Climate Change Salience and International Equity Returns*

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Abstract

In this study, we examine climate change salience risk in international equity markets. We find that (1) exposure to a single, broad measure of climate change salience risk is pervasive; notably it arises regardless of firms' greenhouse gas emissions, (2) the exposure is priced: a return discount emerges for equities that perform well when climate change salience is high, and (3) the pricing is nonlinear: the return discount itself rises when the gauge of climate change salience is high. We also find that firms in countries with low weather-related losses and those in countries with high per-capita GDP exhibit greater marginal exposure to climate change salience risk. Oveall, the results suggest climate change salience risk is not merely a reflection of narrowly defined stranded assets or of investor distaste for high-emission firms; instead, the findings indicate that climate change salience risk is widespread and nondiversifiable, and, we interpret its pricing as reflecting a compensated risk exposure.

Keywords— Climate change risk, climate change salience, climate finance, carbon risk, global warming, climate beta, international financial markets, global equity markets

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1 Introduction

This study examines a broad indicator of climate change risk and its pricing among firms in 51 emerging and developed equity markets between 2004 and 2020. In examining the role of climate change risk, we consider the risk's potential mutability and ubiquity. Perceptions of climate change risk adjust continuously, and climate change risk is not limited to firms that have direct exposure through ownership of physical assets at risk from rising sea levels or through transition risk stemming from a reliance on carbon-intensive technologies that may be shunned or restricted in the transition to a low-carbon economy. For example, financial firms, such as banks, that hold the liabilities of directly exposed firms are themselves exposed to risk.[1] So too are firms reliant on labor productivity and on research and development that are affected by temperature.[2] At the same time, some firms (for example, those able to successfully implement CO_2 sequestration) may do well during the transition. Thus, in assessing climate change risk exposure and its pricing, it is important to restrict as little as possible the perception of climate change risk, the range of potential avenues of exposure to the risk, and the sign of the exposure. In this paper, we measure firm exposure to a single, broad indicator of climate change risk, one that captures climate change salience; we estimate how much of the exposure to that risk is related to key firm characteristics, such as reported greenhouse gas emissions and physical assets; and we examine how climate change salience risk is priced in equity markets.

To our knowledge, this is the first paper to document the exposure and the pricing of such a broad, aggregate measure of climate change risk across U.S. and international equity markets. Numerous papers–notably those by Gorgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2020), by Bolton and Kacperczyk (2021), by Aswani, Raghunandan, and Rajgopal (2022), and by Zhang (2023)–have explored the comovement between international returns and firms' greenhouse gas emissions. With their focus on emissions, such papers capture an important portion

[1]For broad surveys of climate change risks affecting the financial sector, see e.g. Basel Committee on Banking Supervision (2021) and Campiglio, Daumas, Monnin, and von Jagow (2022). See also Ehlers, Packer, and de Greiff (2022) for evidence of carbon risk pricing in the syndicated loan market.

[2]See, for example, Custodio, Ferreira, Garcia-Appendini, and Lam (2022) who identify the effect of both average and extreme weather shocks on U.S. supplier sales and who summarize earlier studies relating labor productivity, hours worked, and output to temperature; and see Donadelli, Grüning, Jüppner, and Kizys (2021), who document the negative effect of temperature on research and development in the G7 countries.

of climate change transition risk. Our paper's gauge of climate change risk is instead closer to the spirit of Engle, Giglio, Kelly, Lee, and Stroebel (2020) and of Sautner, van Lent, Vilkov, and Zhang (Forthcoming), who rely on natural language processing to capture climate change related risks more broadly. Restricting their work to U.S. equity markets, Engle, Giglio, Kelly, Lee, and Stroebel create an aggregate indicator of climate change news using textual analysis of the *Wall Street Journal*.[3] Sautner, van Lent, Vilkov, and Zhang (Forthcoming) examine international markets, and rather than creating an aggregate climate change risk measure and firm-level exposure to that risk, they construct individual firm-level measures of risk using textual analysis of earnings calls.

This paper takes a simpler approach to allow for a similarly broad range of climate-change related risks. Specifically, we construct innovations in monthly Google searches of 'climate change' to provide a gauge of climate change salience.[4] We note that the search innovations that we construct align well with known, climate policy events. That said, we acknowledge there are tradeoffs in using the search measure rather than a natural language processing approach. On one hand, the search measure can miss related concerns that would show up in richer natural language approaches, and any stable keyword choice such as ours can potentially become stale going forward in time and be irrelevant going backward in time. (Of course, the staleness concern also applies to those natural language approaches–such as Engle, Giglio, Kelly, Lee, and Stroebel–that fix keywords.) On the other hand, the simple search measure is publicly available, and its use avoids the problems of: editorial artifact in news publications, strategic phrasing in business contexts, the context narrowing that can arise in discovery algorithms, and the subjective judgments involved in the application of some of the natural language processing approaches. The search innovations and individual firm returns together give us an indicator of the firm's unhedged exposure; and, ultimately, the usefulness of the search approach for this purpose is an empirical issue. We find that the measure has empirical purchase: the exposure measured this way appears to be both widespread and priced internationally.

