Climate Change Salience and International Equity Returns*

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This version: May 6, 2024
(Original Version: May 7, 2022)

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. Overall, 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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*We are grateful to Megan Croly, Jeffrey Fowler, and Kendal Myers for careful research assistance. The paper has also benefitted from the comments of Olga Balakina, Nicola Borri, Sanjiv Das, Yaying Geng, Josh White, Victoria Wenxin Xie, three anonymous referees, and the participants of the 2022 'International Conference on Sustainability, Environment, and Social Transition in Economics and Finance', the 2022 Conference on 'Climate Change, Regulatory Responses and Sustainable Finance', and the 2022 European Winter Meeting of the Econometric Society.

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1 Introduction

In this paper, we explore how equities in 51 emerging and developed markets, from 2004 to 2020, respond to a single, broad indicator of climate change risk, one that captures climate change salience. 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.[3] 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.

To assess exposure to climate change risk and its pricing in this paper, we use world-wide Google searches of 'climate change', and we extract the innovations to provide an indicator of climate change salience. We then use rolling time series regressions to estimate the sensitivity of returns to this indicator in a factor model. Next, we examine if and how the sensitivity to climate change salience is priced in equity markets, and how much of the exposure to that risk is related

[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]While Addoum, Ng, and Ortiz-Bobea (2020) find little U.S. evidence that heat affects sales or productivity, Custodio, Ferreira, Garcia-Appendini, and Lam (2022) identify the effect of both average and extreme weather shocks on U.S. supplier sales, and they summarize earlier studies relating labor productivity, hours worked, and output to temperature; Donadelli, Grüning, Jüppner, and Kizys (2021) document the negative effect of temperature on research and development in the G7 countries, and Hsiang (2010) documents a strong, negative response of production to increased temperatures among 28 Caribbean-basin countries.

[3]While this is an example of how a firm may benefit from technological innovation, it can be characterized more broadly as a type of technology risk, as described by Venturini (2022) and by Semieniuk, Campiglio, Mercure, Volz, and Edwards (2021).

to key firm characteristics, such as reported greenhouse gas emissions and physical assets.

We find that U.S. and international equity markets price in a meaningful return discount for positive climate change salience covariance. Put differently, we find an equity premium associated with additional climate change salience risk. In our baseline estimates, for example, a firm with a median exposure to climate change salience risk has an annual return two percentage points higher than a firm with exposure at the 75^{th} percentile. 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 its greatest effect on decision making when it stands out most.

Notably, we also find that climate change salience risk is not limited to firms with high emissions or substantial physical assets, and both financial and nonfinancial firms exhibit exposure to the risk. 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.

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 of climate change *transition* risk.

In contrast, our paper's gauge of climate change risk is designed to capture a broader range of risks. It is closer in spirit to Engle, Giglio, Kelly, Lee, and Stroebel (2020), who rely on natural language processing to capture both physical and transition risks in a single measure. 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*.[4] The simpler approach of our paper allows for a similarly broad range of climate change related risks while using publicly available information and avoiding the editorial artifact that arises in news publications.

[4] Engle, Giglio, Kelly, Lee, and Stroebel also use a larger set of news sources to create a secondary, sentiment indicator, which we touch on below in section 2.

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 (using Engle, Giglio, Kelly, Lee, and Stroebel's measure) find that climate change risk is priced in the market for U.S. bonds. As in their study of U.S bonds, our study of international equities is motivated by theoretical models such as those of Barnett (2023) and of Giglio, Kelly, and Stroebel (2020). At the heart of these models is the combination of (1) the classic 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–and (2) the role that climate change plays in altering investment and consumption opportunities over time. With this combination, these models predict that assets that are exposed to climate change risk trade at premium or discount, as we find here.

The next section of this paper discusses the climate change salience indicator in more detail. The sensitivity of returns to this indicator is estimated in section 3, and the pricing of that sensitivity is explored in section 4. In section 5, we look more closely at our estimates from Equation 1 of firms' sensitivities to climate change salience, and–in particular–we assess whether a firm's sensitivity to climate change salience reflects its greenhouse gas emissions or its physical assets. Section 6 concludes.

2 Measuring climate change salience

In this section, we construct the indicator of climate change salience.[5] To do so, we begin with historic data taken from Google Trends' worldwide index of English language searches for the term

[5]One might alternatively use the term 'attention' rather than 'salience'. We acknowledge the overlap of these words in our context. The choice of 'salience' relies in part on Bordalo, Gennaioli, and Shleifer (2013), who explain that a stimulus is considered salient when it significantly attracts a decision maker's attention, particularly when it's surprising. As we discuss below, our climate change salience indicator is constructed as an innovation, which captures the 'surprise' in search volume, rather than underlying, ongoing attention. Surprisingly high search volume indicates the issue is suddenly prominent, noticeable, or important in the public domain, which is the essence of salience. In contrast, 'attention' might suggest a sustained engagement with a subject, which changes in search frequencies don't quite reflect. See Parr and Friston (2019) for their 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.

