounds capture the expected returns of investors who consider second moments to be a sufficient risk statistic. Formally, *MW*'s expected excess return proxy for stock i at the end of the month t is

$$MW_{i,t,t+\Delta t}/R_{f,t} = IV_{t,t+\Delta t} + \frac{1}{2}\left(IV_{i,t,t+\Delta t} - \sum_{i=1}^{N} w_{i,t} IV_{i,t,t+\Delta t}\right), \quad (4)$$

where $w_{i,t}$ is the value weight of stock i in the market index (S&P 500), $IV_{t,t+\Delta t}$ is the implied variance of market returns (S&P 500), and $IV_{i,t,t+\Delta t}$ is stock i's implied variance.[17]

The generalized lower bounds of Chabi-Yo et al. (2023) (*GLB*) account for the entire risk-neutral distribution, implicitly considering all higher order moments, and capture the expected returns of investors who also care about higher moments (in the portion unspanned by the variance).[18] Formally, it is calculated as

$$GLB_{i,t,t+\Delta t} = \max_{\theta \in \underline{\Theta}_{i,t}} \left\{ \mathbb{E}^*_t(\varphi_\theta[R_{i,t,t+\Delta t}]) \Big/ \mathbb{E}^*_t\left(\frac{\varphi_\theta[R_{i,t,t+\Delta t}]}{R_{i,t,t+\Delta t}}\right) - R_{f,t,t+\Delta t} \right\}, \quad (5)$$

where $\mathbb{E}^*_t$ denotes the risk-neutral expectation, $\varphi_\theta(x) = x^{\theta+1}$, and $\underline{\Theta}_{i,t}$ is the stock- and time-varying set identified from historical parameters as described in proposition 2 in Chabi-Yo et al. (2023).[19] We explore differences between the *MW* and *GLB* proxies to obtain insights into climate-related higher order risks and how market participants price these risks.

2.3. Risk Quantities

Some tests use option-implied "risk quantities" that aggregate the forward-looking consensus of market participants for the future return distribution up to a given option maturity.[20] To measure the implied variance ($IV_{i,t}$)

of stock i at time t, we use the Martin (2017) variance swap rate $IV_{t,t+\Delta t}$ for 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 (we omit the subscript i for brevity):

$$IV_{t,t+\Delta t} = \frac{2R_{f,t}}{S_t^2}\left[\int_0^{F_{t,t+\Delta t}} P(t,t+\Delta,K)dK + \int_{F_{t,t+\Delta t}}^{\infty} C(t,t+\Delta,K)dK\right], \tag{6}$$

where S_t and $F_{t,t+\Delta t}$ are the spot and forward prices of the underlying stock and $R_{f,t}$ is the gross risk-free rate. We use a similar approach for the implied skewness ($ISkew_{i,t}$) and for the implied kurtosis ($IKurt_{i,t}$), applying the formulas for the log returns in Bakshi et al. (2003).[21]

We measure the steepness of the implied volatility slope on the left ($SlopeD_{i,t}$) and right ($SlopeU_{i,t}$) from the at-the-money (ATM) point. As in Kelly et al. (2016), the measures are the slopes of functions relating the implied volatilities of OTM options to their deltas. We estimate $SlopeD_{i,t}$ by regressing the implied volatilities of puts with deltas between –0.1 and –0.5 on their deltas (and a constant). For $SlopeU_{i,t}$, we regress implied volatilities of calls with deltas between 0.1 and 0.5 on their deltas and multiply the resulting slope coefficient by -1.[22] An increase in either measure indicates that deep OTM options become more expensive, reflecting a relatively higher cost of protection against tail risks ($SlopeD_{i,t}$) or relatively more expensive growth opportunities ($SlopeU_{i,t}$). The measures are positive, on average, as far OTM options are typically more costly (in terms of implied volatilities) than ATM options.

As risk measures in a given month, we take the averages of daily computed risk measures within this month.

2.4. Institutional and Market Factors

Our time-series regressions include aggregate institutional and market factors that vary at the level of month t. We use $Green\ Innovation_t$, which is a monthly measure of the total number of green patents filed in the United States over the previous three years, and $Adaptation_t$, which exploits that some stocks are exposed to state-led climate change adaptation plans in their headquarters' states. Though these plans vary in their scopes and strategies, they all speak to commitments toward mitigating climate risks.[23] We construct the aggregate monthly time series of $Adaptation_t$ as

$$Adaptation_t = \frac{\sum_i 1[Adapted\ State]_{i,t} \times CCExposure_{i,t}}{\sum_i CCExposure_{i,t}}, \tag{7}$$

where $1[Adapted\ State]_{i,t}$ is one after (or on) date t if a firm's headquarters are located in a state adopting an adaptation plan. Thus, $Adaptation_t$ measures the proportion of climate change exposure in the S&P 500 in month t coming from stocks located in states with adaptation plans.

We also use $ESG\ Fund\ Flows_t$ that reflects monthly net flows into ESG funds. We use the list of sustainable funds from Morningstar's 2021 Sustainable Funds U.S. Landscape Report (Pastor et al. 2022) and match these funds with the CRSP Survivor-Bias-Free U.S. Mutual Funds to calculate the net fund flows of fund j during month t as

$$ESG\ Fund\ Flows_{j,t} = TNA_{j,t} - (1 + R_{j,t}) \times TNA_{j,t}, \tag{8}$$

where $TNA_{j,t}$ is the change in total net assets and $R_{j,t}$ is fund j's reported return (to reflect appreciation). Aggregating this measure across all funds j in month t, we get $ESG\ Fund\ Flows_t$.

The variable $Big\ Three\ IO_t$ is the aggregate *CCExposure*-weighted ownership by Vanguard, BlackRock, and StateStreet (Big Three). The variable is computed each month as the *CCExposure*-weighted holdings by the Big Three across S&P 500 stocks (details in the appendix):

$$Big\ Three\ IO_t = \frac{\sum_i Big\ Three_{i,t} \times CCExposure_{i,t}}{\sum_i CCExposure_{i,t}}, \tag{9}$$

where $Big\ Three_{i,t}$ are the percentage holdings by the Big Three in stock i at time t. Intuitively, $Big\ Three\ IO_t$ reflects the climate change exposure of the Big Three relative to the exposure held in the market. This variable is available from January 2005 to December 2017.[24]

Two variables reflect market prices related to firms' incentives to develop green innovation. $Oil\ Price_t$ is the West Texas Intermediate (WTI) spot price and $CO_2\ Price_t$ is the monthly futures price of CO_2 emission allowances (available since August 2005 from the EU Emission Trading System).

2.5. Summary Statistics

Table 1 reports summary statistics of the measures that vary at the stock–month level. *CCExposure* is nonzero for most stock months (10th percentile is positive) and shows great variation across stocks. $CCExposure^{Ind}$ is, on average, similar to the general measure but less volatile. By construction, $CCExposure^{Res}$ is, on average, zero. The topic-based exposure measures are sparser than the general measure except for $CCExposure^{Opp}$, which is nonzero for at least 90% of the observations. The annualized *RET* equals 13.1% per year, on average, which compares to 7.0% and 9.3% for the expected return proxies by *MW* and *GLB*. *RET*s are noisier (standard deviation of 112.5%) than the *MW* and *GLB* proxies (standard deviations of 9.0% and 10.1%, respectively). Online Table 2 provides unconditional correlations for selected variables computed at the stock–month level.

Table 1. Summary Statistics

Variable	Mean	Standard deviation	10%	25%	50%	75%	90%	Observations
			Panel A: Climate change exposure measures					
$CCExposure_{i,t}$	1,072.642	2,638.769	30.400	124.250	318.921	779.292	2,167.085	118,186
$CCExposure^{Ind}_{i,t}$	1,071.061	1,902.777	190.417	273.636	455.464	815.273	1,926.286	120,945
$CCExposure^{Res}_{i,t}$	−0.000	1,828.488	−730.513	−331.940	−109.691	131.548	691.763	118,186
$CCExposure^{Opp}_{i,t}$	303.622	1081.467	0.000	0.072	16.469	159.451	511.655	118,186
$CCExposure^{Reg}_{i,t}$	54.132	234.557	0.000	0.000	0.000	0.391	111.476	118,186
$CCExposure^{Phy}_{i,t}$	12.782	76.106	0.000	0.000	0.000	0.000	6.156	118,186
$CCExposure^{Ltg}_{i,t}$	2.306	25.344	0.000	0.000	0.000	0.000	0.000	118,186
$CCSentiment^{Neg}_{i,t}$	197.708	504.535	0.000	0.168	21.275	168.048	496.073	118,186
			Panel B: Expected excess return proxies					
$RET_{i,t}$, (p.a.)	0.131	1.125	−1.143	−0.458	0.136	0.709	1.364	120,075
$MW_{i,t}$, (p.a.)	0.070	0.090	0.008	0.020	0.041	0.082	0.157	117,782
$GLB_{i,t}$, (p.a.)	0.093	0.101	0.022	0.034	0.058	0.107	0.197	116,794
			Panel C: Betas for factor models					
$Market_{i,t}$	1.034	0.308	0.681	0.841	1.016	1.208	1.411	119,242
$Size\,(SMB)_{i,t}$	0.186	0.484	−0.310	−0.125	0.106	0.409	0.797	119,242
$Value\,(HML)_{i,t}$	0.017	0.707	−0.724	−0.374	−0.042	0.367	0.890	119,242
$Momentum\,(WML)_{i,t}$	−0.050	0.522	−0.610	−0.290	−0.022	0.211	0.444	119,242
$Profitability\,(RMW)_{i,t}$	0.001	0.796	−0.894	−0.359	0.073	0.439	0.807	119,242
$Investment\,(CMA)_{i,t}$	0.122	0.947	−0.930	−0.330	0.179	0.645	1.107	119,242
			Panel D: Risk quantities					
$IV_{i,t}$	0.165	0.184	0.044	0.065	0.106	0.183	0.332	117,729
$ISkew_{i,t}$	−0.588	0.417	−1.105	−0.795	−0.549	−0.342	−0.137	117,729
$IKurt_{i,t}$	4.886	1.839	3.325	3.614	4.200	5.486	7.741	117,729
$SlopeU_{i,t}$	0.120	0.241	−0.063	−0.021	0.032	0.171	0.457	117,729
$SlopeD_{i,t}$	0.336	0.288	0.106	0.157	0.237	0.406	0.723	117,729
			Panel E: Fundamentals and market characteristics					
$Log(Market\,Cap)_{i,t}$	9.131	1.295	7.536	8.282	9.096	9.923	10.840	115,773
$Log(Assets)_{i,t}$	9.155	1.507	7.383	8.118	9.047	10.121	11.102	115,803
$Debt/Assets_{i,t}$	0.268	0.192	0.025	0.124	0.246	0.379	0.521	115,388
$Cash/Assets_{i,t}$	0.140	0.151	0.012	0.032	0.085	0.194	0.354	115,803
$PP\&E/Assets_{i,t}$	0.252	0.237	0.019	0.068	0.163	0.385	0.648	111,159
$EBIT/Assets_{i,t}$	0.100	0.083	0.019	0.049	0.091	0.144	0.202	115,803
$Capex/Assets_{i,t}$	0.041	0.042	0.002	0.013	0.029	0.056	0.091	115,733
$R\&D/Assets_{i,t}$	0.025	0.048	0.000	0.000	0.000	0.026	0.087	115,803
$Volatility_{i,t}$	0.086	0.049	0.041	0.053	0.073	0.103	0.145	118,805
$Momentum12_{i,t}$	0.140	0.323	−0.234	−0.022	0.147	0.307	0.485	118,934
			Panel F: CO_2 and oil exposure measures					
$Log(Carbon\,Emissions)_{i,t}$	12.774	2.191	10.097	11.201	12.558	14.128	15.849	88,951
$Oil\,Beta_{i,t}$	−0.001	0.098	−0.092	−0.049	−0.008	0.031	0.093	119,242

