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Corporate Climate Risk: Measurements and Responses

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This paper conducts a textual analysis of earnings call transcripts to quantify climate risk exposure at the firm level. We construct dictionaries that measure physical and transition climate risks separately and identify firms that proactively respond to climate risks. Our validation analysis shows that our measures capture firm-level variations in respective climate risk exposure. Firms facing high transition risk, especially those that do not proactively respond, have been valued at a discount in recent years as aggregate investor attention to climate-related issues has been increasing. We document differences in how firms respond through investment, green innovation, and employment when facing high climate risk exposure. (*JEL* G12, G31, G32, Q54)

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Climate change poses severe challenges to businesses and society at large. Scientists predict that climate change will lead to increased incidence and severity of both chronic and acute climate and weather events, leading to unprecedented risks and disruptions that will affect corporations, the financial system, and the aggregate economy (Litterman et al. 2020). Following the pioneering work of Nordhaus (1977), many economists have studied interactions between climate change and the economy (e.g., Golosov et al. 2014; Nordhaus 2019); however, climate finance topics, such as how to assess, mitigate, and hedge climate risk across firms and asset classes, have received limited attention until recently. A major challenge to advancing this research agenda is the lack of credible measures of climate risk exposure across asset classes, in particular measures of equity assets (Hong, Li, and Xu 2019; Engle et al. 2020; Giglio, Kelly, and Stroebel 2021).

Several factors contribute to the above-mentioned lack of measures of firm-level climate risk exposure. First, in spite of stricter mandates imposed by regulators and investor demand, firms remain reluctant to disclose their climate risk exposure. For example, the most-common carbon emissions data have been available for only a limited number of traditional sectors (e.g., manufacturing and utilities), and firms often omit the indirect costs of carbon in supply chains (Shapiro 2021). Second, climate change is ever evolving, and it remains unclear how the climate will eventually change and affect firms, thus introducing significant uncertainty in government and corporate decision-making (Barnett, Brock, and Hansen 2020). Third, while historical emissions data are needed to assess a firm's past business models, data capturing forward-looking views will be more useful in evaluating the firm's climate exposure and adaptability in the transition toward an environmentally sustainable economy, an important goal for climate finance research (Giglio, Kelly, and Stroebel 2021).

In this paper, we fill this gap by quantifying, for the first time, climate risk exposure at the individual firm level, using earnings call transcript data for U.S. public companies. We use textual information from earnings calls in our analysis for several reasons. First, the vast majority of U.S. public firms hold regular earnings conference calls with their analysts and investors to discuss performance and factors related to performance, and, a point that is critical to this study, earnings calls contain detailed discussions with valuable and insightful information about the climate risks a firm faces beyond those that stem from public sources.[1] Second, unlike other firms' disclosures, such as regulatory filings that are highly scripted and may lack informativeness and timeliness (e.g., Brown and Tucker 2011), the content contained in quarterly earnings transcripts is timelier and could vary significantly from quarter to

[1] For instance, a recent Standard & Poor's (S&P) Ratings report reveals that the terms "climate" and "weather" combined were among the most-frequently discussed topics in earnings calls among executives in S&P 500 companies—even more common than "Trump," "the dollar," "oil," and "recession" (S&P Global Ratings 2018).

quarter, allowing us to measure climate risk more accurately in real time. Third, discussions in earnings calls are inherently weighted by importance as an earnings conference call is a relatively short meeting where various parties can discuss only what they view as material factors—a feature that is key to measuring the importance of climate risks to firms. Finally, earnings calls also include discussions on how firms respond to climate risks, which enables us to capture firms' proactiveness in addressing climate issues—a unique and important innovation in our study.

We measure the climate risk faced by a given firm at a given time based on the share of earnings calls conversations that are centered on physical climate risk and transition risk, respectively. Our approach is similar to those used by prior studies (e.g., Baker, Bloom, and Davis 2016; Hassan et al. 2019, 2023, 2020). More importantly, we also measure whether or not the company's attitude or response is proactive regarding the rise of climate risk by analyzing the verbs used in climate risk discussions. To do so, we overcome several challenges in applying standard textual analysis methods. The first is that any such analysis must account for multiple categories of climate risk (e.g., Giglio, Kelly, and Stroebel 2021; Stroebel and Wurgler 2021), which can be broadly classified as (a) physical climate risks, which are related to the physical impacts of acute climate events (e.g., hurricanes and wildfires) or chronic conditions (e.g., abnormal winter) and (b) transition risks. Given the multifaceted nature of climate risk, it is challenging to create a single measure that can capture all aspects of a firm's climate risk exposure. Instead, we measure distinct climate risks separately using a dictionary-based approach.