'climate change'.[6]

Many investors in equity markets around the world conduct their searches in other languages and use other search engines. However, in this work we seek to examine the potential ubiquity of climate change risk using a single, broad measure of that risk. Expansion to include geographic and language-specific searches in each market we examine would result in 51 distinct risk measures, rather than a single measure; and it would conflate variation in climate change salience with country-specific search engine regulation, including–in some markets–time-varying prohibitions on search engine use.[7] Since English still serves as a lingua franca in both science and business, and since English-language searches are used internationally, we take the viewpoint of a U.S. investor and correspondingly use English-language, Google searches.[8] We also note that the use of a single-language search phrase is clear, simple, and reproducible.

Google Trends provides the search term data as a monthly index that is scaled both relative to all Google searches and relative to the sample period. However, we note that searches of 'climate change' exhibit marked predictability and seasonality. As emphasized in Bordalo et al.'s (2013)

[6]That is, we use historic data on searches of the specific combination of words, 'climate change'. By construction, then, the indicator doesn't adapt during the sample period to potential changes in terminology or language usage. That said, as will be seen in section 3, by using rolling regressions, we do capture changes in how individual returns respond to the indicator. So, if the exact phrase gains or loses its relevance, that change in relevance will be reflected in the climate change salience betas. In addition, as discussed in section 4 and section 5, we also examine a Google 'topic' measure as a robustness check. The topic measure, partly based on natural language processing, is intended to capture searches of a wider range of related phrases, such as 'global warming' and 'climate crisis'. However, the terms can also encompass such disparate phrases as 'green economy' and 'sustainability', and the set of terms is neither stable nor observable. It is not just the terms included in a topic that change over time, the underlying algorithm that determines what is included changes over time as well. Moreover, the algorithm is proprietary, not public. All of this makes the topic search opaque and the corresponding results difficult to interpret.

[7]That being said, even in China and Russia, which have notable internet restrictions, we observe strong correlations between our English-language search innovations and the innovations we construct from Chinese and Russian language searches using their local search engines: The correlation is 0.80 for innovations in searches of '气候变化' on China's Baidu, and 0.81 for 'изменение климата' search innovations on Russia's Yandex.

[8]As a practical matter, the choice to take the perspective a U.S. investor sidesteps well-known problems with determining (and being able to measure) individual market-specific factors in international financial studies. Taking the investment perspectives of the investors doing the searching in these multiple markets would require–in addition to the use of local language searches–the construction of separate market models for each one, which would muddy the comparability and interpretation of coefficient estimates. Relatedly, the use of a single language also avoids conflating risk differences with translation differences.

review of the salience literature, it is what is unexpected that exhibits the greatest salience. This makes it particularly important in our work to identify the surprises in the data.[9] So, rather than using the raw search data, we construct the innovations in the series. To do so, we use an autoregressive integrated moving average model.[10] Specifically, we follow the approaches of U.S. Census Bureau (2020) and Dagum and Bianconcini (2016): we use an $ARIMA(111)(011)_{12}$.[11] This yields the required search innovations, which we denote κ.

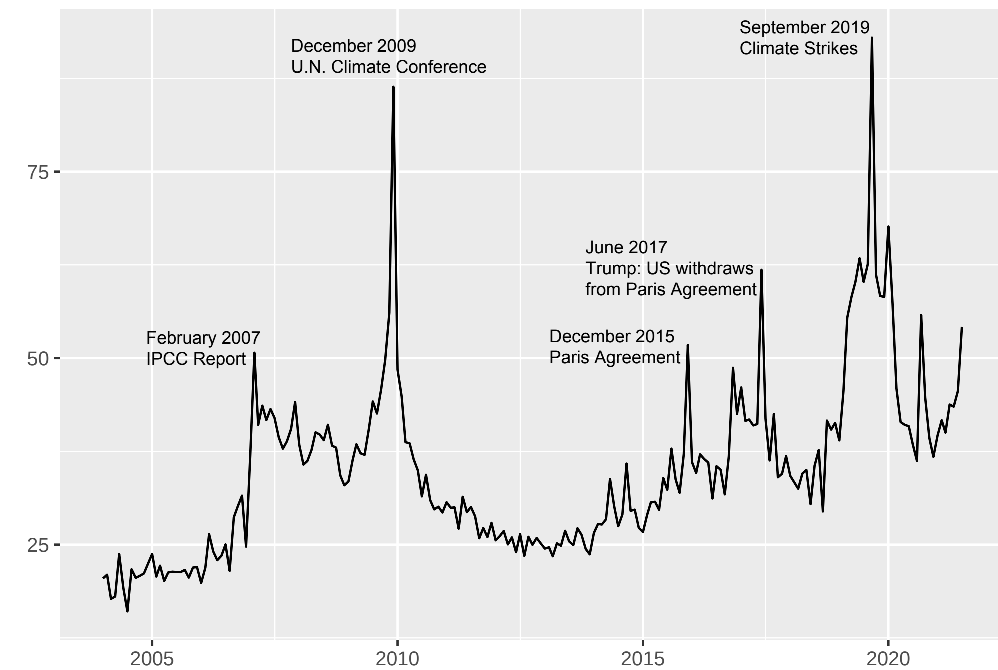

Figure 1: World-wide Google searches of 'climate change' relative to all Google searches, adjusted with an $ARIMA(111)(011)_{12}$, and scaled between zero and 100 over the sample

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

[9]Relatedly, in Pástor, Stambaugh, and Taylor (2021)'s theoretical work, it is the unexpected changes in climate change concerns that affect the relative returns on green vs. brown firms, a prediction that is empirically confirmed by Ardia, Bluteau, Boudt, and Inghelbrecht (2022).