Notes. This table reports summary statistics at the stock–month level. The climate change exposure measures are scaled up by 10^6. The variables in the table are not yet normalized. The sample covers the period from January 2005 to December 2020 and includes S&P 500 stocks.

3. Unconditional Risk Premium for Climate Change Exposure

3.1. Risk Premium for Climate Change Exposure: Predicted Effects

It is not obvious whether investors expect compensation for holding stocks with high values of *CCExposure*. One view holds that high-exposure stocks should be riskier and earn a positive risk premium relative to low-exposure stocks. Specifically, high-exposure stocks face high uncertainty related to future developments in climate-related areas. Hence, their returns should include real option value that depends on the path of climate-related technologies, regulations, or physical climate shifts. Accordingly, the risk premium should depend on investors' risk preferences and the quantity of risk associated with *CCExposure*. These two components may change over time, implying that the risk premium itself also varies. For example, the quantity of risk for stocks with high exposure to climate-related opportunities can decrease if green innovation becomes less uncertain as the success probability for climate-related technologies rises.

Another view holds that the risk premium for *CCExposure* reflects the trend toward ESG and impact investing, and investors might invest in high-exposure stocks for nonpecuniary reasons (Zerbib 2022, Pastor et al. 2021, Pedersen et al. 2021). Investors might then tolerate higher (tail) risks when investing in high-exposure stocks or can accept relatively low expected returns for a small chance of high payoffs of some green technologies. These preferences should affect stock prices and could lead to a risk premium for *CCExposure* that is zero or even.

These views illustrate that the risk premium for *CCExposure* is conceptually ambiguous and even time-varying. Thus, any estimated pricing effects of *CCExposure* may not yet reflect the long-term equilibrium, but rather the path toward it.

3.2. Risk Premium for Overall Climate Change Exposure: Estimation

We test whether *CCExposure* is related to excess returns in the cross-section of stocks using the two-stage approach by Fama and MacBeth (1973). In the first stage, we estimate stock betas with respect to a six-factor model, which combines the four- and five-factor models by Carhart (1997) and Fama and French (2015).[25] Factor betas are estimated at the end of each month with a rolling-window procedure using daily excess returns and factor realizations over the past 12 months. In the second stage, at the end of each month, we estimate cross-sectional regressions of excess stock returns on the estimated factor model betas and a number of stock characteristics that are known return predictors or possibly correlated with *CCExposure*. These stock characteristics include (i) firm fundamentals: *Log(Market Cap)*, *Log(Assets)*, *Debt/Assets*, *Cash/Assets*, *PP&E/Assets*, *EBIT/Assets Capex/Assets*, and *R&D/Assets*; (ii) market variables: *Momentum12* and *Volatility*, and (iii) CO_2 and oil exposure measures: *Log*(*Carbon Emissions*) and *Oil Beta*. To ensure that the firm fundamentals use publicly 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 are publicly available (Fama and French 1992). *Oil Beta* is computed jointly with the six-factor model noted earlier. Values for *Carbon Emissions* for all months in a year are from the previous year to eliminate a look-ahead bias (emissions are updated annually).[26]

3.3. Risk Premium for Climate Change Exposure: Baseline Estimates

Table 2 reports unconditional risk premium estimates for *CCExposure* as well as for its industry ($CCExposure^{Ind}$) and residual ($CCExposure^{Res}$) components.[27] Columns (1) and (2) report estimates for the *RET*. In column (1), the unconditional estimate for *RET* delivers a positive but insignificant risk premium for *CCExposure*. In column (2), we find an insignificant premium for $CCExposure^{Ind}$ and a positive premium for $CCExposure^{Res}$ (*t*-statistic of 1.90). However, we do not put much weight on these estimates as they likely reflect the large amounts of noise in the *RET* measure during our short sample period (indeed, the risk premiums for most common risk factors are also insignificant).

Columns (3) and (4) consider the risk premium estimates for the *MW* proxy of the expected excess return and columns (5) and (6) for the *GLB* proxy. Across all four columns, we find positive and statistically significant risk premiums for *CCExposure*. In column (3) for the *MW* proxy, stocks with higher values of *CCExposure* are expected to deliver higher excess returns (*t*-statistic of 2.88). In column (5), the magnitude of the *CCExposure* premium almost doubles compared with the *MW*-based proxy, and the *t*-statistic grows to 3.11. However, the unconditional compensation for *CCExposure* in both estimations is modest: a one-standard-deviation shock to *CCExposure* increases the expected excess return by 0.09% p.a. in column (3) (*MW* proxy) and by 0.18% p.a. in column (5) (*GLB* proxy). As we demonstrate, these small unconditional effects result from averaging the estimation across the entire sample period; they mask economically large positive risk premiums during parts of the sample period.[28]

When we split *CCExposure* in columns (4) and (6) into industry and residual components, we observe that the overall risk premium originates mostly from the firm-specific part. This finding shows how important it is to consider a firm-level exposure measure. Overall, Table 2 conveys an important economic message: climate change exposure, measured as attention devoted to climate-related topics in earnings calls, is associated with a positive risk premium.

The *GLB*-based premium being twice as large as that for the *MW* proxy raises the question of which climate-related factors cause the two premiums to deviate. Recall that both proxies differ—by construction—in how they weigh investors' risk preferences. Whereas the *MW* proxy is based on preferences that do not consider higher order risks unspanned by variances, the *GLB* proxy also considers the role of unspanned higher order risks. Therefore, the divergence in results might arise because investors, on average and across the full sample, associate relatively high crash risk (left tail) or relatively low opportunities (right tail) with high-exposure stocks. This conjecture emerges because, compared with the *MW* proxy, the *GLB* proxy increases more strongly in the left tail and decreases more strongly in the right tail; this causes stocks with relatively high climate-related crash risks (or stocks with low climate-related opportunities) to earn higher risk premium under the *GLB* proxy. The following sections pursue two directions to understand better these issues by (i) decomposing *CCExposure* into its topic-based components and (ii) analyzing the time-series pattern of the conditional risk premiums.

Table 2. Risk Premium for Climate Change Exposure: Unconditional Evidence

	$RET_{i,t}$		$MW_{i,t}$		$GLB_{i,t}$	
Expected excess return	(1)	(2)	(3)	(4)	(5)	(6)
$Market_{i,t}$	−0.035	−0.035	0.013	0.014	0.044	0.044
	(−0.967)	(−0.954)	(3.345)	(3.375)	(8.749)	(8.678)
$Size\,(SMB)_{i,t}$	0.029	0.028	0.014	0.014	0.007	0.007
	(1.553)	(1.506)	(10.192)	(10.037)	(4.466)	(4.427)
$Value\,(HML)_{i,t}$	−0.014	−0.015	0.004	0.004	0.005	0.005
	(−0.679)	(−0.730)	(1.808)	(1.802)	(3.279)	(3.271)
$Momentum\,(WML)_{i,t}$	0.009	0.012	−0.013	−0.012	−0.009	−0.009
	(0.335)	(0.448)	(−3.040)	(−3.016)	(−2.317)	(−2.287)
$Profitability\,(RMW)_{i,t}$	0.021	0.020	−0.005	−0.005	−0.003	−0.003
	(1.597)	(1.571)	(−4.685)	(−4.748)	(−1.885)	(−1.960)
$Investment\,(CMA)_{i,t}$	−0.009	−0.009	−0.002	−0.002	−0.002	−0.002
	(−0.748)	(−0.775)	(−2.027)	(−2.047)	(−2.165)	(−2.127)
$CCExposure_{i,t}$	0.469	–	0.093	–	0.178	–
	(1.007)	–	(2.878)	–	(3.113)	–
$CCExposure^{Ind}_{i,t}$	–	−0.048	–	0.042	–	0.096
	–	(−0.080)	–	(1.195)	–	(2.127)
$CCExposure^{Res}_{i,t}$	–	0.577	–	0.081	–	0.145
	–	(1.902)	–	(3.177)	–	(3.463)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample period	January 2005–December 2020	January 2005–December 2020	January 2005–December 2020	January 2005–December 2020	January 2005–December 2020	January 2005–December 2020
Observations	83,114	83,114	82,653	82,653	82,653	82,653
R^2	0.001	0.001	0.302	0.302	0.067	0.067

Notes. This table reports the results of Fama–MacBeth regressions at the stock–month level. We report the risk premium estimates for firm-level climate change exposure (*CCExposure*). We also split *CCExposure* into an industry ($CCExposure^{Ind}$) and residual ($CCExposure^{Res}$) component. All climate change exposure risk premiums are reported in % p.a. after controlling for a six-factor model (combination of four- and five-factor models) and stock characteristics (described in Section 3.2). As proxies for expected excess returns, we use *RET* and the forward-looking proxies by Martin and Wagner (2019) (*MW*) and Chabi-Yo et al. (2022) (*GLB*). All explanatory variables (except for the factor betas) are normalized at each point in time to have a standard deviation of 0.01. *t*-statistics based on Newey and West (1987) standard errors with three lags are reported in parentheses. The sample covers the period from January 2005–December 2020 and includes S&P 500 stocks.