[3] They also use a larger set of news sources to create a secondary, sentiment indicator, which we touch on below in section 2.

[4] One might alternatively use the term 'attention' rather than 'salience'. We acknowledge the ambiguity of these words in our context. See Parr and Friston (2019) for an explicit discussion of the distinction between attention and salience in the context of the psychology literature; see Bordalo, Gennaioli, and Shleifer (2022) for a recent survey of salience in the context of decision making; and see Bordalo, Gennaioli, and Shleifer (2013) for an earlier discussion of salience and asset pricing.

Our use of search data builds on that of Choi, Gao, and Jiang (2020), who link searches and returns to abnormal temperatures, and to the work of Brogger and Kronies (2021), who link climate searches to inflows to ESG investing. It is also related to the work of Ilhan, Sautner, and Vilkov (2021), who briefly use search data in their larger study of the effect of climate policy uncertainty on option prices, though they rely mainly on the climate change news index of Engle, Giglio, Kelly, Lee, and Stroebel (2020). Interestingly, Ilhan et al.'s (2021) use of search data does not corroborate their main results. While they provisionally attribute the difference in results to the possibility that climate change searches may not reflect the negative aspect of sentiment, we find that–on the contrary–innovations in the Google data are indeed correlated with the negative sentiment index. It may be that the use of innovations (as we introduce here), rather than their use of the raw data, would have corroborated their main findings (since what is unexpected has the most salience). Relatedly, Santi (2020) conducts a detailed study of StockTwits sentiment and its link to the returns of a portfolio of firms in high-emission industries less firms in low-emission industries. While documenting the StockTwits sentiment effect, Santi also examines Google search volume and finds no link between searches and the high minus low emission industry portfolio. Like Ilhan, Sautner, and Vilkov, she also uses search volume levels rather than innovations. Additionally (and appropriately for her transition-risk study), the returns she examines are based on industry emissions. While we find a clear link between innovations in climate change searches and equity returns–and we find that the link is priced, we note that it is not determined by emissions.

Our contribution to the understanding of how this broad risk is priced in equities also builds closely on the empirical work of Huynh and Xia (2021), who study the pricing of climate change risk in the market for U.S. bonds. As in their study, our approach to pricing is motivated by the models such as those of Giglio, Maggiori, Rao, Stroebel, and Weber (2021) and of Bansal, Ochoa, and Kiku (2017). These models predict that assets that are negatively exposed to climate risk (that is, their payoff is expected to be high when climate damage is high) have a negative risk premium. At the heart of these models is the principle that investors are willing to forego some return in exchange for payoffs that can be expected to be high when the marginal utility of consumption is high–that is, when consumption is low.[5]

We find that U.S. and international equity markets now price in a return discount for positive

[5]Numerous authors have found that rising temperatures reduce income and consumption in both rich countries (e.g. Deryugina and Hsiang (2014)) and in poor ones (e.g. Dell, Jones, and Olken (2012)).

climate change salience covariance. That is, we find an equity premium associated with additional climate change salience risk. In addition, we find that the risk premium is nonlinear: it changes more than proportionally with climate change salience. This accords with other work on salience, which suggests that information has a greater effect on decision making when it stands out. Notably, we also find that climate change risk is not limited to firms with high emissions or substantial physical assets, and both financial and nonfinancial firms exhibit exposure. The widespread nature of climate salience risk suggests it is not merely a reflection of narrowly defined stranded assets or of investor distaste for high-emission firms. Instead, our findings tie returns to perceptions of the broader risks of climate change damage. It is such beliefs about future damage that drives the related asset pricing model predictions–specifically the predictions of the climate change related models mentioned above (Giglio, Kelly, and Stroebel (2020), Giglio, Maggiori, Rao, Stroebel, and Weber (2021), and Bansal, Ochoa, and Kiku (2017)). Perhaps surprisingly, we also find that firms in countries with low weather-related losses and those in countries with high per-capita GDP exhibit (ceteris paribus) greater exposure to climate change salience risk. Overall, the findings indicate that climate change salience risk is widespread, non-diversifiable, and nonlinearly priced in equity markets.

2 Climate Change Salience

To construct the climate change salience indicator, which we denote κ, we begin with historic data taken from Google Trends' worldwide index of searches for the term 'climate change'. We use only English-language searches of this phrase for several reasons. First, and most importantly, throughout the study we take the perspective of a U.S. investor, for which English-language searches are most relevant. Second, expansion to include geographic and language-specific searches would conflate variation in climate change salience with country-specific search engine regulation (including time-varying prohibitions on search engine use) and language-specific differences in the meanings of translated phrases. Third, English still serves as a lingua franca in both science and business, and English-language searches are used internationally. Finally, the use of a single-language phrase is clear, simple, and reproducible.