[10]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.

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

Conference, the Paris Agreement of December 2015, President Trump's June 2017 announcement 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, even more so, 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). Like Engle, Giglio, Kelly, Lee, and Stroebel (2020), we provisionally interpret increases in our measure as indicative of heightened negative concern over climate change, and following their provisional interpretation, we note that the correlation between our measure and their richly developed, negative sentiment index is higher than the correlation between their own benchmark measure and their sentiment index. (Specifically, 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.) Our higher correlation vis-a-vis theirs may reflect the fact that editorial artifact can afflict any single source news measure, such as the *Wall Street Journal*; while, in contrast, (as mentioned above) the Google search measure that we use here is not directly subject to editorial artifact, and the Crimson Hexagon index (by including numerous sources) mitigates some of the editorial artifact.[12]

Our use of search data builds on the work of Choi, Gao, and Jiang (2020a), who link searches and returns to abnormal temperatures, and on 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). Our work differs from earlier work in using search innovations rather than search volume.

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 now know that search innovations are indeed positively correlated with the negative sentiment index. It's possible that the use of

[12] Of course, public sentiment itself is shaped by the editorial choices made by all information sources; so even the searches can be indirectly shaped by the full set of editorial choices made by all available information providers.

innovations, as we use here, rather than their use of the raw data, would have corroborated their main findings. 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 levels rather than innovations. In Santi's (2020) case, however, we might conjecture that the null finding would hold up to the use of innovations since Santi (appropriately for a transition-risk study) examines the returns of portfolios constructed based on emissions. While, as we discuss below, we find a clear (and priced) link between innovations in climate change searches and equity returns, we find that the link it is not determined by emissions. Before getting to those results, however, we turn to the next section, where we combine the search innovations with individual firm returns to give us an indicator of the firm's unhedged exposure to this climate change salience indicator.

3 The sensitivity of returns to climate change salience

We can now measure the sensitivities of firms' returns to our new indicator of climate change salience. While we examine how these sensitivities are priced below in section 4, and we then explore their underpinnings in section 5, at this juncture we present no hypotheses regarding their determinants. In this section, we simply estimate the climate change salience sensitivities.

In measuring each firm's sensitivity, we allow for change over time by using rolling 60-month windows, and we take the viewpoint of a U.S. investor. The sensitivities must be allowed to change throughout the period since over time a firm may alter such things as its climate change related operations, supply chain, balance sheet, regulatory responsiveness, and engagement strategy. The choice of the U.S. investor perspective, as discussed above, sidesteps well-known problems with choosing individual market-specific factors in financial studies, and–more importantly, it allows us to use a single, broad, English-language indicator of climate change salience.

We begin with raw data on the monthly equity returns, retrieved from Refinitiv's (now LSEG) Datastream, of 7496 firms across the 51 markets between 2004 through 2020. Following the recommendations of Ince and Porter (2006), who carefully examine 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 (2020a)), 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, since we include firms from many emerging markets, we winsorize the returns at five percent and 95 percent.[13] For readability, we express all returns in percent.

To measure the sensitivity, β^{κ}, of each firm's excess return to climate change salience, we then estimate for each firm the following rolling, 60-month time series regressions,

$$r_t = \alpha + \beta^{\kappa}\kappa_t + \boldsymbol{f}'_t\boldsymbol{\beta}^f + \eta_t \tag{1}$$

where α, β^{κ}, and the vector $\boldsymbol{\beta}^f$ are estimated parameters, the subscript t indexes each monthly observation within the rolling window, and:

r is the firm's return less the risk-free rate

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

κ is the climate change salience measure

η is a regression error.

Since 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; and, $\boldsymbol{f}$ includes Fama and French's U.S. market excess return, and their U.S. size and value factors.[14] (We examine country-specific characteristics in other contexts below.) Recall that κ_t essentially captures a change in (the innovation in) climate change salience, not its level.[15] Finally, note that, because Equation 1 is estimated over rolling 60-month periods, the estimated parameters, α, β^{κ}, and $\boldsymbol{\beta}^f$, themselves change over time: for each one of the more than 7000 firms, there are up to 145 estimates of β^{κ}.

[13] We also winsorize at 99 percent, and we find that the results are largely the same.

[14] Specifically, the three-factor model includes the market excess return, $r^m - r$; the long-small firm, short-large firm portfolio return, *smb*; 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).