3.4. Risk Premium for Climate Change Exposure: Topic-Based Estimates

We next explore the risk premiums for exposure to climate-related opportunity, regulatory, and physical shocks. Climate-related opportunities are risky with plenty of uncertainty surrounding investments in green technologies. Hence, stocks with greater exposure to climate-related opportunities should earn a risk premium. Likewise, stocks with higher regulatory exposure are more strongly affected by regulations to combat global warming, and investors should require a risk premium because of the uncertainty surrounding such restrictions. Similarly, stocks exposed to physical shocks originating from storms, heat, or other natural disasters might also need to compensate investors for the associated risks.

Table 3 reports risk premium estimates separately for $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$. As exposure to these topics is more sparse than overall exposure, the sample in the table starts in January 2009, the year in which we observe nonzero exposure values for at least 30% of the sample for each topic. Columns (1)–(3) report the results for *RET*, columns (4)–(6) for the *MW* proxy, and columns (7)–(9) for the *GLB* proxy.

For all three exposure topics, columns (1)–(3) report insignificant realized risk premiums with *t*-statistics ranging between −0.52 and 0.71. In columns (4)–(9), this is very different for the *MW*- and *GLB*-based proxies. Notably, in columns (4) and (7), stocks with high values of $CCExposure^{Opp}$ earn a positive and significant risk premium for the *MW* and *GLB* proxy. The risk premium estimate is larger for the *GLB* proxy compared with the *MW* proxy (0.26% p.a. in column (7) versus 0.17% in column (4)). In columns (5) and (8), the risk premium for $CCExposure^{Reg}$ is also positive and statistically significant, but the magnitude of the risk premium is smaller compared with that for $CCExposure^{Opp}$. The risk premium for regulatory exposure is larger for the *GLB* proxy compared with the *MW* proxy (0.11% in column (8) versus 0.08% in column (5)). In columns (6) and (9), $CCExposure^{Phy}$ is priced (at the 5% level) only with the *GLB* proxy. Our data structure could be a reason for the insignificant effects: $CCExposure^{Phy}$ is far more sparse than $CCExposure^{Opp}$ or $CCExposure^{Reg}$, and the discussions in earnings calls on physical shocks gain momentum mostly in the late sample years. Hence, $CCExposure^{Phy}$ is either zero or close to zero (because of exponential smoothing if some discussions took place in the previous earnings calls) for most observations. Consequently, we do not obtain sufficient variation of the $CCExposure^{Phy}$ measure across stocks, which leads to an

Table 3. Risk Premium for Climate Change Topics: Unconditional Evidence

	$RET_{i,t}$			$MW_{i,t}$			$GLB_{i,t}$		
Expected excess return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Market_{i,t}$	−0.014	−0.014	−0.015	0.007	0.007	0.006	0.042	0.042	0.041
	(−0.324)	(−0.323)	(−0.341)	(2.143)	(1.977)	(1.864)	(8.287)	(8.054)	(7.930)
$Size\,(SMB)_{i,t}$	0.030	0.028	0.028	0.017	0.017	0.016	0.007	0.007	0.007
	(1.518)	(1.410)	(1.422)	(11.963)	(11.897)	(11.633)	(3.376)	(3.278)	(3.177)
$Value\,(HML)_{i,t}$	−0.014	−0.016	−0.017	0.003	0.003	0.003	0.007	0.006	0.006
	(−0.599)	(−0.686)	(−0.720)	(1.203)	(1.125)	(1.119)	(3.221)	(3.119)	(3.075)
$Momentum\,(WML)_{i,t}$	−0.007	−0.002	−0.003	−0.013	−0.013	−0.013	−0.009	−0.009	−0.009
	(−0.212)	(−0.072)	(−0.093)	(−2.816)	(−2.823)	(−2.822)	(−1.993)	(−1.987)	(−2.034)
$Profitability\,(RMW)_{i,t}$	0.0025	0.026	0.026	−0.006	−0.006	−0.006	−0.004	−0.004	−0.004
	(1.563)	(1.613)	(1.616)	(−4.518)	(−4.468)	(−4.418)	(−2.075)	(−2.153)	(−2.069)
$Investment\,(CMA)_{i,t}$	−0.013	−0.013	−0.014	−0.001	−0.001	−0.001	−0.002	−0.002	−0.002
	(−0.996)	(−0.984)	(−1.036)	(−0.985)	(−1.153)	(−1.203)	(−1.653)	(−1.812)	(−1.993)
$CCExposure^{Opp}_{i,t}$	0.347	–	–	0.167	–	–	0.260	–	–
	(0.707)	–	–	(4.396)	–	–	(3.708)	–	–
$CCExposure^{Reg}_{i,t}$	–	−0.189	–	–	0.075	–	–	0.105	–
	–	(−0.524)	–	–	(2.906)	–	–	(2.058)	–
$CCExposure^{Phy}_{i,t}$	–	–	0.128	–	–	0.031	–	–	0.065
	–	–	(0.503)	–	–	(1.623)	–	–	(2.226)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample period	January 2009–December 2020								
Observations	65,067	65,067	65,067	64,848	64,848	64,848	64,848	64,848	64,848
R^2	0.004	0.004	0.005	0.332	0.333	0.333	0.091	0.093	0.093

Notes. This table reports the results of Fama–MacBeth regressions at the stock-month level. We report the risk premiums for firm-level topic-based climate change exposure measures (*CCExposureOpp, CCExposureReg, CCExposurePhy*). All climate change exposure risk premiums are reported in % p.a. after controlling for a six-factor model (combination of four- and five-factor models) and stock characteristics (described in Section 3.2). As proxies for expected excess returns, we use in columns (1)–(3) the realized excess returns (RET), in columns (4)–(6) the forward-looking proxy by Martin and Wagner (2019) (MW), and in columns (7)–(9) the forward-looking proxy by Chabi-Yo et al. (2023) (GLB). All explanatory variables (except for the factor betas) are normalized at each point in time to have a standard deviation of 0.01. *t*-statistics based on Newey and West (1987) standard errors (with three lags) are reported in parentheses. The sample covers the period from January 2009 to December 2020 and includes S&P 500 stocks. The sample starts in January 2009 to ensure that we observe non-zero exposure values for each of the three topics for at least 30% of the sample.

ill-defined estimation problem (we still obtain a positive slope, on average, but the estimates are noisy). Our results are broadly consistent with the analysis of Faccini et al. (2022), which does not find evidence for a significant risk premium related to natural disasters and global warming factors.[29] Overall, we conclude that the unconditional risk premium for *CCExposure* primarily comes from the higher compensation earned by stocks with larger exposure to climate-related opportunities shocks and, to a smaller extent, from stocks with higher exposure to regulatory shocks.

3.5. Risk Premium for Climate Change Exposure: Extensions

We compare our estimates with those obtained from two alternative metrics of how stocks are affected by climate change. As the ESG industry has grown, several data vendors created their own metrics, focusing on one particular risk associated with climate change: carbon risk. Two data vendors in particular offer measures of carbon risk, namely ISS (part of Deutsche Börse) and Sustainalytics (part of Morningstar). Whereas fundamentally different from us in how they approach climate change exposure, it is insightful to explore whether their metrics are priced.

ISS Score assesses the carbon-related performance of firms and take a value between one (poor performance) and four (excellent performance)—our data on these scores are available from 2015 to 2019. *Sustainalytics Score* measures a firm's exposure and management of material carbon risks. This rating ranges between 0 and 100 (higher values indicate more risk) and is available to us between 2013 and 2020. As is obvious from the descriptions, both ratings center on carbon-related aspects of climate change.

Online Table 3 repeats the risk premium estimation for the *ISS Score*; for comparison, we report results using *CCExposure* for the same sample period (the observations differ as the ISS ratings are not available for all S&P 500 stocks). Across all three excess return proxies, we cannot detect that the ISS rating is priced between 2015 and 2019. Online Table 4 considers the *Sustainalytics Score*. Stocks with higher carbon risks earned a significantly lower risk premium based on the *MW* proxy and a lower but insignificant premium based on the *GLB*.[30] In both tables, the coefficient estimates on the ISS and Sustainalytics ratings change very little when we add *CCExposure*; this suggests that these and our measures capture different economic concepts. The risk premium for *CCExposure* for the *MW* and *GLB* proxies in both tables is smaller (and often significant) compared with Table 2, which, as we carefully explain, is related to the specific sample periods in these tables.

We next provide a series of extensions of our Table 2 baseline results. We show that we obtain similar results if we replace *CCExposure* with $CCSentiment^{Neg}$ in Online Table 5, suggesting that negative tone words about *CCExposure* mostly drive the risk premiums. We also obtain similar results if we replace *CCExposure* with $Log(1 + CCExposure)$ in Online Table 6.