The second challenge faced when measuring climate risk is that a well-constructed dictionary of climate-related keywords is not readily available in the literature, and a significant number of false positive and false negative cases arise if we apply a set of commonly known weather or climate keywords to a large set of transcripts. We adopt the dictionary approach over the machine learning (ML) method, with careful human supervision to minimize the occurrence of false positives and negatives. This approach allows researchers to make careful and deliberate judgment calls when classifying text based on complex concepts, such as climate risks, while preserving transparency and replicability.[2] Through careful selection over many iterations, we construct three comprehensive dictionaries consisting of over 1,600 climate keywords that are not directly related to either energy costs or general environmental risks.

[2] Humans are better at correctly teasing out the nuances of how the language of climate issues is used in a particular context (e.g., earnings calls). Our choice builds on the premise that no algorithm understands the context of human conversations better than human beings. See, for example, studies based on the most advanced conversational AI algorithms, such as Google Meena (Adiwardana et al. 2020) and Facebook BlenderBot (Roller et al. 2020; Xu, Szlam, and Weston 2021). See Section 3.1 for additional discussion of the advantages of our approach of relying on human-constructed dictionaries over ML methods.

To construct climate risk measures, we require the respective physical climate risk keywords to appear in the vicinity (± 1 sentence) of at least one risk synonym to ensure that firms are indeed exposed to uncertainty related to climate-related events (as in Hassan et al. 2019).[3] Transition risk differs in that it may not materialize in the short term and is thus measured based on discussions of keywords in our transition risk dictionary without having to appear near a risk synonym. Our approach produces three climate risk measures for each firm at quarterly frequency. In addition, using a list of verbs that capture firms' proactive attitudes when discussing transition risk, we decompose our transition risk measure into proactive and nonproactive components.

After establishing our measures, we conduct a battery of analyses to validate that they indeed capture a firm's exposure to climate risks. First, we examine the list of most frequently discussed keywords in each of the measures and find that the patterns are consistent with intuitions. Second, we examine the time-series patterns as well as industry and firm-level variations in the climate risk measures. While relative industry rankings vary across different types of climate risks, they all exhibit significant variations that are consistent with industry-level exposure to climate risks. Third, in our validation analysis using various external benchmarks, we further demonstrate the validity of our climate risk measures. Our analysis shows that the presence of natural disasters in a local area is associated with a significant increase in both acute and chronic climate risk measures for firms headquartered in that area over the subsequent quarter.

Validating the transition risk measure, we examine its correlations with two sets of existing external benchmarks: (1) firm-level MSCI Climate Change Index (CCI) and (2) industry-level carbon dioxide (CO_2) intensity constructed by Shapiro (2021) and firm-level CO_2 intensity based on the U.S. Environmental Protection Agency's (EPA) emissions data. First, we find that our transition risk measure is positively and significantly correlated with MSCI CCI. Second, we find a strong and positive correlation between the average transition risk and CO_2 intensity as measured by Shapiro (2021) at the NAICS six-digit level for the manufacturing sector. Finally, analyzing firm-level emissions data, we find that our transition risk measure—albeit only its nonproactive component—is positively correlated with a firm's CO_2 intensity in subsequent years. This relationship is significant in only one direction, suggesting that firms that face higher transition risk but proactively respond to such risks are indeed more active and effective in reducing their carbon footprints.

[3] Note that mentioning a well-publicized weather/climate event alone, without explicitly mapping onto a firm's risk profile, could reflect attention or shifting blame, but these factors do not contribute to our physical climate risk measures.