[15] It is the $ARIMA(111)(011)_{12}$ innovation described in detail in section 2.

Table 1: Summary Statistics

The data run from January 2004 through December 2020, with 7496 firms from 51 countries (listed in Appendix A); r_{rf} is the U.S. one-month Treasury Bill rate in percent; r_m, smb, and hml are the Fama-French market, small minus big, and high minus low factors; r is the firm return less r_{rf}; κ is the climate change salience index, described in detail in section 2; $scope1$, $scope2$, and $scope3$ 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_{rf}	0.1012	0.1300	0.0000	0.0000	0.0200	0.1600	0.4400	monthly
r_m	0.9056	4.3233	-17.1500	-1.4000	1.3500	3.5200	13.6500	monthly
smb	0.1030	2.3453	-4.8900	-1.7200	0.1350	1.5000	6.0400	monthly
hml	-0.2481	2.7273	-14.0200	-1.8500	-0.2550	1.1850	8.2100	monthly
r	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
β^{κ}	2.234	15.848	-187.123	-5.771	2.057	9.885	183.010	monthly
$size$	7869	25077	0.0200	552	1847	6027	2294819	monthly
$ln\ scope\ 1$	-2.44	3.22	-18.42	-4.62	-2.60	-0.29	8.19	annual
$ln\ scope\ 2$	-2.32	2.30	-13.82	-3.62	-2.14	-0.76	3.82	annual
$ln\ scope\ 3$	-2.32	3.40	-14.31	-4.66	-2.79	-0.07	7.90	annual
$\frac{b}{m}$	0.8259	1.6400	0.0006	0.3425	0.6061	0.9901	100	annual
$sales$	6851	21000	0.001	328	1339	4768	559000	annual
ppe	3283	11600	0.001	101	477	1984	303000	annual

Table 1 provides summary statistics of the observed 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 each estimated climate change sensitivity does not reflect those aspects of the individual firm's returns that are already captured by their comovement with the market return, which itself covaries with κ: each β^{κ} reflects only the marginal effect of a change in climate salience. The next sections examine the market relevance of these estimated marginal sensitivities.

4 The price of climate salience risk

While the previous section estimated the firm-specific return sensitivity to climate change salience, this section examines empirically if and how the sensitivity is priced in international equity markets. First, we briefly discuss the motivation for examining the pricing.

That the sensitivity might be priced is suggested by theoretical models as disparate as Merton's (1973) classic intertemporal capital asset pricing model and Barnett's (2023) richly nonlinear model in which uncertainty over climate change dynamics is interconnected with heterogenous producers and technological innovation. Its pricing arises in Merton's model to the extent that climate change salience covaries with variables that predict changes in consumption and investment opportunities; and, using individual, firm-level measures of risk using textual analysis of earnings calls, Sautner, van Lent, Vilkov, and Zhang (Forthcoming) (Sautner et al.) find that these risks are indeed associated with future changes in investment opportunities.[16] In Barnett's model, pricing arises explicitly because uncertainty over climate change concerns bring about real changes in investment allocations. Relatedly, Giglio, Kelly, and Stroebel (2020) provide a very general framework in which an asset that is negatively exposed to climate risk (its payoff is high when climate damage is high) can have either a positive or negative risk premium, depending on whether the climate change risk reflects uncertainty about the process of climate change itself, which reduces economic activity, or about economic activity, which generates damaging climate change.

[16]Relatedly, 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)). And, in keeping with Merton's approach, Bansal, Ochoa, and Kiku (2017) provide a related model in which temperature risk has pricing implications related to long-run growth risks in cash flows.

In all of these models, the pricing ultimately rests on the ability of an asset to act as a consumption hedge. To the extent that climate change salience, κ, is indicative largely either of expected climate damage to production 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. In such cases, a high β^{κ} indicates that an asset's payoff is relatively high when the marginal utility of consumption is high. That is, in these cases, an asset that is negatively exposed to climate salience risk should have a negative risk premium. Of course, in keeping with Giglio, Kelly, and Stroebel's framework, if the most important link between climate change and economic activity stems from the effect of economic activity on climate change, rather than the reverse, then a high β^{κ} indicates that an asset's payoff is high when the marginal utility of consumption is low, and the risk premium is positive.

While the pricing remains an open empirical question, for specificity we write the following hypothesis:

Hypothesis 1: There is a negative relationship between a firm's β^{κ} and its subsequent returns.

In the remainder of this section, we examine this prediction empirically. That is, using the estimated climate change salience betas of Equation 1, we study whether or not markets accord a discount (or a premium) to this form of climate change risk. Specifically, we estimate out-of-sample expected returns in a panel of individual equities, and then we examine the coefficient on the lagged measure of return exposure to climate change salience.