In Online Figure 1, we consider how robust the risk premium estimates for *CCExposure* are to changes in the bigram set $\mathbb{C}$, which is used to construct the measure. We randomly drop 5% of the bigrams in $\mathbb{C}$ and reconstruct new versions of *CCExposure*. In this way, we create 50 new perturbated *CCExposure* measures and reestimate for each of those the risk premiums for the *RET*, *MW*, and *GLB* proxies. Online Figure 1 reports histograms of the *t*-statistics for these estimates, showing that our inferences are not sensitive to variations in the bigram set $\mathbb{C}$.[31]

We argue that measured climate change exposure reflects firm-level idiosyncratic exposure to climate change. An alternative interpretation is that part of the firm-level variation reflects idiosyncratic measurement error. To address this alternative, we follow SvLVZ and quantify in Online Table 7 the measurement error in *CCExposure* (using the original quarterly variable). The estimation is based on three instruments for *CCExposure*, which are assumed to measure "true" but unobservable climate change exposure with independent and identically distributed measurement error. Under the assumption that true climate change exposure follows a first order autoregressive process, we can back out the share of variation in *CCExposure* consisting of measurement error. Our estimates range between 3% and 13%, which is consistent with the estimates reported in SvLVZ, using their full sample rather than S&P 500 stocks. The conclusion of this exercise reads that measurement error is unlikely to have a large impact on inferences.

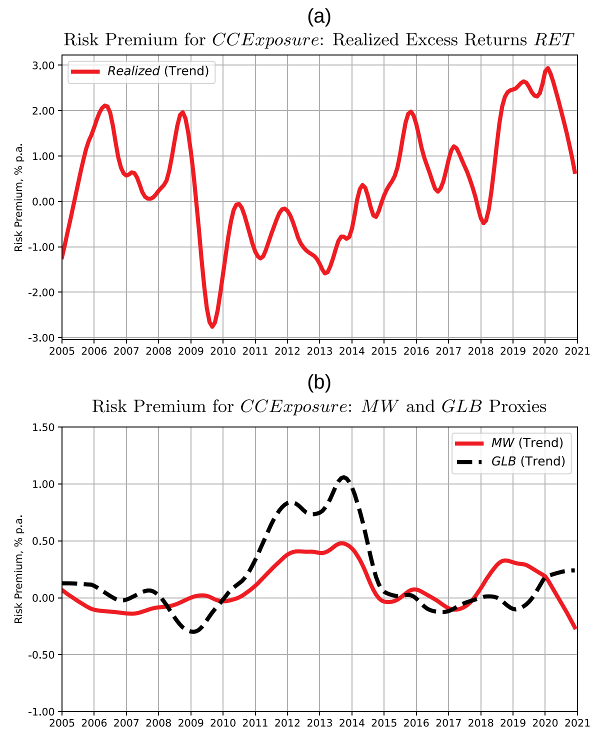
Finally, Online Table 8 tests whether climate-related litigation exposure ($CCExposure^{Ltg}$) commands a risk premium. Across all three proxies, we cannot detect positive risk premiums. Climate-related litigation is a relatively recent phenomenon in the United States with successful lawsuits still being the exception, which might explain this finding.

4. Conditional Risk Premium for Climate Change Exposure

4.1. Conditional Risk Premium Dynamics

SvLVZ demonstrate that *CCExposure* fluctuates over time because of changes in investor attention to climate topics as climate-related risk quantities or investor preferences might also. Hence, we expect the climate-related risk premiums also to vary over time. Figure 1 reports

Figure 1. (Color online) Risk Premium for Climate Change Exposure: Time-Series Dynamics



Notes. This figure shows the trend component of the time series of the risk premium for *CCExposure* (in % p.a.), estimated in panel (a) from *RET* and in panel (b) from the expected excess return proxies of *MW* and *GLB*. Risk premiums are obtained jointly with the six-factor model (four- and five-factor models combined) premiums and stock characteristics (described in Section 3.2). *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 et al. 1990) with a period of 12 months. The sample covers the period from January 2005 to December 2020 and includes S&P 500 stocks.

the estimated time series of the risk premiums with panel (a) plotting the dynamics of the realized risk premium (*RET*) and panel (b) the dynamics for the *MW*- and *GLB*-based risk premiums. Both panels report the trend component of the time series.

Panel (a) shows that the insignificant unconditional realized risk premium (using *RET*) masks that the compensation for *CCExposure* was positive (around 1% p.a.) before 2008. This period ended with a sharp decline in the risk premium in the financial crisis (2008–2009). At that time, the realized premium became negative, probably reflecting an excessive sell-off by investors worried about the prospects of uncertain and long-term climate-related investments. A recession-motivated readjustment of the weighting of climate concerns relative to a freezing up of the economy might be another reason.[32] A secular upward trend in the realized premium followed the crisis-related drop until the end of the sample period. Panel (a) demonstrates that the realized compensation for *CCExposure* was nonzero for a significant amount of time.

The changes in the climate-related risk premiums around the financial crisis can be related to theoretical work by Bansal et al. (2021), who find that "good" stocks significantly outperform "bad" stocks during good economic times but underperform during bad times. The reason is that wealth-dependent investor preferences are more favorable toward stocks with high values of *CCExposure* during good times, resulting in higher temporary demand and higher realized returns. As a result, there is less appreciation expected in the future as discussed subsequently for the *MW* and *GLB* proxies. This interpretation rests on the assumption that stocks with high values of *CCExposure* are good stocks.

Panel (b) depicts the time series of the risk premiums for *CCExposure* based on the *MW* and *GLB* proxies. The panel confirms that Table 2 masks important time-series heterogeneity in the forward-looking risk premium. Before 2011, the premiums for *CCExposure* based on the *MW* and *GLB* proxies fluctuated around zero. Starting in 2011, both premiums turned positive with the *MW*-based premium gradually rising to about 0.5% p.a. in 2012. The *GLB*-based premium experienced an even faster increase to about 1% p.a. between 2012 and 2014.[33] From 2015, both premiums revert to almost zero with the *MW* proxy being slightly higher (the *MW*-based premium equals 0.09% with a t-statistic of 1.87; the *GLB*-based premium is insignificant).

4.2. Explaining Conditional Risk Premium Dynamics

4.2.1. Economic Channel: Risk Quantities. What can we learn from the diverging dynamics between the *MW*- and *GLB*-based risk premiums in Figure 1? If higher order risks are not explicitly considered in the risk premium estimation (*MW* proxy), then *CCExposure* was priced since 2011 (with a small premium since 2015). If all risks encoded in the return distribution are considered (*GLB* proxy), then *CCExposure* was priced only between 2011 and 2014. The diverging dynamics indicate that the compensation for *CCExposure* is linked to higher order risks, especially the left and right tails and that these risks changed over time. To explore this more formally, we test how the risk premiums for *CCExposure* are linked to risk quantities that investors associate with *CCExposure*.

To identify this link, we calculate in a first step the sensitivity of a set of risk quantities (labeled as *Risk*) to *CCExposure* (*CCE*); this allows us to quantify how changes in *CCExposure* are linked to the changes in various (perceived) risks. We compute the risk sensitivities each month as slope coefficients $Sens_t^{CCE,Risk}$ from regressions of a particular risk quantity on *CCExposure*.[34] In a second step, we regress the monthly time-series values of the risk premiums for *CCExposure* (RP_t^{Proxy}) on the time-series values of the cross-sectional sensitivities of the risk quantities to *CCExposure* ($Sens_t^{CCE,Risk}$). RP_t^{Proxy} is estimated in the cross-sectional stage of the Fama–MacBeth procedure. We are interested in the γ_{Risk} coefficients of the following regressions:

$$RP_t^{Proxy} = \alpha + \sum_{Risk} \gamma_{Risk} \times Sens_t^{CCE,Risk} + \varepsilon_t, \qquad (10)$$

where the expected return proxy is $Proxy \in (RET, MW, GLB)$, CCE = *CCExposure*, and *Risk* is a risk quantity

Table 4. Conditional Link: Risk Premiums and Risk Sensitivities

	RP_t^{RET}		RP_t^{MW}		RP_t^{GLB}	
Risk premium	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.097	−0.512	0.018	0.017	0.067	0.200
	(−0.110)	(−0.540)	(0.870)	(0.730)	(1.360)	(3.690)
$Sens_t^{CCE,IV}$	−87.650	−77.664	21.801	22.354	23.213	29.076
	(−1.500)	(−1.500)	(15.100)	(17.370)	(6.930)	(9.870)
$Sens_t^{CCE,ISkew}$	–	−49.229	–	−1.479	–	−9.520
	–	(−0.840)	–	(−1.020)	–	(−2.870)
$Sens_t^{CCE,IKurt}$	–	48.771	–	0.031	–	−10.680
	–	(0.780)	–	(0.020)	–	(−3.000)
$Sens_t^{CCE,SlopeD}$	43.079	–	2.308	–	10.683	–
	(0.560)	–	(1.210)	–	(2.420)	–
$Sens_t^{CCE,SlopeU}$	21.842	–	−1.179	–	−6.357	–
	(0.300)	–	(−0.660)	–	(−1.550)	–
Sample period			January 2005–December 2020			
Observations	192	192	192	192	192	192
Adjusted R^2	−0.004	0.007	0.654	0.654	0.331	0.348

Notes. This table reports the results of time-series regressions at the monthly level. We report slope coefficients (γ_{Risk}) from regressing the time-series estimates of the risk premiums for *CCExposure* on the time-series estimates of the cross-sectional sensitivities ($Sens_t^{CCE,Risk}$) of different risk quantities to *CCExposure* (*CCE*). All sensitivities are normalized to have a standard deviation of 0.01. The regression specification is given in Equation (10). t-statistics using OLS standard errors are in parentheses. The sample covers the period from January 2005–December 2020 and includes S&P 500 stocks.

from (*IV*, *ISkew*, *IKurt*) or (*IV*, *SlopeD*, *SlopeU*). We split the risk quantities into two sets to avoid multicollinearity; $Sens^{CCE,ISkew}$ and $Sens^{CCE,IKurt}$ are highly correlated with $Sens^{CCE,SlopeD}$ and $Sens^{CCE,SlopeU}$.