Google Trends provides search term data as a monthly index that is scaled both relative to all Google searches and relative to the sample period. We note that searches of 'climate change' exhibit marked predictability and seasonality. To account for this, rather than using the raw data, we use the innovations in an autoregressive integrated moving average model. Some recent climate news studies that do adjust for seasonality instead subtract the 12^{th} lag. However, while offering simplicity, that approach can–and does in our sample–generate inappropriately low values in the 12^{th} month following each peak event. So, we use the more general time series approach. Specifically, we follow the approaches of U.S. Census Bureau (2020) and Dagum and Bianconcini (2016): we use an $ARIMA(111)(011)_{12}$.[6] Since, as emphasized in Bordalo et al.'s (2013) review of the salience literature, it is the unexpected that exhibits the greatest salience, the use of innovations is particularly important in our work.

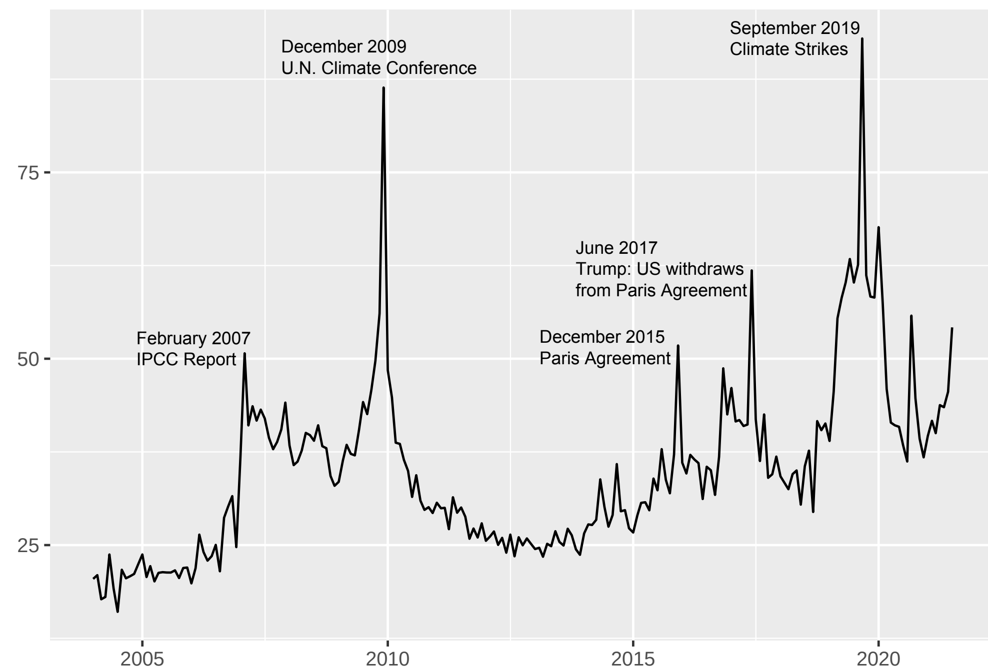

Figure 1: World-wide Google searches of 'climate change' relative to all Google searches, adjusted with an $ARIMA(111)(011)_{12}$, and scaled between zero and 100 over the sample

Figure 1 provides a plot of the resulting series. The figure calls out some of the notable peaks, which coincide with major climate-change related events, including: the Intergovernmental Panel on Climate Change (IPCC) report of December 2007, the December 2009 United Nations Climate Conference, the Paris Agreement of December 2015, President Trump's June 2017 announcement

[6] This approach has built over decades on the classic work of Dagum (1980).

of the U.S. withdrawal from the Paris Agreement, and the September 2019 climate strikes. In capturing such events, the saliency series is similar to the climate change news series of Engle, Giglio, Kelly, Lee, and Stroebel (2020) and, separately, to their text-based sentiment analysis of climate-related articles in a much larger set of news sources (their Crimson Hexagon's negative climate change news index). We note that our measure's correlation is greater with their richly developed sentiment index than with their benchmark index (and the correlation between our measure and their sentiment index is greater than the correlation between their own benchmark *Wall Street Journal* measure and their sentiment index.[7]). So, like Engle, Giglio, Kelly, Lee, and Stroebel (2020), we provisionally interpret increases in our measure as indicative of heightened concern over climate change. As mentioned above, the Google search measure that we use here has the advantages of being publicly available and not being directly subject to editorial artifact.[8]

3 Return Sensitivity to Climate Change Salience

We begin with the monthly equity returns of 7496 firms in 51 markets between 2004 through 2020, which we retrieve from Refinitiv's Datastream. Following the recommendations of Ince and Porter (2006), who carefully examined the reliability of this source of international returns data (and in keeping with many other studies using these data, including the climate-related work of Hong, Li, and Xu (2019) and Choi, Gao, and Jiang (2020)), we remove: those firms that are not domestically incorporated in the markets listed as their home country, those with prices less than the equivalent of one dollar, zero return strings occurring at the end of a return series, and returns that exceed 300 percent; and we winsorize the returns at five percent and 95 percent. For readability, we express all returns in percent.