The choice to use individual equities in a panel (rather than the traditional use of portfolios of equities in a cross section) relies on the work of Ang, Liu, and Schwarz (2020) and of Harvey and Liu (2021), and it aligns with the closely related work of Huynh and Xia (2021).[17] Ang, Liu, and Schwarz carefully compare the portfolio approach with the individual asset approach; and they examine how the two approaches fare in estimating risk premia in financial markets. Importantly, their work supports the use of individual assets by showing that the use of portfolios destroys cross-sectional information. As they explain, because portfolios average across assets, their use results in less dispersed betas than arise from the use of individual assets; so portfolios yield less

[17] Huynh and Xia (2021) in turn follow Ben-Rephael, Carlin, Da, and Israelsen (2021).

efficient estimates of pricing equations (such as Equation 2 below). Separately, Harvey and Liu compare the cross-section approach and the panel approach. They show that the panel approach is typically more resilient to misspecification because it allows for a separate intercept for each asset, while the cross-section approach forces firm-specific variation due to omitted variables into the regression coefficients.

Recall we estimate Equation 1 over rolling five-year windows; so, in order to use only prior known variables in the return equations here, our estimation in this section begins in 2009, five years after the start of the sample. Letting i index the firm and t index the time period, we estimate the parameters γ^0, γ^{β^κ}, $\boldsymbol{\gamma}^g$, $\boldsymbol{\gamma}^h$, and $\boldsymbol{\gamma}^{h\beta}$ in the following forward-looking specification that includes interaction terms:

$$r_{i,t+1} = \gamma^0 + \gamma^{\beta^\kappa}\hat{\beta}^\kappa_{i,t} + \boldsymbol{g}'_{i,t}\boldsymbol{\gamma}^g + \boldsymbol{h}'_{i,t}\boldsymbol{\gamma}^h + \hat{\beta}^\kappa_{i,t}\boldsymbol{h}'_{i,t}\boldsymbol{\gamma}^{h\beta} + \varepsilon_{i,t}, \qquad (2)$$

$\hat{\beta}^\kappa_{i,t}$ is the sensitivity to climate change salience

$\boldsymbol{g}_{i,t}$ is a vector of control variables

$\boldsymbol{h}_{i,t}$ is a vector of interaction variables

The initial primary variable of interest is γ^{β^κ}, the coefficient on the sensitivity of returns to climate change salience. To accord with Hypothesis 1–the hypothesis that investors are willing to accept a lower return in order to reduce climate change salience risk– γ^{β^κ} would be negative.

In our first specification, the vector of controls, $\boldsymbol{g}_{i,t}$, includes the lagged estimated coefficents on the Fama French factors, along with country fixed effects, and we eschew interaction terms (we return to them below). 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 coefficient, $\hat{\gamma}^{\beta^\kappa}$, on the sensitivity of returns to climate change salience (given in the first row) is negative in both cases, 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

Table 2: Expected Returns

This table gives the parameter estimates and firm-clustered standard errors from panel regressions of forward looking firm returns (less the risk-free rate), $r_{i,t+1}$, on prior, known variables: climate change salience betas, $\hat{\beta}^{\kappa}_{i,t}$; climate change salience, κ_t; interaction terms, $\kappa_t\hat{\beta}_{i,t}$; along with Fama-French factor betas, $\beta^{r^m}_t$, β^{smb}_t and β^{hml}_t. 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)
$\gamma^{\beta^{R_m}}$	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

high earn lower returns. The magnitude of the effect is economically meaningful.[18] 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^{th} percentile. As shown in the second column, the estimated difference is slightly greater when firm effects are included. These results provide support for Hypothesis 1. In other words, international equity markets discount the returns to assets that comove positively with climate change salience.

The findings here build 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 (2017), 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. Overall, the findings contribute 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 interaction variables) back into the picture to examine whether the climate change salience-beta discount is time varying. Specifically, we examine whether the discount varies as climate change salience itself varies. In other words, we ask: Does an increase in climate change salience itself amplify the demand for assets that hedge climate change concerns? To the extent that increases in climate change salience are accompanied by correspondingly greater concerns about future costs and revenues, we might expect this to be the case; and in the related model of Barnett (2023), an increase in climate change amplifies the negative price of climate risk. This brings us to our second hypothesis:

Hypothesis 2: The return discount for high β^{κ} firms deepens as climate change salience rises.

To evaluate this hypothesis, we set $\boldsymbol{h} = \kappa$ in Equation 2, we examine the coefficient, $\gamma^{h\beta}$, on the interaction term, along with the new coefficient, $\gamma^{\beta^{\kappa}}$, on the climate change salience beta. Hypothesis 2 implies that the interaction term coefficient, $\gamma^{h\beta}$ is negative, and that the coefficient

[18] The pricing of climate change salience risk remains economically meaningful and highly statistically significant in our robustness tests, though the magnitude of the effect is somewhat smaller (-0.0059) when the Google Topic measure is used. The robustness tests include (in addition to the Google 'Topic' measure) separate estimates of emerging and developed markets, the first and second halves of the sample, a 5-factor model, and a less aggressive (99%) winsorization.

on the climate change salience beta is either negative or small enough that the linear effect is swamped by the interaction term.