Estimates of Model (10) are reported in Table 4 with the *RET*-based premium in columns (1) and (2), the *MW*-based premium in columns (3) and (4), and the *GLB*-based premium in columns (5) and (6). Three insights emerge. First, the sensitivities of the risk quantities to *CCExposure* in columns (1) and (2) are largely unrelated to the risk premium based on realized returns (*RET*) as reflected in the low adjusted R^2s and the insignificant coefficients. Second, the *MW*-based premium in columns (3) and (4) primarily originates from the sensitivity of *CCExposure* to *IV* ($Sens^{CCE,IV}$); all other sensitivities are small and insignificant. This corroborates that the *MW*-based premium is driven by second order moments and, hence, is most suitable for investors who do not care about higher order risks unspanned by variance. If we consider the *GLB*-based premium in columns (5) and (6), then higher order risk (column (5)) and tail (column (6)) sensitivities emerge as important regressors on top of $Sens^{CCE,IV}$. The additional role of these sensitivities is plausible as the *GLB* proxy assumes that investors consider the full shape of the return distribution. That said, the effect of $Sens^{CCE,IV}$ dominates the effects of the other sensitivities as reflected in the larger coefficients. Third, the *GLB*-based premium goes up when $Sens^{CCE,SlopeD}$ increases (high-exposure stocks' downside tail protection gets more expensive) and when $Sens^{CCE,ISkew}$ becomes more negative (high-exposure stocks get more risky).[35]

All in all, we conclude that the primary source of risk for high-exposure stocks is volatility, which is priced in the expected excess returns of the *MW* and *GLB* proxies. Moreover, any observed differences in the time series of the risk premiums in Figure 1 predominantly result from asymmetric risks related to *CCExposure*, captured by skewness or implied volatility slopes. To further corroborate this conclusion, we directly relate *CCExposure* to higher order moments and tail risks, thereby explicitly accounting for the three time regimes that emerged from Figure 1. Specifically, we estimate the following panel regression for stock *i* in month *t*, separating the sample into the subperiods January 2005–December 2010, January 2011–December 2014, and January 2015–December 2020:

$$CCExposure_{i,t} = \alpha + \sum_{Risk} \gamma_{Risk} Risk_{i,t} + X_{i,t} + \varepsilon_{i,t}, \qquad (11)$$

where *CCExposure* is the climate change exposure of stock *i* at the end of month *t* and $Risk_{i,t}$ is a risk quantity from the sets (*IV*, *ISkew*, *IKurt*) or (*IV*, *SlopeD*, *SlopeU*) calculated for stock *i* in month *t*. We split the risk quantities again to avoid multicollinearity (*ISkew* and *IKurt* are highly correlated with *SlopeD* and *SlopeU*). $X_{i,t}$ indicates that our estimates control for a six-factor model based on stock returns and for stock characteristics. To account for heterogeneity in *CCExposure* across industries, we include industry fixed effects.

Table 5 reports the estimates of Model (11) and reveals several insights: First, there is a positive association between *CCExposure* and *IV* but only during the

Table 5. Conditional Link: Climate Change Exposure and Risk Quantities

	$CCExposure_{i,t}$		$CCExposure_{i,t}$		$CCExposure_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$IV_{i,t}$	−0.002	−0.004	0.034	0.025	−0.009	−0.010
	(−0.808)	(−1.399)	(5.021)	(3.347)	(−3.135)	(−3.782)
$ISkew_{i,t}$	0.003	–	−0.004	–	−0.001	–
	(0.889)	–	(−1.328)	–	(−0.524)	–
$IKurt_{i,t}$	0.014	–	0.011	–	0.025	–
	(5.557)	–	(2.578)	–	(8.707)	–
$SlopeU_{i,t}$	–	0.002	–	0.006	–	0.006
	–	(0.913)	–	(1.816)	–	(2.292)
$SlopeD_{i,t}$	–	0.007	–	0.017	–	0.015
	–	(3.914)	–	(3.993)	–	(4.737)
Factor model	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample period	January 2005–December 2010		January 2011–December 2014		January 2015–December 2020	
Observations	27,381	27,381	20,142	20,142	35,110	35,110
R^2	0.222	0.206	0.278	0.283	0.269	0.260

Notes. This table reports the results of panel regressions at the stock–month level. We report the regressions for three different subperiods: (i) January 2005–December 2010 in columns (1) and (2), (ii) January 2011–December 2014 in columns (3) and (4), and (iii) January 2015–December 2020 in columns (5) and (6). The regressions include risk quantities (*IV*, *ISkew*, *IKurt*, *SlopeU*, and *SlopeD*) in two different combinations and control for the six-factor model betas (of the underlying stocks), stock characteristics (described in Section 3.2), and industry fixed effects (*SIC*2). All explanatory variables (except for the factor betas) are normalized at each point in time to have a standard deviation of 0.01. *t*-statistics are based on standard errors robust to heteroskedasticity, serial correlation, and spatial correlation (Driscoll and Kraay 1998). The full sample covers the period from January 2005–December 2020 and includes S&P 500 stocks.

period in which we obtained positive risk premiums for the *MW* and *GLB* proxies in Figure 1. This result is reassuring; according to both proxies, investors command a higher risk premium if the variance of high-exposure stocks increases. Second, in all three periods, *CCExposure* is positively linked to a higher cost of tail protection (*SlopeD*), and the effect is strongest from 2011 to 2014. This pattern helps explain why the *GLB*-based premium exceeds the *MW*-based premium during the 2011–2014 period (the *GLB* proxy reflects preferences related to the tails). Third, the diminishing risk premiums since 2015 can be explained by higher values of *CCExposure* being associated with less volatility. Since 2015, high-exposure stocks also have more expensive tails on both sides of the distribution (*SlopeU* and *SlopeD*) (evident also from the increase in the *IKurt* coefficient). The coefficient on *SlopeD* between 2015 and 2020 goes down by about 12% relative to the 2011–2014 period, which indicates that some probability mass is redistributed from low to high returns. This finding is consistent with an anticipation of better opportunities for high-exposure stocks since 2015, and these better opportunities reduce the *GLB*-based premium.

The results in this section are based on how investors associate difference risk quantities with climate change exposure. In the following, we connect these risk-based insights more directly with observable climate-related economic channels.

4.2.2. Economic Channel: Institutional and Market Factors. We consider several climate-related economic channels to understand better the effects of the risk quantities and to provide economic interpretations of the time series in Figure 1. The first channels reflect institutional factors, broadly defined, and are captured using *Green Innovation*, *Adaptation*, *ESG Fund Flows*, and *Big Three IO*. The second set of variables captures channels related to important climate-related market prices, namely, CO_2 *Price* and *Oil Price*.

We regress the monthly time-series values of the risk premiums for *CCExposure* (RP_t^{Proxy}) on the time-series values of these two sets of variables (labeled as $Channel_t$). RP_t^{Proxy} is estimated in the cross-sectional stage of the Fama–MacBeth procedure. We are interested in the $\gamma_{Channel}$ coefficients of the following regressions:

$$RP_t^{Proxy} = \alpha + \sum_{Channel} \gamma_{Channel} \times Channel_t + \varepsilon_t, \qquad (12)$$

where the expected return proxy is $Proxy \in (RET, MW, GLB)$ and $Channel_t$ includes the variables $Green\ Innovation_t$, $Adaptation_t$, $ESG\ Fund\ Flows_t$, $Big\ Three\ IO_t$, $CO_2\ Price_t$, and $Oil\ Price_t$. Because of differences in data availability across these variables, regressions including $CO_2\ Price_t$ start in August 2005, and those including $Big\ Three\ IO_t$ end in December 2017. All regressors are normalized to have standard deviation of 0.01 for the respective period used in a regression.[36]

Table 6 reports results from estimating Model (12) with the *RET* premium in columns (1)–(3), the *MW*-based premium in columns (4)–(7), and the *GLB* premium in columns (7)–(9). The *RET* risk premium in columns (1)–(3) is mostly not significantly related to the institutional and market variables, and the explanatory power of the estimation is also very low. But there are some exceptions. In column (2), the coefficient on the CO_2 *Price* is positive and significant, which may be explained by the prices of high-exposure stocks being pushed up as CO_2 becomes more expensive (an example is Tesla, which generated significant earnings from selling CO_2 quotas, benefiting from increasing CO_2 prices).

Columns (4)–(9) show that the drivers of the expected risk premiums are very different. First, more successful developments of green technologies, as reflected in more green patenting, decrease the risk premiums. This effect of *Green Innovation* is plausible because the successful development of climate-related technologies reduces the uncertainty of stocks exposed to high opportunity shocks, which is what the risk premium for *CCExposure* primarily reflects. The larger magnitudes of the coefficients for the *GLB*-based premium in columns (7)–(9) compared with those in columns (4)–(6) for the *MW*-based risk premium indicate that this effect operates primarily through the tails.

Second, the compensation for *CCExposure* is increasing in *Adaptation*, that is, in the proportion of *CCExposure* by stocks from states with adaptation plans. State-led adaptation plans can have two potential effects. On the one hand, they increase the likelihood of new regulations and standards in the climate sphere, making the prospects of high-exposure stocks riskier and leading to a higher risk premium. On the other hand, state-led adaption plans also provide opportunities for some stocks, which would reduce the risk premium. Our finding of an overall positive effect of *Adaptation* suggests that the first channel dominates.

Third, flows into ESG funds decrease the risk premium in columns (4) and (7). As we have shown in Section 3.4, the risk premium for *CCExposure* is strongly driven by climate-related opportunities. Hence, funds seeking to invest in such opportunities push up these stocks' prices, thus reducing the risk premium for *CCExposure*. This effect is not robust in some specifications that control for market prices (column (8)) or *Big Three IO* (columns (6) and (9)) and is also sensitive to the sample period.