To measure the sensitivity, $\beta^{\kappa}_{i,t}$, of each firm's excess return to climate change salience, we

[7] The correlation between our measure and their sentiment index is 0.53, while the correlation between their own benchmark measure and their sentiment index is 0.35. This may reflect the fact that their Crimson Hexagon index, by including numerous sources, mitigates some of the editorial artifact of the single-source, *Wall Street Journal* measure.

[8] Of course, public sentiment itself is shaped by the editorial choices made by all information sources; so the searches are indirectly shaped by the full set of choices made by all information providers.

estimate for each firm the following rolling, 60-month time series regressions:

$$r_{i,t} = \alpha_i + \beta_i^{\kappa}\kappa_t + \boldsymbol{f}'_t\boldsymbol{\beta}_i^f + \eta_{i,t} \tag{1}$$

where:

$r_{i,t}$ is the firm-i, period-t return less the period-t risk-free rate, r_t

$\boldsymbol{f}_j$ is a vector of Fama-French factors

κ_t is log of the period-t climate change salience measure, described in detail in section 2

$\eta_{i,t}$ is the regression error.

Because of well-known international comparability limitations, we take the point of view of a U.S. investor. We express all returns in dollars; the U.S. one-month Treasury bill proxies for the risk-free rate, r_t; and, $\boldsymbol{f}$ includes the U.S. market excess return, and Fama and French's U.S. size and value factors.[9] (We examine country-specific characteristics in other contexts below.)

Table 1 provides summary statistics of the estimated sensitivities, along with summary statistics for the other key variables we use. Note that the inclusion of the excess market return in Equation 1 means that β_i^{κ} does not reflect those aspects of individual returns that are captured by their comovement with the market return, which itself covaries with κ: each β_i^{κ} reflects only the marginal effect of a change in climate salience. The next sections examine the relevance of these estimated marginal sensitivities.

4 The β^{κ} discount

To the extent that climate change salience, κ, is indicative either of expected climate damage or of expected aggregate mitigation activities that entail reduced economic activity, a high β^{κ} means an asset is expected to have a high payoff when economic activity, and correspondingly consumption, is low. That is, a high β^{κ} indicates that an asset's payoff is high when the marginal utility of

[9]Specifically, the three-factor model includes the market excess return, $r_t^m - r_t$; the long-small firm, short-large firm portfolio return, *SML*; and the long-high book-to-market, short-low book-to-market portfolio return, *hml*. These three factors are downloaded from the data library of French (2012).

Table 1: Summary Statistics

The data run from January 2004 through December 2020, with 7496 firms from 51 countries (listed in Appendix A); r_t is the U.S. one-month Treasury Bill rate in percent; r_t^m, smb_t and hml_t are the Fama-French market, small minus big, and high minus low factors; $r_{i,t}$ is the firm-i, period-t return less r_t; κ_t is the period-t climate change salience index, described in detail in section 2; *scope*1, *scope*2, and *scope*3 are firm-specific greenhouse gas emissions in CO2-equivalent tonnes, described briefly in the appendix and in more detail in Refinitiv (2021); *size* is the market value in millions of U.S. dollars; and $\frac{b}{m}$ is the book to market value.

variable	mean	standard deviation	min	25th percentile	median	75th percentile	max	frequency
r_t	0.1012	0.1300	0.0000	0.0000	0.0200	0.1600	0.4400	monthly
r_t^m	0.9056	4.3233	-17.1500	-1.4000	1.3500	3.5200	13.6500	monthly
smb_t	0.1030	2.3453	-4.8900	-1.7200	0.1350	1.5000	6.0400	monthly
hml_t	-0.2481	2.7273	-14.0200	-1.8500	-0.2550	1.1850	8.2100	monthly
$r_{i,t}$	1.1262	8.7069	-22.6569	-4.3364	0.8045	6.2498	28.6974	monthly
κ	0.3462	0.1166	0.1605	0.2602	0.3348	0.4005	0.9296	monthly
$\beta_{i,t}^{\kappa}$	2.234	15.848	-187.123	-5.771	2.057	9.885	183.010	monthly
$size_{i,t}$	7869	25077	0.0200	552	1847	6027	2294819	monthly
$ln\ scope\ 1_{i,t}$	-2.44	3.22	-18.42	-4.62	-2.60	-0.29	8.19	annual
$ln\ scope\ 2_{i,t}$	-2.32	2.30	-13.82	-3.62	-2.14	-0.76	3.82	annual
$ln\ scope\ 3_{i,t}$	-2.32	3.40	-14.31	-4.66	-2.79	-0.07	7.90	annual
$\frac{b}{m}_{i,t}$	0.8259	1.6400	0.0006	0.3425	0.6061	0.9901	100	annual
$sales_{i,t}$	6851	21000	0.001	328	1339	4768	559000	annual
$ppe_{i,t}$	3283	11600	0.001	101	477	1984	303000	annual

consumption is high. Thus, a return discount for such assets in the context of climate change is a natural hypothesis. It is what is predicted by the models of Giglio, Kelly, and Stroebel (2020), of Giglio, Maggiori, Rao, Stroebel, and Weber (2021), and of Bansal, Ochoa, and Kiku (2017). In these models, an asset that is negatively exposed to climate risk (its payoff is high when climate damage is high) has a negative risk premium.