The final three columns in Table 2 provide the results from the estimation that allows 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 include additional interaction terms that allow the pricing to vary by country. While the estimated coefficients on the climate change beta itself (shown again in the first row) are now positive, the estimated coefficients on the interaction term, 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 climate change salience level, a firm with a median climate change salience 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, we find support for Hypothesis 2: 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. Overall, the estimates suggest that sensitivity to climate change salience is priced in international equity markets, and its price is amplified when climate change salience itself rises.

5 Are high emitting firms most sensitive?

We now return to look more closely at our estimates from Equation 1 of firms' sensitivities to climate change salience. Of particular interest is whether a firm's sensitivity to climate change salience reflects its greenhouse gas emissions or its physical assets. Investor preference for green firms or concerns about regulatory changes directed at emitting firms, for example, would both suggest that a firm's greenhouse gas emissions would at least in part determine its sensitivity to climate change salience. Likewise, a firm's potential for direct damage from climate events might also affect its sensitivity. However, as discussed in section 1, climate change salience risk may instead reflect a much broader range of concerns, such as future climate change induced production cost increases, infrastructure disruptions, or falling aggregate demand.[19] Such concerns may be faced by a wide range of firms irrespective either of their emissions or of any directly vulnerable physical property. That is, β^{κ} may reflect a more ubiquitous climate change salience risk, and the role of emissions and property in comparison may be relatively unimportant. This suggests the following two hypotheses:

Hypothesis 3: β^{κ} is unrelated to greenhouse gas emissions.

Hypothesis 4: β^{κ} is unrelated to physical plant, property, and equipment.

To examine these issues, we include emissions, and property, plant and equipment in the following panel regression:

$$\hat{\beta}^{\kappa}_{i,t} = \delta^0 + \boldsymbol{m}'_{i,t}\boldsymbol{\delta}^m + \delta^{fin} d_{i,t} + \boldsymbol{c}'_{i,t}\boldsymbol{\delta}^c + \epsilon_{i,t}, \tag{3}$$

where the subscripts i and t index the firm and time period; δ^0, $\boldsymbol{\delta}^m$, δ^{fin}, and $\boldsymbol{\delta}^c$ are estimated parameters, and:

$\boldsymbol{m}'_{i,t}$ is a vector of reported emissions

$d_{i,t}$ is an indicator variable for financial firms[20]

$\boldsymbol{c}'_{i,t}$ is a vector of additional time-varying, firm-specific and country-specific variables, including property, plant, and equipment

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; but we also look at emission intensities (emissions deflated by sales).[21] In $\boldsymbol{c}'_{i,t}$, we include size; sales; book to market value; and property, plant, and equipment.

[19]The value of physical assets that are not themselves directly harmed by climate change may nevertheless 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.

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

[21]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 (conceptually) 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: Bulgaria, Cyprus, Pakistan, Romania, Slovenia, and Sri Lanka.

These variables in $\boldsymbol{c}'_{i,t}$ can be thought of as control variables with respect to emissions, though property, plant, and equipment is of interest for its own sake. Notably, the inclusion of firm size as a control variable is not merely a matter of convention here: it is called for as a control variable by the findings of Aswani, Raghunandan, and Rajgopal (2022), who find that the apparent pricing of emissions in U.S. equity markets appears to spuriously reflect firm size.

Hypothesis 3 implies that the coefficients, $\boldsymbol{\delta}^m$, on emissions are small or statistically insignificant. Likewise, hypothesis 4 implies that the element of $\boldsymbol{\delta}^c$ corresponding to plant, property, and equipment is small or statistically insignificant. The estimation results 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. We note that scope 3, the broadest gauge of greenhouse gas emissions, is typically (and opaquely) constructed from firm's other non-emission 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.[22]

Column four provides the results of a regression that uses emission intensities instead 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 firms' sensitivities to climate change salience. Again, only the intensity of scope 3 is even mildly significant (and recall that scope 3 data are constructed using firms' time-varying characteristics, not emissions per se). Overall, the results appear to support Hypothesis 3: it appears that returns are sensitive to climate change salience largely irrespective of the level of firms' greenhouse gas emissions. Relatedly, the baseline results are in keeping with Hypothesis 4: property, plant and

[22]We conduct a number of alternative specifications, including separately estimating emerging and developed markets, the first and second halves of the sample, a 5-factor model, a Google 'Topic' search, and a less aggressive winsorization. The insignificance of scope 1 and scope 2 emissions is robust to all of these changes; and scope 3 emissions are marginally significant only for developed markets and insignificant in the others.