Fourth, the oil price is positively related to both forward-looking risk premiums. High oil prices incentivize investment in traditional oil and gas activities (Acemoglu et al. 2020), which should make investments in green technologies riskier. The risk premium for *CCExposure* originates mostly from climate-related opportunity shock, and high oil prices should increase

Table 6. Explaining Conditional Risk Premium Dynamics

	RP_t^{RET}			RP_t^{MW}			RP_t^{GLB}		
Risk premium	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Green Innovation$_t$	1.208	−6.377	69.007	−13.744	−10.578	−12.985	−26.234	−21.263	−22.687
	(0.020)	(−0.098)	(1.009)	(−5.033)	(−3.309)	(−3.642)	(−5.860)	(−4.219)	(−4.519)
Adaptation$_t$	7.999	41.587	−97.056	20.680	19.669	20.623	29.742	24.400	33.892
	(0.125)	(0.679)	(−1.513)	(7.947)	(8.136)	(6.590)	(5.528)	(5.643)	(6.930)
ESG Fund Flows$_t$	−3.168	−96.812	−61.675	−7.986	−5.418	0.127	−10.595	4.042	3.051
	(−0.074)	(−1.859)	(−1.453)	(−4.912)	(−2.350)	(0.069)	(−3.032)	(1.114)	(1.067)
Oil Price$_t$	–	−83.106	–		5.906	–		17.674	–
	–	(−1.732)	–		(2.063)	–		(3.446)	–
CO_2 *Price*$_t$	–	130.929	–		−0.397	–		−16.338	–
	–	(2.749)	–		(−0.154)	–		(−4.354)	–
Big Three IO$_t$	–		21.417	–		−5.425	–		−16.172
	–		(0.401)	–		(−2.120)	–		(−4.260)
Sample period	January 2005–December 2020	May 2005–December 2020	January 2005–December 2017	January 2005–December 2020	May 2005–December 2020	January 2005–December 2017	January 2005–December 2020	May 2005–December 2020	January 2005–December 2017
Observations	192	185	162	192	185	162	192	185	162
Adjusted R^2	−0.016	0.013	−0.006	0.298	0.328	0.376	0.237	0.427	0.452
Predicted change in the risk premium (% p.a.)									
Period 1 to period 2	0.000	−1.343	0.000	0.284	0.327	0.324	0.368	0.603	0.584
Period 2 to period 3	0.000	1.146	0.000	−0.145	−0.210	−0.303	−0.266	−0.634	−0.659

Notes. This table reports the results of time-series regressions at the monthly level from regressing the time-series estimates of the risk premiums for *CCExposure* on the time-series values of *Green Innovation*$_t$, *Adaptation*$_t$, *ESG Fund Flows*$_t$, CO_2 *Price*$_t$, *Oil Price*$_t$, and *Big Three IO*$_t$. All explanatory variables are normalized to have a standard deviation of 0.01. The regression specification is given in Equation (12). The sample covers the period from January 2005–December 2020 and includes S&P 500 stocks (regressions using CO_2 *Price*$_t$ start in August 2005, and regressions using *Big Three IO*$_t$ end in December 2017 because of data limitations). The predicted change in the risk premium at the bottom of the table is computed as the change in the average value of the predictors from one period to the next, multiplied by the respective model coefficients. Only significant predictors ($abs(t-stat) \geq 1.96$) are considered. Period 1 refers to the period from the beginning of the sample to December 2010, period 2 from January 2011–December 2014, and period 3 from January 2015 to the end of the sample.

the risk premium among stocks for which this exposure is high.[37]

Fifth, the negative sign on *Big Three IO* in columns (6) and (9) suggests that higher holdings of Big Three funds decrease both the *MW*- and *GLB*-based premiums. This finding lines up with evidence in Azar et al. (2021), who document increased shareholder engagement on climate topics by the Big Three over the last years, intending to reduce firms' carbon risks. This engagement may have reduced the downside tail risk of some high-exposure stocks and reduced the risk premiums. This result is stronger in magnitude for the *GLB* proxy, which corroborates that the risk premium channel goes through volatility and tail risk.

Whereas our model cannot account for all of the dynamics of the conditional risk premiums, we report at the bottom of Table 6 predicted risk premium changes across the periods from January 2005–December 2010 (period 1), from January 2011–December 2014 (period 2), and from January 2015–December 2020 (period 3).[38] The models with market variables and *Big Three IO* perform especially well, almost matching the increase in the risk premiums from around zero (-0.05% for MW and -0.01% for GLB) in period 1 to 0.33% (*MW*-based premium) and 0.72% (*GLB*-based premium) in period 2 and a subsequent decline to 0.09% (*MW*-based premium) and zero (*GLB*-based premium) in period 3.

Finally, we relate Table 6 to the three regimes identified in Figure 1 and the corresponding links between *CCExposure* and the risk quantities in Table 5. For each of the three subperiods identified in Table 6, Online Table 9 reports the mean values of the institutional and market factors (normalized as in Table 6). *Green Innovation*, *ESG Fund Flows*, and *Big Three IO* took their largest values between 2015 and 2020 when high-exposure stocks exhibited lower downside tail risk and better upside opportunities as well as lower volatility. This pattern is consistent with the effects of green innovation, the flows into ESG funds, and Big Three engagement playing a role in the documented changes of the risk quantities, thereby contributing to the decline in the expected risk premium after 2015 (especially for the *GLB*-based premium). The *Oil Price* was largest between 2011 and 2014, the years in which high-exposure stocks were associated with high volatility, downside risk, and the largest risk premium. Again, these figures are plausible because, as we argue, high oil prices make investments in green technologies riskier. *Adaptation* has increased over the sample period, gradually contributing to the risk of high-exposure stocks.

5. Conclusion

We estimate the risk premium for firm-level climate change exposure and its dynamics over time. The measure of climate change exposure builds upon the recent work of SvLVZ, who use quarterly earnings calls to identify the attention paid by market participants to firms' climate-related risks and opportunities. Unconditionally, the realized risk premium for measured climate change exposure is indistinguishable from zero. However, investors buying 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 differ in the assumed investor preferences used to derive the risk premium estimates. The expected return proxy by Martin and Wagner (2019) (*MW*) assumes that variance is the sufficient risk statistic for investors. The approach by Chabi-Yo et al. (2023) (*GLB*) explicitly accounts for returns' higher order moments. The unconditional risk premium for these two proxies originates mostly from climate-related opportunity shocks. There is also a positive risk premium effect of regulatory shocks, but it is smaller.

Turning to the time-series dynamics, the realized compensation for climate change exposure was around 1% p.a. before 2008. This period ended with a sharp decline in the risk premium in the financial crisis (2008–2009). After the crisis, there is a secular upward trend in the realized premium until the end of the sample period. For both expected return proxies, the risk premium fluctuated around zero before 2011. Then both premiums turned positive with the premium based on the *MW* proxy gradually rising to 0.5% in 2012. The *GLB*-based premium experienced a more rapid gain to 1% between 2012 and 2014. From 2015 onward, both premiums revert to almost zero, but the *MW*-based risk premium stays at a slightly higher level.

The dynamics of the expected return proxies can be attributed to how investors map climate change exposure into variance and higher order risks. Between 2011 and 2014, investors perceived high-exposure stocks as highly volatile and with elevated crash risk, whereas beginning in 2015, they started to associate smaller variance and relatively higher opportunities with such stocks. Whereas the lower variance of high-exposure stocks decreases the risk premium for both proxies, the reallocation of the likelihood of right- versus left-tail events further reduces the premium among investors with preferences over higher order risks (reflected in the *GLB* proxy).

Several climate-related economic channels explain the effects of the risk quantities. First, green innovation in the economy decreases the risk premiums. Second, the compensation for high-exposure stocks increases in the proportion of climate change exposure by firms from U.S. states that adopt climate change adaptation plans. Third, flows into ESG funds decrease the risk premium (this effect is not robust to all controls). Fourth, the oil price is positively related to the risk premium. Fifth, higher aggregate holdings of Big Three funds, weighted by climate change exposure, significantly decrease the risk premium.

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 the potential changes in investors' attitudes toward climate topics and ESG awareness.

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Appendix. Variable Definitions