In this section, we examine whether this prediction holds in international equity markets. We use the estimated climate change salience betas of Equation 1 to determine whether or not markets accord a premium or discount to this form of climate change risk.

Specifically, we estimate out-of-sample expected returns, and then examine the coefficient on the lagged measure of return exposure to climate change salience. (For efficiency, we follow Ang, Liu, and Schwarz (2020) in using individual stocks rather than portfolios.)[10] The general

[10] Ang, Liu, and Schwarz show that the use of portfolios reduces the informativeness of the data.

specification is the following:

$$r_{i,t} = \alpha + \gamma^{\beta^{\kappa}} \hat{\beta}^{\kappa}_{i,t-1} + \boldsymbol{g}'_{i,t-1}\boldsymbol{\gamma}^{g} + \boldsymbol{h}'_{i,t-1}\boldsymbol{\gamma}^{h} + \hat{\beta}^{\kappa}_{i,t-1}\boldsymbol{h}'_{i,t-1}\boldsymbol{\gamma}^{h\beta} + \varepsilon_{i,t}, \tag{2}$$

where: $\hat{\beta}^{\kappa}_{i,t-1}$ is the coefficient estimated in Equation 1 over the 60-months prior to period t;[11] $\boldsymbol{g}_{i,t-1}$ is a vector of control variables, and $\boldsymbol{h}_{i,t-1}$ is a vector of variables that will interact with $\beta^{\kappa}_{i,t-1}$. Initially, we eschew interaction terms, and the primary variable of interest is simply $\gamma^{\beta^{\kappa}}$, the coefficient on the sensitivity of returns to climate change salience. If investors are willing to accept a lower return in order to potentially reduce this risk, we should expect $\gamma^{\beta^{\kappa}}$ to be negative.

In our baseline specification, the vector of controls, $\boldsymbol{g}_{i,t-1}$, includes Equation 1's estimated coefficents, $\hat{\boldsymbol{\beta}}^{f}_{i}$; the fama french factors, $\boldsymbol{f}_{j}$; and country fixed effects. (While we initially exclude the interaction terms, $\boldsymbol{h}_{i,t-1}$, we return to them below.) Following Petersen (2009), we use a panel approach so that we can account for correlation in the errors both across time and across firms. We estimate the equations both with and without firm fixed effects. The results of these regressions are reported in the first two columns of Table 2 with standard errors clustered at the firm level given in parentheses.

As shown in these first two columns, the estimated coefficents on $\hat{\beta}^{\kappa}_{i,t-1}$ (given in the first row) are negative, and the standard errors (shown in the second row) are small enough that we can reject at any conventional confidence level the hypothesis that $\gamma^{\beta^{\kappa}} = 0$. That is, firms whose returns are high when climate change salience is high earn lower returns. The magnitude of the effect is economically meaningful. For example, using the estimates in the first column, the return of a firm with a median value of β^{κ} has an annual return that is two percentage points greater than a firm whose β^{κ} is at the 75$^{\text{th}}$ percentile. (As shown in the second column, the estimated difference is slightly greater when firm effects are included.) In other words, international equity markets discount the returns to assets that comove with climate change salience.

The finding here builds on recent related empirical work, including: Huynh and Xia (2021), who find a return discount to climate change news betas in the U.S. bond market; Bolton and Kacperczyk (2021), who document international equity carbon premia; and Bansal, Ochoa, and Kiku, who find return discounts for assets with high temperature betas. Our findings show that the discount is not restricted to the bond market, to the U.S. market, or to carbon sensitive firms.

[11] Thus, while we estimate Equation 1 over the full sample period, our estimation of Equation 2 begins five years after the first period, then it continues with rolling subsamples.

Table 2: Expected Returns

This table gives the parameter estimates and firm-clustered standard errors from a panel regression of returns less the risk-free rate ($r_{i,t}$) on lagged variables, including the Fama-French factors, r_t^m, smb_t and hml_t, climate change salience, κ_{t-1}, the estimated climate change salience beta, $\hat{\beta}_{i,t-1}$, and the interaction term, $\kappa\hat{\beta}_{i,t-1}$. The precise specification is given in Equation 2, and additional details are given in Table 1 and in section 2.