While maintaining high correlation when overlapping, our newly developed measures provide improved coverage and quantification of firm-level exposure to climate risk compared to existing measures. Compared with ESG ratings, our measures are available at the quarterly level for 4,719 public firms over a long period of time, and are less prone to the selection bias that occurs commonly with ESG data. Unlike the EPA's plant-level CO_2 emissions data, which are limited only to firms that operate in the manufacturing, mining, and trade sectors, our measures cover all sectors where earnings call data are available, thus offering a comprehensive assessment of climate risk exposure across the economy. Of all public firms with earnings call data available, about 61.8% (2,918 firms) show at least one positive value in the transition risk measure, which corresponds to 34.7% of the firm-years that have positive values in transition risk. Even when considering the years when MSCI CCI data become available, our measure, on average, provides coverage of transition risk to an additional 952 firms with nonmissing values and 480 firms with positive values. Furthermore, we show in a variance decomposition analysis that the majority of variations in our three climate risk measures occur at the firm level, capturing not only cross-firm but also within-firm variations in climate risk exposure.

Having established the validity of our measures, we next study one of the most important issues in the climate finance literature—the extent to which climate risk, especially transition risk, is priced in capital markets (e.g., Bolton and Kacperczyk 2021a; Giglio, Kelly, and Stroebel 2021). We first relate the firm-level transition risk measure to a firm's market valuation measured by Tobin's q, and find that our transition risk measure is negatively correlated with a firm's Tobin's q, suggesting that the firm's transition risk exposure is priced in equity markets. Second, we find that this relationship has only become significant since 2010, likely because of rising aggregate investor attention to climate risk (e.g., Choi, Gao, and Jiang 2020; Engle et al. 2020), as well as climate-related initiatives and regulations implemented around this time.[4] Third, when analyzing the relative effects of the proactive and nonproactive components of the transition risk measure, we find that only the nonproactive component has a significantly negative relation with Tobin's q, suggesting that equity markets appear to discount only firms that do not actively manage their transition risk, while not penalizing those that address risk proactively. Importantly, these findings remain robust even after controlling for firm fixed effects, providing additional support for the idea that changes in climate risk discussion correlate with changes in Tobin's q.

Further analysis shows that our measures capture unique information that is useful in studying the pricing effects of climate risk based on horse-race regressions with various alternative measures. In particular, we consider (1) a transition climate risk measure constructed with the same dictionary but

[4] For instance, in January 2010, the SEC issued its first interpretation of how existing disclosure requirements apply to climate-related issues for public firms.

using textual information from firms' 10-K/10-Q filings, (2) a transition risk measure constructed based on climate-related company news from Dow Jones Newswires, (3) MSCI CCI or ESG ratings, and (4) measures constructed by Sautner et al. (2023) using different climate dictionaries and methods. In all of these tests, the coefficients for our transition risk measure and its nonproactive component remain negative and significant at the 1% level, confirming the unique value added by both the earnings calls data and our construction method. In summary, our transition risk measure generates new and valuable information that is not already available in other public sources and also provides comprehensive coverage over a large sample of public firms from 2002 onward.

In the last set of analysis, we explore how firms respond, in terms of investments, innovation, and employment, to transition risk exposure. Our results show that firms' attitudes toward climate issues—their proactiveness—matter significantly in how they respond to climate risk along these dimensions. First, we find that, while there is no significant relation between transition risk and investment as measured by total capital expenditures (CapEx) in nonproactive firms, firms that proactively respond to climate risk tend to increase their investment subsequently. Second, we find a negative relation between transition risk and subsequent R&D expenditures, a finding that is driven entirely by nonproactive firms. In contrast, proactive firms innovate more actively by producing more green patents in subsequent years. Given this relationship, we conduct further analysis to explore the attributes of proactive firms and their potential differential impact on firm valuation. We find some evidence that the equity markets tend to value proactive responses to transition risk from green patenting firms more than nongreen proactive responses. Finally, our employment analysis shows that firms that do not proactively respond reduce employment following a rise in transition risk, while the firms that proactively respond to transition risk do not reduce employment subsequently. Taken together, our measures are useful not only for understanding the pricing of transition risk in capital markets, but also for predicting real outcomes as firms proactively respond to changes in climate risk.

1. Related Literature

Our paper contributes to the literature by constructing firm-level climate risk measures. Properly measuring climate risk exposure across assets is critical to any study of climate risk and its impact on the underlying assets. A growing body of literature studies the effects of climate change on real estate assets and housing markets using properties' exposure to physical climate risk factors, such as projected sea-level rise (SLR), flooding, and hurricanes (e.g., Bernstein, Gustafson, and Lewis 2019; Baldauf, Garlappi, and Yannelis 2020; Goldsmith-Pinkham et al. 2023; Keys and Mulder 2020; Giglio et al.