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

This table gives the parameter estimates and firm-clustered standard errors from panel regressions of firms' climate change salience betas ($\hat{\beta}^{\kappa}_{i,t}$) on the logs of firm-level greenhouse gas emissions (scope 1, 2, and 3), and plant and equipment (ppe); on an indicator for financial firms (d); on the logs of firm size ($size$), book-to-market ($\frac{b}{m}$), and sales ($sales$); 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	-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

equipment appear largely unrelated to firms' climate change salience betas.[23] 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 link to return sensitivity. Here we find that the marginal contribution of size and book to market is typically positive: Conditional on emissions and the other firm-specific variables, the returns of large firms and the returns of high value firms tend marginally to comove more positively with climate change salience than the returns of other firms.[24] That is, there is some evidence that large firms and value firms exhibit less climate change salience risk. In essence, large firms and value firms typically seem to be better hedges against climate change salience risk.[25]

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

[23]While the property, plant, and equipment result is robust to the alternative winsorization, to the 5-factor model, to separate estimates for emerging and developed markets, and to the first and second halves of the sample (as well as all of the specifications in Table 3), the coefficient, $\boldsymbol{\delta}^c$, on property, plant, and equipment is statistically significant when the innovations are constructed using Google 'Topics'.

[24]Like the previous finding, these findings are robust to the alternative winsorization, to the 5-factor model, to separate estimates for emerging and developed markets, and to the second half of the sample (as well as all of the specifications in Table 3); but they are not robust to the use of Google 'Topics'. Additionally, the size coefficient changes sign in the first half of the sample.

[25]The work of Azar, Duro, Kadach, and Ormazabal (2021) and of Krueger, Sautner, and Starks (2020) may be read as suggesting that the size effect may reflect investor engagement with large firms; and Bansal, Kiku, and Ochoa (2019) find that the returns of high book-to-market assets exhibit a negative temperature elasticity.

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 concerns 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 the exposure of returns to changes in this indicator is priced in international equity markets. Specifically, we find that there is a significant climate change salience beta discount. Put differently: investors earn a meaningful return premium for holding assets with high exposure to climate change salience risk. Our analysis also indicates that climate change salience risk is widespread and not limited to firms with high greenhouse gas emissions or substantial physical plant. This suggests that investors perceive climate change as a broad risk that can impact firms across various sectors and industries.

We also find that the pricing of the exposure is time varying: the climate change salience beta discount is magnified when climate change salience is high. This nonlinearity is in keeping with the broader salience literature, which shows that information plays a greater role in decision making when it is particularly pronounced. Together with that broader literature, our finding suggests that traditional models may benefit from incorporating nonlinear dynamics to more accurately capture the effects of climate change on equity markets.

While the search innovations that we construct align well with known, climate policy events, 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 in 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 opacity and 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. As we show, the measure has empirical purchase: the exposure measured this way appears to be both ubiquitous and priced internationally.

We emphasize that the estimated pricing is a marginal risk: the evidence suggests that climate change salience is currently compensated for in a way that is consistent with it representing an unhedged risk that has not yet been fully rolled into the market. In one sense, that is understandable since in the aggregate, climate change risk must be held. However, this leaves open the question of why climate change risk remains distinct from the market beta, and the question of how long that might continue. We suspect the answers have something to do with how differing views of climate change affect investor behavior–as is suggested by, e.g., Bernstein, Billings, Gustafson, and Lewis (2022) and by Choi, Gao, and Jiang (2020b); and one might expect views to converge over time as uncertainty over climate change becomes resolved. But, evaluating such conjecture is fodder for future work.

We interpret our results as evidence of the currently far-reaching nature of climate change risk. Additional work is needed to explore how it is linked to such things as existing and potential production cost increases, or infrastructure and demand disruptions. That said, the results do not support the proposition that it is merely 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.

References

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea (2020). Temperature shocks and establishment sales. *The Review of Financial Studies 33*(3), 1331–1366.

Ang, A., J. Liu, and K. Schwarz (2020). Using stocks or portfolios in tests of factor models. *Journal of Financial and Quantitative Analysis 55*(3), 709–750.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht (2022). Climate change concerns and the performance of green vs. brown stocks. *Management Science*.

Aswani, J., A. Raghunandan, and S. Rajgopal (2022). Are carbon emissions associated with stock returns? *Columbia Business School Research Paper*.

Azar, J., M. Duro, I. Kadach, and G. Ormazabal (2021). The big three and corporate carbon emissions around the world. *Journal of Financial Economics 142*(2), 674–696.

Bansal, R., D. Kiku, and M. Ochoa (2019). Climate change risk. *Federal Reserve Bank of San Francisco Working Paper*.

Bansal, R., M. Ochoa, and D. Kiku (2017). Climate change and growth risks. Technical report, National Bureau of Economic Research.

Barnett, M. (2023). Climate change and uncertainty: An asset pricing perspective. *Management Science*.

Basel Committee on Banking Supervision (2021). Climate-related risk drivers and their transmission channels.

Ben-Rephael, A., B. I. Carlin, Z. Da, and R. D. Israelsen (2021). Information consumption and asset pricing. *The Journal of Finance 76*(1), 357–394.

Bernstein, A., S. B. Billings, M. T. Gustafson, and R. Lewis (2022). Partisan residential sorting on climate change risk. *Journal of Financial Economics 146*(3), 989–1015.

Bohn, J. (2020). Resilience-adjusted valuation for commercial properties: Quantifying resilience to climate-driven catastrophe event risk. Working paper, One Concern.