Variable	(1)	(2)	(3)	(4)	(5)
$\gamma^{\beta^{\kappa}}$	-0.0186	-0.0219	0.0149	0.0181	0.0277
	(0.0008)	(0.0009)	(0.0034)	(0.0036)	(0.0062)
$\gamma^{\kappa:\beta^{\kappa}}$	.	.	–0.0967	-0.1161	-0.0993
	.	.	(0.0095)	(0.0100)	(0.0096)
γ^{κ}	.	.	-1.5382	-0.15434	-1.5828
	.	.	(0.0817)	(0.0845)	(0.0823)
$\gamma^{\beta^{Rm}}$	0.4834	0.6341	0.3684	0.5056	0.3543
	(0.0414)	(0.0465)	(0.0426)	(0.0482)	(0.0425)
$\gamma^{\beta^{smb}}$	0.0004	0.0133	0.0552	0.0833	0.0559
	(0.0291)	(0.0346)	(0.0296)	(0.0355)	(0.0298)
$\gamma^{\beta^{hml}}$	0.1371	0.2155	0.0598	0.1270	0.0700
	(0.0279)	(0.0326)	(0.0290)	(0.0340)	(0.0289)
Country:β^{κ} Interactions	no	no	no	no	yes
Firm Effects	no	yes	no	yes	no
Country Effects	yes	yes	yes	yes	yes
Number of Observations	662,803	662,803	662,803	662,803	662,803
$\bar{R}^2$	0.003	0.012	0.003	0.012	0.004

Overall, the results contribute in key ways to the growing evidence that investors accept a lower return in order to hedge against climate-change related risk.

We next bring $\boldsymbol{h}$ (the vector of variables that interact with $\beta^{\kappa}_{i,t-1}$ in Equation 2) back into the picture to examine whether the climate change salience-beta discount is time varying. Specifically, we examine whether the β^{κ} discount is particularly high when climate change interest, κ, itself is high. In the notation of Equation 2, we let $\boldsymbol{h} = \kappa$, and we examine both the coefficients on β and the coefficient on $\beta^{\kappa}\kappa$, the interaction between the salience beta and salience.

The final three columns in Table 2 provide the results from the estimation that allow for the interaction: columns three and four give the results, with and without firm fixed effects, and column 5 gives the results in a regression that expands $\boldsymbol{h}$ to allow the pricing to vary by country. While the estimated coefficients on β_{κ} itself (shown again in the first row) are now positive, the estimated coefficients on the interaction term, $\kappa\beta^{\kappa}$, shown in the third row, are negative and substantial enough to more than outweigh the now-positive linear effect. (And, the standard errors are again small enough that we can reject at every conventional confidence level the hypotheses that these coefficients are zero.) Again, the estimates are economically meaningful: The point estimates in the third column imply that at the median salience level, a firm with a median beta has an annual return that is about 1.9 percentage points greater than that of a firm with a median beta at the 75^{th} percentile. (The net effects in columns four and five are modestly greater.) That is, once we account for nonlinearity, we see that the price effect of climate change salience risk is time varying–it is magnified by climate change salience itself, and the nonlinearity is substantial.

5 Accounting for β_{κ}.

We now return to our estimates of β^{κ} from Equation (1). Of particular interest is whether a firm's sensitivity to climate change salience reflects its greenhouse gas emissions or its physical assets. Climate change salience risk may reflect such things as investor preference for green firms, regulatory changes directed at emitting firms, or direct damage from climate events. However, as discussed in section 1, the risk may also (or instead) reflect a much broader range of concerns, such as future climate change induced production cost increases or falling aggregate demand. Such concerns may be faced by a wide range of firms irrespective of their emissions or of any directly vulnerable physical property.[12] That is, β_κ may reflect a more ubiquitous climate change risk, and the role of emissions and property may be relatively small.

To examine these issues, we include emissions in the following panel regression:

$$\hat{\beta}^{\kappa}_{i,t} = \gamma_0 + \boldsymbol{m}'_{i,t}\boldsymbol{\gamma}^m + \gamma_{fin} d_{fin} + \boldsymbol{c}'_{i,t}\boldsymbol{\gamma}^c + \epsilon_{i,t}, \tag{3}$$

where: $\boldsymbol{m}'_{i,t}$ is a vector of reported emissions data; d_{fin} is an indicator variable for financial firms;[13] and, $\boldsymbol{c}'_{i,t}$ is a vector of additional time-varying, firm-specific and country-specific variables that may be thought of as control variables with respect to emissions but may be of interest for their own sake. In our initial estimate of Equation 3, $\boldsymbol{m}'_{i,t}$ contains the *levels* of scope 1, scope 2, and scope 3 emissions, taken from Refinitiv;[14] but we also look at emission intensities (emissions deflated by sales). In $\boldsymbol{c}'_{i,t}$, we include size; sales; book to market value; and property, plant, and equipment. Notably, the inclusion of firm size is not merely a matter of convention here: it is called for by the findings of Aswani, Raghunandan, and Rajgopal (2022), who emphasize that the apparent pricing of emissions in U.S. equity markets may spuriously reflect firm size. The results from this estimation are given in Table 3.