2021).[5] With regard to equity assets, however, the literature still lacks a set of measures with which to measure firms' exposure to climate risks systematically, and researchers must use alternative measures, for instance, CO_2 emissions data or ESG ratings (e.g., Engle et al. 2020)[6] despite concerns about their coverage and reliability (Stanny 2018; Berg, Koelbel, and Rigobon 2022). As a result, Giglio, Kelly, and Stroebel (2021) conclude in their survey that there is "substantial scope for improvements of the measures of climate risk exposure, in particular for equity assets." Our paper represents valuable progress toward developing new ways to quantify firms' climate risk exposure.

More broadly, our paper adds to the climate finance literature in several ways. First, our measures can be used to study how capital markets price climate risk. Several studies examine whether equity markets price risks related to long-run temperature shifts, drought, sea-level rise, or carbon emissions (e.g., Hong, Li, and Xu 2019; Bolton and Kacperczyk 2021a,b; Hsu, Li, and Tsou 2023; Ilhan, Sautner, and Vilkov 2021). Other evidence points to climate risks affecting fixed-income and real estate markets.[7] Different from all these studies, we show, using our novel firm-level climate risk measures, that climate risk is priced in equity markets, especially following a rise in aggregate investor attention in recent years. We also document that firms' proactiveness attenuates the discounting of high climate risk in equity markets. Second, our measures could help investors implement effective hedging strategies, which is of great importance considering that many effects of climate change will manifest far into the future and neither financial derivatives nor insurance markets is available to directly hedge those long-horizon risks. Engle et al. (2020) propose an approach to dynamically hedging climate risk using historical responses of individual stocks to their "Climate News Index." Our firm-level climate risk measures, along with their proactive component, also can be used by investors to assess, construct, and hedge portfolio exposure to aggregate climate risk in accordance with their risk tolerance.

Our study is closely related to a contemporaneous paper by Sautner et al. (2023). While both papers propose firm-level measures of climate exposure using earnings call data, there are major differences in both the methodology and the scope of the economic questions explored. Unlike Sautner et al.

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5 Relatedly, Engle et al. (2020) and Giglio et al. (2021) construct novel measures of market-level attention paid to climate risk by analyzing textual descriptions of climate keywords in newspaper articles and property listings, respectively.

6 Emissions data can be obtained from the EPA or the Carbon Disclosure Project (CDP). The former are mandatory, as explained in Section 2.4, while the latter involve voluntary disclosure of emissions by firms. See, for example, Bolton and Kacperczyk (2021a,b), Choi, Gao, and Jiang (2020), and Ramadorai and Zeni (2021).

7 For studies of climate risk and fixed-income markets, see, among others, Painter (2020), Goldsmith-Pinkham et al. (2023), and Huynh and Xia (2021). For studies of climate risk and real estate markets, see, among others, Bakkensen and Barrage (2018), Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020), Murfin and Spiegel (2020), and Giglio et al. (2021).

(2023), who use an ML algorithm, we construct climate-related dictionaries manually through careful human supervision and iterative testing. Like that of Loughran and McDonald (2011) and Baker, Bloom, and Davis (2016), our approach is more transparent and less sensitive to initial inputs and parameter choices than ML algorithms, providing us with what we consider as a necessary and effective tool given the complexity of climate issues. More importantly, the scope of the economic questions we explore in our study is quite different from theirs. While they focus primarily on economic factors that correlate with firms' climate change exposure, we explore whether transition risk and, especially, firms' proactiveness in addressing it, are priced in equity markets as well as how firms respond to transition risk. Our paper is unique as the first in the literature to measure firms' proactiveness in addressing climate issues. One of our key contributions lies in documenting that proactive attitudes are priced in equity markets and that proactive firms respond, in terms of investment, green innovation, and employment, differently to rising transition risk.