Bolton, P. and M. Kacperczyk (2021, February). Global pricing of carbon-transition risk. Working Paper 28510, National Bureau of Economic Research.

Bordalo, P., N. Gennaioli, and A. Shleifer (2013). Salience and asset prices. *American Economic Review 103*(3), 623–28.

Bordalo, P., N. Gennaioli, and A. Shleifer (2022). Salience. *Annual Review of Economics 14*, 521–544.

Brogger, B. and A. Kronies (2021, April). Skills and sentiment in sustainable investing. Working paper, Copenhagen Business School.

Cai, Y., C. H. Pan, and M. Statman (2016). Why do countries matter so much in corporate social performance? *Journal of Corporate Finance 41*, 591–609.

Campiglio, E., L. Daumas, P. Monnin, and A. von Jagow (2022). Climate-related risks in financial assets. *Journal of Economic Surveys*.

Choi, D., Z. Gao, and W. Jiang (2020a). Attention to global warming. *The Review of Financial Studies 33*(3), 1112–1145.

Choi, D., Z. Gao, and W. Jiang (2020b). Attention to global warming. *The Review of Financial Studies 33*(3), 1112–1145.

Custodio, C., M. A. Ferreira, E. Garcia-Appendini, and A. Lam (2022). Economic impact of climate change. *Nova SBE Working Paper Series* (645).

Dagum, E. (1980). The Xll arima seasonal adjustment method. Technical report, Statistics Canada.

Dagum, E. B. and S. Bianconcini (2016). *Seasonal adjustment methods and real time trend-cycle estimation*. Springer.

Dell, M., B. F. Jones, and B. A. Olken (2012, July). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Deryugina, T. and S. M. Hsiang (2014). Does the environment still matter? daily temperature and income in the united states. Technical report, National Bureau of Economic Research.

Donadelli, M., P. Grüning, M. Jüppner, and R. Kizys (2021). Global temperature, r&d expenditure, and growth. *Energy Economics 104*, 105608.

Ehlers, T., F. Packer, and K. de Greiff (2022). The pricing of carbon risk in syndicated loans: which risks are priced and why? *Journal of Banking & Finance 136*, 106180.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel (2020, February). Hedging Climate Change News. *The Review of Financial Studies 33*(3), 1184–1216.

French, K. R. (2012). Kenneth r. french-data library. *Tuck-MBA program web server. http://mba. tuck. dartmouth. edu/pages/faculty/ken. french/data_library. html (accessed September 20, 2021)*.

Giglio, S., B. T. Kelly, and J. Stroebel (2020, December). Climate Finance. NBER Working Papers 28226, National Bureau of Economic Research, Inc.

Gorgen, M., A. Jacob, M. Nerlinger, R. Riordan, M. Rohleder, and M. Wilkens (2020). Carbon risk. *Available at SSRN 2930897*.

Harvey, C. R. and Y. Liu (2021). Lucky factors. *Journal of Financial Economics 141*(2), 413–435.

Hong, H., F. W. Li, and J. Xu (2019). Climate risks and market efficiency. *Journal of econometrics 208*(1), 265–281.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the caribbean and central america. *Proceedings of the National Academy of sciences 107*(35), 15367–15372.

Huynh, T. D. and Y. Xia (2021). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis 56*(6), 1985–2009.

Ilhan, E., Z. Sautner, and G. Vilkov (2021). Carbon tail risk. *The Review of Financial Studies 34*(3), 1540–1571.

Ince, O. S. and R. B. Porter (2006). Individual equity return data from thomson datastream: Handle with care! *Journal of Financial Research 29*(4), 463–479.

Krueger, P., Z. Sautner, and L. T. Starks (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies 33*(3), 1067–1111.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, 867–887.

Parr, T. and K. J. Friston (2019). Attention or salience? *Current opinion in psychology 29*, 1–5.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2021). Sustainable investing in equilibrium. *Journal of Financial Economics 142*(2), 550–571.

Refinitiv (2021). Refinitiv esg carbon data and estimate models. `https://www.refinitiv.com/content/dam/marketing/en_us/documents/fact-sheets/esg-carbon-data-estimate-models-fact-sheet.pdf`. Accessed on 2022-09-10.

Santi, C. (2020). Investors' climate sentiment and financial markets. *Available at SSRN 3697581*.

Sautner, Z., L. van Lent, G. Vilkov, and R. Zhang (Forthcoming). Firm-level climate change exposure. *Journal of Finance*.

Semieniuk, G., E. Campiglio, J.-F. Mercure, U. Volz, and N. R. Edwards (2021). Low-carbon transition risks for finance. *Wiley Interdisciplinary Reviews: Climate Change 12*(1), e678.

U.S. Census Bureau (2020, July). X-13arima-seats reference manual. Technical report, Washington, DC.

Venturini, A. (2022). Climate change, risk factors and stock returns: A review of the literature. *International Review of Financial Analysis 79*, 101934.

Zhang, S. (2023). Carbon returns across the globe. *Available at SSRN 4378464*.

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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)