The table's first three columns provide the estimates using firms' reported levels of greenhouse gas emissions, with and without fixed effects. We cannot reject at any standard confidence level the hypothesis that the coefficients on scope 1 and scope 2 emissions each equal zero, or that all three measures of emissions collectively equal zero in any of the three regressions; and, only at modest significance levels can we reject the hypothesis that the coefficients are zero on scope 3 emissions.[15] Column four provides the results of a regression that uses emission intensities instead

[12]Note that the value of physical assets that are not themselves directly harmed by climate change may decline because of the risk that the cost of using them will rise with climate change–for example if their use is hampered by power outages or other infrastructure damages. See, Bohn (2020), who provides one approach to quantifying such risks.

[13]We designate as 'financial firms' those firms with SIC codes between 6000 and 6449.

[14]The scope breakdowns follow the Greenhouse Gas Protocol: scope 1 includes emissions from firms' owned or controlled sources, scope 2 adds purchased energy, and scope 3 includes emissions from upstream and downstream activities, disposal, and resale. For non-reporting firms, Refinitive calculates emissions as documented in Refinitiv (2021). We note that scope 3 emissions are entirely missing for six countries: Bulagria, Cyprus, Pakistan, Romania, Slovenia, and Sri Lanka.

[15]We note that scope 3, the broadest gauge of greenhouse gas emissions, is typically (and opaquely) constructed from firm's other characteristics, such as employment–characteristics that change over time, so they would not be captured by firm fixed effects. This implies that scope 3 likely measures important time-varying firm characteristics *other than emissions*, so its estimated coefficient reflects those other characteristics. This makes its marginal significance uncompelling.

Table 3: Accounting for $\beta^{\kappa}_{i,t}$

This table gives the parameter estimates and firm-clustered standard errors from a panel regression of firms' climate change salience betas ($\hat{\beta}^{\kappa}_{i,t}$) on the logs of firm-level greenhouse gas emissions, plant and equipment (ppe), firm size, an indicator for financial firms (d_{fin}), book-to-market ($\frac{b}{m}$), and sales; and on country-level characteristics. The precise specification is given in Equation 3, and data details are given in Appendix A.

Variable	(1)	(2)	(3)	(4)	(5)
ln scope 1	-0.2514	0.1298	0.0819	.	0.1829
	(0.1971)	(0.1807)	(0.1792)	.	(0.2059)
ln scope 2	0.0015	0.1734	0.1909	.	0.1453
	(0.2250)	(0.2337)	(0.2382)	.	(0.2484)
ln scope 3	0.0498	0.1829	0.1798	.	0.2140
	(0.1084)	(0.1047)	(0.1051)	.	(0.1178)
$ln\frac{scope1}{sales}$	.	.	.	0.1229	.
	.	.	.	(0.1780)	.
$ln\frac{scope2}{sales}$	.	.	.	0.3313	.
	.	.	.	(0.2377)	.
$ln\frac{scope3}{sales}$	.	.	.	0.1901	.
	.	.	.	(0.1053)	.
ln ppe	0.3424	-0.0080	-0.0376	-0.4479	0.1154
	(0.2519)	(0.2604)	(0.2651)	(0.2699)	(0.2693)
d_{fin}	-2.1879	0.4352	-0.0520	-0.4247	0.6080
	(0.9504)	(0.8912)	(0.8809)	(0.8636)	(1.0187)
ln size	3.1429	2.6844	2.7888	1.9627	2.5762
	(0.4874)	(0.4817)	(0.4924)	(0.4430)	(0.5453)
ln $\frac{b}{m}$	2.3874	1.7250	1.6922	1.4391	1.4723
	(0.4090)	(0.3737)	(0.3763)	(0.3736)	(0.4629)
ln sales	-0.7039	-2.6843	-2.6482	.	-2.3508
	(0.4867)	(0.4662)	(0.4688)	.	(0.5052)
Country Characteristics					
emissions per capita	.	.	.	.	-0.4402
	.	.	.	.	(0.4082)
climate risk index	.	.	.	.	1.0277
	.	.	.	.	(0.3998)
climate change policy score	.	.	.	.	-0.4717
	.	.	.	.	(0.3584)
political stability index	.	.	.	.	-0.3010
	.	.	.	.	(0.6888)
non-renewable energy use	.	.	.	.	0.1765
	.	.	.	.	(0.6473)
oil producer	.	.	.	.	1.7250
	.	.	.	.	(1.2092)
emerging market	.	.	.	.	0.4179
	.	.	.	.	(1.0491)
GDP per capita	.	.	.	.	-1.7630
	.	.	.	.	(0.7195)
country effects	no	no	yes	yes	no
time effects	no	yes	yes	yes	no
Observations	111,699	111,699	111,699	111,699	90,277
$\bar{R}^2$	0.00105	0.151	0.200	0.205	0.898
$\chi^2(3)$	1.24	4.48	3.7	6.69	6.72
p-value	0.7434	0.2137	0.2954	0.0826	0.0814

of emission levels. Again, we can reject at any significance level the hypothesis that scope 1 or scope 2 emission intensities individually matter, or that the three emission intensities collectively matter for $\beta^{\kappa}_{i,t}$. Again, only the intensity of scope 3 is even mildly significant. Overall, it appears that returns are sensitive to climate change salience largely irrespective of the level of firms' greenhouse gas emissions. Relatedly, we find no evidence that property, plant and equipment are related to returns' climate change salience betas. And, in terms of their return sensitivity to climate change salience, there is no apparent difference between financial and nonfinancial firms.