Variable	Years	Definition
Climate change exposure measures		
$CCExposure_{i,t}$	2005–2020	Relative frequency with which bigrams related to climate change occur in quarterly earnings calls. Resampled to a monthly frequency by matching the transcript date to a given stock month and applying exponential smoothing with a half-life of three months. Source: Sautner et al. (2023).
$CCExposure^{Ind}_{i,t}$	2005–2020	Industry-level component of $CCExposure_{i,t}$, calculated by averaging $CCExposure_{i,t}$ across all stocks in an industry at a point in time (based on two-digit SIC codes).
$CCExposure^{Res}_{i,t}$	2005–2020	Firm-specific component of $CCExposure_{i,t}$. For each stock, calculated as $CCExposure_{i,t} - CCExposure^{Ind}_{i,t}$.
$CCExposure^{Opp}_{i,t}$	2005–2020	Relative frequency with which bigrams that capture opportunities related to climate change occur in quarterly earnings calls. Resampled to a monthly frequency by matching the transcript date to a given stock month and applying exponential smoothing with a half-life of three months. Source: Sautner et al. (2023).
$CCExposure^{Reg}_{i,t}$	2005–2020	Relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the quarterly earnings calls. Resampled to a monthly frequency by matching the transcript date to a given stock month and applying exponential smoothing with a half-life of three months. Source: Sautner et al. (2023).
$CCExposure^{Phy}_{i,t}$	2005–2020	Relative frequency with which bigrams that capture physical shocks related to climate change occur in quarterly earnings calls. Resampled to a monthly frequency by matching the transcript date to a given stock month and applying exponential smoothing with a half-life of three months. Source: Sautner et al. (2023).
$CCSentiment^{Ltg}_{i,t}$	2005–2020	Relative frequency with which bigrams related to climate change litigation are mentioned in quarterly earnings conference calls. Resampled to a monthly frequency by matching the transcript date to a given stock month and applying exponential smoothing with a half-life of three months. Source: Self-constructed.
$CCSentiment^{Neg}_{i,t}$	2005–2020	Relative frequency with which bigrams related to climate change are mentioned together with the negative tone words that are summarized by Loughran and McDonald (2011) in one sentence in quarterly earnings calls. Resampled to a monthly frequency by matching the transcript date to a given stock month and applying exponential smoothing with a half-life of three months. Source: Sautner et al. (2023).
Expected excess return proxies		
$RET_{i,t}$	2005–2020	Next-month realized returns minus the one-month T-bill rate for the corresponding period. Winsorized at 1% and 99%. Source: CRSP.
$MW_{i,t}$	2005–2020	Expected excess return proxy proposed by Martin and Wagner (2019) (*MW*). Derived as lower bounds for the conditional expected excess return from out-of-the-money options. Winsorized at 1% and 99%. Source: Vilkov (2020) based on Volatility Surface File of Ivy DB OptionMetrics.
$GLB_{i,t}$	2005–2020	Expected excess return proxy proposed by Chabi-Yo et al. (2023) (*GLB*). Derived as the generalized lower bounds for the conditional expected excess return from out-of-the-money options. Winsorized at 1% and 99%. Source: Chabi-Yo et al. (2023) based on Volatility Surface File of Ivy DB OptionMetrics.
Betas for factor models		
$Market_{i,t}$	2005–2020	Market beta estimated for each month using daily excess returns and factor realizations over the past 12 months. Source: K. French's DataLibrary.
$Size\,(SMB)_{i,t}$	2005–2020	Size factor beta estimated for each month using daily excess returns and factor realizations over the past 12 months. Source: K. French's DataLibrary.
$Value\,(HML)_{i,t}$	2005–2020	Value factor beta estimated for each month using daily excess returns and factor realizations over the past 12 months. Source: K. French's DataLibrary.
$Momentum\,(WML)_{i,t}$	2005–2020	Momentum factor beta estimated for each month using daily excess returns and factor realizations over the past 12 months. Source: K. French's DataLibrary.
$Profitability\,(RMW)_{i,t}$	2005–2020	Profitability factor beta estimated for each month using daily excess returns and factor realizations over the past 12 months. Source: K. French's DataLibrary.
$Investment\,(CMA)_{i,t}$	2005–2020	Investment factor beta estimated for each month using daily excess returns and factor realizations over the past 12 months. Source: K. French's DataLibrary.

Appendix. (Continued)

Variable	Years	Definition
Risk quantities		
$IV_{i,t}$	2005–2020	Implied variance calculated as the Martin (2017) variance swap rate from 30-day out-of-the-money options. Source: Volatility Surface File of Ivy DB OptionMetrics.
$ISkew_{i,t}$	2005–2020	Implied skewness of log returns computed from 30-day out-of-the-money options following Bakshi et al. (2003). Winsorized at 1% and 99%. Source: Vilkov (2020) based on Volatility Surface File of Ivy DB OptionMetrics.
$IKurt_{i,t}$	2005–2020	Implied kurtosis of log returns computed from 30-day out-of-the-money options following Bakshi et al. (2003). Winsorized at 1% and 99%. Source: Vilkov (2020) based on Volatility Surface File of Ivy DB OptionMetrics.
$SlopeD_{i,t}$	2005–2020	Steepness of the implied volatility slope on the left from the ATM point. As in Kelly et al. (2016), the measure is the slope 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). Winsorized at 1% and 99%. Source: Vilkov (2020) based on Volatility Surface File of Ivy DB OptionMetrics.
$SlopeU_{i,t}$	2005–2020	Steepness of the implied volatility slope on the right from the ATM point. Similar to *SlopeD*, the measure is the slope of functions relating implied volatilities of OTM options to their deltas. We estimate $SlopeU_{i,t}$ by regressing implied volatilities of calls with deltas between 0.1 and 0.5 on their deltas. We multiply the resulting number by minus one and take the resulting slope coefficient as the *SlopeU* measure. Winsorized at 1% and 99%. Source: Vilkov (2020) based on Volatility Surface File of Ivy DB OptionMetrics.
Fundamentals and market characteristics		
$Market\ Cap_{i,t}$	2005–2020	A stock's market capitalization. Source: CRSP.
$Assets_{i,t}$	2005–2020	Total assets (Compustat item AT). Winsorized at 1% and 99%. Source: Compustat NA Annual.
$Debt/Assets_{i,t}$	2005–2020	Sum of the book value of long-term debt (Compustat data item DLTT) and the book value of current liabilities (DLC) divided by total assets (Compustat data item AT). Winsorized at 1% and 99%. Source: Compustat NA Annual.
$Cash/Assets_{i,t}$	2005–2020	Cash and short-term investments (Compustat data item CHE) divided by total assets (Compustat data item AT). Winsorized at 1% and 99%. Source: Compustat NA Annual.
$PP\&E/Assets_{i,t}$	2005–2020	Property, plant, and equipment (Compustat data item PPENT) divided by total assets (Compustat data item AT). Winsorized at 1% and 99%. Source: Compustat NA Annual.
$EBIT/Assets_{i,t}$	2005–2020	Earnings before interest and taxes (Compustat data item EBIT) divided by total assets (Compustat data item AT). Winsorized at 1% and 99%. Source: Compustat NA Annual.
$Capex/Assets_{i,t}$	2005–2020	Capital expenditures divided by assets. Winsorized at 1% and 99%. Source: Compustat NA Annual.
$R\&D/Assets_{i,t}$	2005–2020	R&D expenditures (Compustat data item XRD) divided by total assets (Compustat data item AT). Missing values set to zero. Winsorized at 1% and 99%. Source: Compustat NA Annual.
$Volatility_{i,t}$	2005–2020	Annualized volatility of stock *i* from daily returns from month $t-12$ to t. Winsorized at 1% and 99%. Source: CRSP.
$Momentum12_{i,t}$	2005–2020	Cumulative return of stock *i* from $t-13$ to $t-1$ estimated at the end of month *t*. Winsorized at 1% and 99%. Source: CRSP.
CO_2, oil exposure, and carbon risk measures		
$Carbon\ Emissions_{i,t}$	2005–2020	Sum of scope 1 and 2 emissions. We follow Bolton and Kacperczyk (2021, 2023) in using emission levels. Scope 1 emissions are caused by the combustion of fossil fuels or from the release during manufacturing. Scope 2 emissions originate from the purchase of electricity, heating, or cooling. As this variable is available at the annual frequency, we use the emissions data from year $t-1$ for all months in year *t*. Winsorized at 1% and 99%. Source: S&P Global Trucost.
$ISS\ Score_{i,t}$	2015–2019	Carbon risk rating of ISS assesses the carbon-related performance of firms and takes values between one (poor performance) and four (excellent performance). As this variable is available at the annual frequency, we merge with monthly returns data by stock year for all months in a given year *t*. Source: ISS (part of Deutche Börse).
$Sustainalytics\ Score_{i,t}$	2013–2020	Carbon risk rating of Sustainalytics with a focus on firms' exposures and management of material carbon risks. As this variable is available at the variable frequency, we merge with monthly returns data by stock month and fill forward for up to 12 months. Source: Sustainalytics (part of Morningstar).
$Oil\ Beta_{i,t}$	2005–2020	Oil beta of the stock, estimated using daily excess returns and oil price (WTI spot) percentage changes over the past 12 months (jointly with the six-factor model). Source: U.S. Energy Information Administration.
Institutional and market factors		
$Green\ Innovation_t$	2005–2020	Monthly total number of green patents filed in the United States in the previous three years according to the Google Patents database. To identify "green" patents, we follow the approach in Cohen et al. (2021) and apply the Organisation for Economic Co-operation and Development classification to identify what constitutes a patent with the potential to address environmental problems. As this variable is available at the annual frequency, we propagate the same value for all observations in a given year. Source: Google Patents.

Appendix. (Continued)

Variable	Years	Definition
$Adaptation_t$	2005–2020	Monthly measure of the proportion of climate change exposure in the S&P 500 coming from states with adaptation plans. In a first step, we create the firm-level variable $\mathbf{1}^{Adapted\ State}$, which equals one from a particular date if the firm's headquarters are located in a state adopting state-led climate change adaptation plans. Stocks are matched to states based on their headquarters location. In a second step, we construct monthly values of $Adaptation_t$ by weighting $CCExposure$ with $1[Adapted\ State]_{i,t}$ $$Adaptation_t = \frac{\sum_i 1[Adapted\ State]_{i,t} \times CCExposure_{i,t}}{\sum_i CCExposure_{i,t}}.$$ Source: Georgetown Climate Center.
$ESG\ Fund\ Flows_t$	2005–2020	Monthly net flow into ESG funds. We first obtain the list of sustainable funds from Morningstar's 2021 Sustainable Funds U.S. Landscape Report (Pastor et al. 2022), which contains fund tickers, inception dates, and repurpose dates (when a fund was repurposed as "sustainable"). We then match these sustainable funds with the CRSP Survivor-Bias-Free U.S. Mutual Funds by their tickers and inception dates. For funds that reposition themselves as sustainable funds, we use their repurposed date to match with the CRSP database. We calculate the net fund flows as the change in total net assets (TNA) minus appreciation (computed using reported fund's return $R_{j,t}$) during the month. We then aggregate this measure across all funds j in month t. Source: Morningstar's 2021 Sustainable Funds U.S. Landscape Report, CRSP Survivor-Bias-Free U.S. Mutual Funds.
$Big\ Three\ IO_t$	2005–2017	Monthly climate change exposure of the Big Three (Vanguard, BlackRock, and StateStreet) in the S&P 500 relative to the climate change exposure held in the market. Computed each month t as the $CCExposure_{i,t}$-weighted holdings by the Big Three in S&P 500 stocks. First, we obtain data on Big Three holdings ($Big\ Three_{i,t}$) by using the quarterly stock ownership data from Schedule 13F filings compiled by Backus et al. (2021). The data has better coverage than Thomson Reuters. We follow Ben-David et al. (2021) and use the following Thomson-Reuters mgrno to identify Big Three holdings: Vanguard (90457), StateStreet (81540), BlackRock (9385, 11386, 39539, 56790, 91430, and 12588). Holdings are matched with monthly data by the end of the quarter and propagated forward using exponential smoothing (half-life of three months). Second, to obtain $CCExposure_{i,t}$-weighted holdings each month, we multiply the Big Three's percentage holdings $Big\ Three_{i,t}$ in stock i at time t by $CCExposure_{i,t}$, sum the product across stocks, and divide the total by the sum of $CCExposure_{i,t}$: $$Big\ Three\ IO_t = \frac{\sum_i Big\ Three_{i,t} \times CCExposure_{i,t}}{\sum_i CCExposure_{i,t}}.$$ Available from January 2005 to December 2017. Source: Backus et al. (2021).
$Oil\ Price_t$	2005–2020	Monthly WTI spot price, created as the average of daily WTI spot price prices. Source: U.S. Energy Information Administration.
$CO_2\ Price_t$	2005–2020	Monthly futures price of CO_2 emission allowances. Available from August 2005 to December 2020 based on front-month data. Source: EU Emission Trading System.