Only when we look at the standard trio of size, book to market, and sales, do we find a clear and consistent link to return sensitivity. Here we find that–in all specifications–the marginal effect of size and book to market is positive. Conditional on emissions and the other firm-specific variables, the returns of large firms and the returns of high value firms tend to comove more positively with climate change salience than the returns of other firms. That is, large firms and value firms exhibit less climate change salience risk. In contrast, conditional on these variables, sales are indicative of lower–more negative–climate change salience betas (more climate salience risk).

Columns three and four add country fixed effects to the regressions, and the results are robust to their inclusion. That said, their inclusion is nevertheless important. It is motivated by the idea that a firm's climate change salience risk might depend on the characteristics of its home country–such as the country's climate policy, its experience with weather-related disasters, and its ability (perhaps through such things as political stability and per capita GDP) to collectively mitigate climate change damage. Indeed, Cai, Pan, and Statman (2016) document that country effects are important in explaining firm-level corporate social responsibility ratings, and they suggest that political institutions and per-capita income are of particular importance. Thus, we further unpack the country fixed effects by replacing them in column five with key motivating variables.

Specifically, column five of Table 3 reports the results from a regression that includes a country's overall greenhouse gas emissions, its climate risk index, its climate change policy score, its political stability index, its non-renewable energy use, indicators for whether or not it is an oil producer or an emerging market, and its per capita GDP. Like the firm-level greenhouse gas emissions, the country-level emissions appear unimportant to firm-level climate change salience exposure. However (and perhaps surprisingly) the coefficient on the climate risk index, 1.03, is positive (and statistically significant at all conventional confidence levels), while the coefficient on per-capita GDP, -1.76, is negative (and statistically significant at modest confidence levels). That is, firms in countries that have experienced more extreme weather-related losses have lower exposures, and firms in rich countries appear to have more exposure. One may speculate that firms in countries that have experienced substantial weather-related losses have already undertaken steps to hedge further climate change, while those in rich countries–impacted or not by weather disasters so far–have not.

Overall, the table's estimates indicate that unhedged climate change salience risk it is not restricted to emitting firms, to those with substantial physical assets, or to nonfinancial firms. The finding that climate change salience risk is priced–but at the same time largely unrelated to emissions or physical assets–suggests that the risk is a wide-ranging one.

6 Conclusions

This study examines the relationship between climate change concens and equity returns in international markets. Using internet search innovations to provide a broad indicator of the salience of climate change concerns, we find that return exposure to changes in this indicator is priced in international equity markets. In addition, the pricing of this exposure is time varying: the climate salience beta discount is magnified when climate change salience is high. This nonlineary is in keeping with the broader salience literature, which suggests that information plays a greater role in decision making when it is particularly pronounced.

We also find that small firms, growth firms, and firms in countries with so far comparatively low weather related losses are de facto relatively unhedged against climate change salience risk. Our analysis also reveals that climate change salience risk is widespread and not limited to firms with high greenhouse gas emissions or substantial physical plant.

We interpret our results as evidence of the far-reaching nature of climate change risk. The results do not support the proposition that it is investor distaste for greenhouse gas-emitting firms that is priced in equity markets; instead, they suggest that investors accept a lower return in order to protect against the potentially broad range of adverse outcomes related to climate-change.

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A Data Notes

Firm-specific variables

***scope* 1, 2, and 3** are CO_2-equivalent emissions are from Refinitiv, variables ENERDP024, ENERDP025, and ENERDP096.

ppe is Property, Plant, and Equipment, from Refinitiv

$\boldsymbol{d_{fin}}$ is an indicator variable if the firm's SOC code is greater than 6000 and less than 6412, from Refinitiv

size is the market value of a firm as reported by Refinitiv

$\ln \frac{b}{m}$ is the Book to Market value of equity of a firm as reported by Refinitiv

Countries with included equity markets

Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Cyprus, Czech Rep, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Romania, Russia, Singapore, Slovenia, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, United States

Country-specific variables

emissions per capita World Bank (2018 data)

climate risk index the CRI score from Germanwatch https://www.germanwatch.org/en/cri

climate change policy score https://ccpi.org/

political stability index World Bank governance indicators (2019 data).

non-renewable energy use total energy production less renewables production from the US Energy Information Administration: https://www.eia.gov/international/data/world/world/total-energy

oil producer an indicator variable which takes the value 1, if the country is an oil producer as defined in the IMF Fiscal Monitor.

emerging market an indicator variable for emerging markets, as defined by MSCI.

GDP per capita World Bank (2020 data)