Endnotes

[1] As recently highlighted by the Task Force on Climate-related Financial Disclosures, financial markets need information on risks and opportunities to evaluate the impact of climate change (see https://www.fsb-tcfd.org/).

[2] We follow SvLVZ in defining "exposure" to climate change based on the share of the conversation in an earnings call that is devoted to that topic. This definition of exposure is different from how risk exposure is defined in the asset-pricing literature. Hence, SvLVZ's measures are not intended to capture the covariance with aggregate fluctuations. This terminology follows a broader literature that uses earnings calls to identify firms' various risks and opportunities (Hassan et al. 2019, 2023a, b, c; Jamilov et al. 2021).

[3] We do not find significant effects for a measure of climate-related litigation exposure. One reason could be that climate litigation is still a relatively recent phenomenon in the United States, and successful lawsuits are the exception.

[4] Results are robust to applying an exposure measure that reflects the negative tone (or sentiment) of the climate change discussions and to using perturbed exposure measures that randomly drop 5% of the bigrams used to construct the measure.

[5] This time-series pattern aligns with the model in Bansal et al. (2021), who find that good stocks significantly outperform bad stocks during good economic times but underperform during bad times (assuming that stocks with high climate change exposure are perceived as good stocks).

[6] This conclusion is consistent with Bolton and Kacperczyk (2023), whose analysis also reveals the distinct effects of the carbon risk premium over time and across countries.

[7] Stocks with high exposure to climate-related opportunity shocks may command an unconditional risk premium because of a higher expected variance. The associated risk premium declines when the variance decreases, and it may even reach zero if higher exposure also means higher upside potential and lower downside crash risk.

[8] Adaptation plans also provide new opportunities for firms, which should reduce the risk premium. However, our result suggests that the regulation channel dominates the opportunity channel for this variable.

[9] This effect disappears in some specifications that control for the oil price, the price of carbon emission allowances, and Big Three holdings.

[10] A step in the same direction is provided by Kölbel et al. (2023), who show that a 10-K-based measure of climate change exposure affects the credit default swap term structure.

[11] At the same time, Avramov et al. (2022) and De Angelis et al. (2023) show that uncertainty about environmental risks reduces the effect of the "green" premium.

[12] SvLVZ's quarter-level data can be accessed publicly on https://osf.io/fd6jq/. The SvLVZ data are available from January 2002 onward, but our tests include data from January 2005 to match the measures with other data sources and to allow for a burn-in period (this ensures that a reasonable number of stocks obtain nonzero exposure values at the start of the estimation). Our sample includes all stocks included in the S&P 500 from 2000 onward. Note that we use transcript-level data, which is then aggregated to monthly frequency, whereas the public SvLVZ data is sampled at the quarterly frequency.

[13] For illustration, Online Table 1 contains the top 100 bigrams found for *CCExposure* (the table is a replica of a table for the global sample from SvLVZ). SvLVZ evaluate how strongly *CCExposure* depends on individual bigrams in the initial bigram list by performing a perturbation test. They successively exclude one initial bigram at a time and then recompute each time the modified set of bigrams as well as the modified exposure measure. When they calculate the correlation of each of these exposure measures with *CCExposure*, the correlations are all above 85%. This means that *CCExposure* does not depend much on the specific initial seed bigrams.

[14] Some transcripts may contain fewer climate change bigrams, not because climate issues are not perceived as important anymore, but because they were exhaustively discussed in a recent earnings call.

[15] Elton (1999, p. 1199) notes, "Almost all the testing I am aware of involves using realized returns as a proxy for expected 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."

[16] For recent applications, see Cieslak et al. (2019), who use the equity risk premium proxy from Martin (2017), and Ai et al. (2022), who take an implied variance measure as a proxy for a stock's expected return.

[17] The weights are rescaled to add up to one for all stocks with nonmissing implied variance.

[18] Back et al. (2022) find that, in conditional settings, bounds based on second order moments are not necessarily tight; that is, they provide a well-performing but biased proxy for conditional expected returns. Chabi-Yo et al. (2023) show that the *GLB* measure is a conditionally valid and tight proxy of expected excess returns.

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

[20] The benefit of these variables, compared with equivalents under the physical measure, is their forward-looking character. For example, the implied variance is a 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 et al. 2016). The cost includes a potential bias stemming from the risk premium effect (see Vanden 2008, Chang et al. 2012, DeMiguel et al. 2013, Cremers et al. 2015).

[21] We approximate each integral in Equation (6) for $IV_{i,t}$ using a finite sum of 500 option prices (we do likewise for similar integrals in the formulas for $ISkew_{i,t}$ and $IKurt_{i,t}$). 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 interpolate the implied volatilities as a function of moneyness (strike over spot price) for the range between available moneyness points and 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 piecewise cubic Hermite interpolating polynomial.

[22] The regression coefficient approximates an average derivative of the volatility smile. Because deltas of far OTM puts are less negative than ATM deltas, with more expensive OTM puts, we get a larger positive regression coefficient; for calls, the deltas decrease with an option getting more OTM, and with more expensive OTM calls, the regression coefficient is more negative.

[23] As of 2020, 17 states and the District of Columbia have finalized climate change adaptation plans.

[24] $Big\,Three\,IO_t$ is highly correlated with $Adaptation_t$ and $ESG\,Fund\,Flows_t$. To mitigate multicollinearity concerns, we regress $Big\,Three\,IO_t$ on the two other variables (and a constant) to obtain a regression residual that we use in the following estimation.

[25] The factors are Market, Size (SMB), Value (HML), Momentum (WML), Profitability (RMW), and Investment (CMA).

[26] SvLVZ document that *CCExposure* and carbon emissions, although correlated, do not overlap greatly.

[27] Following a rule of thumb from Greene (2002) and Baum et al. (2007), we use Newey and West (1987) standard errors with three lags.

[28] The risk premium's magnitude should be interpreted, taking into account that we impose a high bar by controlling the six-factor model and various stock characteristics. Note that the *MW* and *GLB* proxies exhibit meaningful risk premiums for the standard risk factors. There is significant compensation for market, size, and profitability exposure (consistent with Martin and Wagner 2019, Kadan and Tang 2020, Chabi-Yo et al. 2023). The same holds for the negative momentum premium. The insignificant CMA premium may be the result of our specific sample period. These estimates corroborate that the option-implied expected return proxies are more appropriate than the realized return proxies, at least in our context.

[29] $CCExposure^{Phy}$ bears positive and significant risk premiums in some estimations when aggregated to the industry level (the aggregation leaves the measure less sparse as even stocks with zero values of residual exposure now have positive industry-level exposure). Results are available upon request.

[30] This may indicate that the market overprices stocks with high carbon risk and that investors expect a relatively low return (which originates from relatively low levels of expected volatility according to the *MW* proxy).

[31] This finding underlines the argument that, for text-based measures, the face validity of each individual bigram matters little compared with the properties of the final compound measure (such as *CCExposure*) (Bae et al. 2023).

[32] The dynamics around the financial crisis are also consistent with a higher importance attributed by investors to elevated risk regimes, broadly defined and covering any potential tail risk sources (Gennaioli et al. 2015).

[33] When we estimate the risk premiums for the period of 2011 to 2014, we obtain highly significant premiums of 0.33% p.a. and 0.72% p.a. for the *MW* and *GLB* proxies, respectively.

[34] We control for the six-factor model and stock characteristics. The sensitivities are the coefficients obtained in the first stage of the Fama–MacBeth procedure with a given risk quantity as the dependent variable and *CCExposure* as the independent variable. A higher particular risk quantity for a stock with higher values of *CCExposure* implies a positive coefficient for *IV*, *IKurt*, and *SlopeD* and a negative coefficient for *ISkew* and *SlopeU*.

[35] The negative sign of $Sens^{CCE,ISkew}$ is consistent with the positive effects of $Sens^{CCE,SlopeD}$ and the negative effects of $Sens^{CCE,SlopeU}$. The negative coefficient on $Sens^{CCE,IKurt}$ indicates that the risk premium goes down when high-exposure stocks are characterized by fatter tails. This effect indicates that kurtosis grows predominantly because of the fatter right tail, indicating better perceived growth potential.

[36] We test for autocorrelation in residuals, and the maximum significant lag across all the models is three; thus, we compute t-statistics using Newey and West (1987) standard errors with three lags.

[37] Results reported for the sample period up to December 2020 are robust to shortening the time series to December 2017 except for the result on $ESG\,Fund\,Flows_t$, which hints at a link between a decreasing risk premium for *CCExposure* and a rapid growth in ESG investments in the more recent sample period.

[38] The exact cutoff points for periods 1 and 3 depend on the availability of the data for *Big Three IO* and CO_2 *Price*. To compute the predicted risk premium changes, we select significant coefficients for a particular column in Table 6, multiply them by the respective changes in the average predictive variables, and add up the resulting products.

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