2. Data

2.1 Earnings calls

To measure firm-level exposure to climate risk, we use as our primary data source transcripts of earnings calls involving all U.S. public firms obtained from Thomson Reuters' StreetEvents database. These transcripts record discussions between a public company's management team, industry analysts, investors, and the media regarding the company's corporate strategy, operating conditions, and financial performance for a given quarter. The same data are used in several other papers, for example, Hassan et al. (2019), who study corporate exposure to political risk, and Li et al. (2021), who create novel measures of corporate culture. Firms typically hold one conference call in each fiscal quarter following their earnings releases. Thus, we conduct most of our analysis at the firm-quarter level. One important benefit, among others, of using the earnings calls data is that, because the data are available for almost all public firms, we can construct climate risk measures that place all public firms on a level playing field, as opposed to using ESG scores only or other measures that are available for only a small subset of firms that may be subject to selection bias.[8]

[8] We note that several caveats apply to the use of the earnings calls data. First, the data are available only for public firms, thus missing a large number of private firms. This may introduce bias in estimating the effect of high climate risk on firms' responses if high-emitting firms choose to operate as private firms (Gilje and Taillard 2016). This factor should not, however, affect our estimates of the pricing effect of high climate risk because Tobin's q is a market valuation measure that is available only for public firms. Second, like any voluntary source of disclosure data, earnings calls are not completely immune to how or when management chooses to discuss climate-related topics. We believe that such strategic factors are less salient in earnings conference calls than other disclosure data, as analysts could ask climate-related questions even if management chooses not to disclose any information. More importantly, we carry out several additional analyses that we discuss in Section 7.5 to alleviate the concern that our references will be materially changed by strategic disclosure.

We use all earnings call data from January 2002 through the first half of 2018 in our analysis, and extract the texts of entire conference calls from the raw XML transcript files using Python, which includes both presentations by management and subsequent Q&A sessions. We also extract firm identifiers (e.g., firm names, tickers, CUSIP numbers) and earnings call information (e.g., date and time) from the transcript files.

2.2 Firm-level financial data

We obtain firms' financial data from Compustat. We use Tobin's q as the main measure of a firm's market valuation to examine whether the stock market has priced the climate risks captured by our measures. To study a firm's responses to climate risk, we consider CapEx, R&D, and employment as outcomes. Other firm-level attributes, such as total assets, property, plant, and equipment (PPE), and the book leverage ratio, are used as control variables. All the firm-level attributes are available at the quarterly level, except for employment data, which are available only annually. Information about firms' stocks is obtained from the Center for Research in Security Prices (CRSP).

We match the earnings call data with other firm-level data using firm identifiers and apply several filters. First, because many financial firms, especially insurance companies, sell insurance products to others to hedge climate- or disaster-related risks, we exclude financial firms (North American Industry Classification System or NAICS 52) from our main analysis. Second, we exclude firms whose headquarters are located outside the continental United States. Our sample includes 4,719 unique firms and 139,959 firm–quarter observations. Table 1 presents summary statistics for Tobin's q, CapEx, R&D expenditures, Property, Plant, and Equipment (PPE), book leverage, return on assets (ROA), employment, and total assets. CapEx, R&D expenditures, and PPE are all scaled by a firm's total assets in the preceding quarter.[9]

2.3 Additional textual data

We also use textual information from firms' regulatory filings, in particular 10-K and 10-Q filings, as alternative data sources to construct our climate risk measures. We focus on the two most relevant sections in 10-K/10-Q filings: (1) management discussion and analysis (MD&A) and (2) Item 1A "Risk Factors." MD&A section contains management discussions of firms' performance, risks, and future plans. The risk factors (RF) section provides information about the risk factors a firm identifies that might influence the company or its equity return. MD&A section is available for our entire sample period, from 2002 through 2018, while RF section is available only from 2006 onward following the implementation of Regulation S-K Item 105.

[9] Table A.1 in the appendix reports the descriptions and sources of the variables we use in our analysis.

Table 1
Summary statistics

Variable	N	Mean	SD	Min	P25	P50	P75	Max
Firm-level measures constructed from earnings calls								
Acute Climate Risk	139,959	0.06	0.61	0.00	0.00	0.00	0.00	11.75
Chronic Climate Risk	139,959	0.20	1.26	0.00	0.00	0.00	0.00	17.72
Transition Climate Risk	139,959	3.38	13.17	0.00	0.00	0.00	0.00	186.59
Transition Risk/Proactive	139,959	0.32	1.70	0.00	0.00	0.00	0.00	22.40
Transition Risk/Nonproactive	139,959	3.05	12.10	0.00	0.00	0.00	0.00	174.03
Energy Price Exposure	139,959	0.00	0.01	0.00	0.00	0.00	0.00	0.07
Action Index	139,959	0.02	0.01	0.01	0.02	0.02	0.02	0.04
Other firm-level data								
Tobin's q	130,450	2.03	1.50	0.46	1.16	1.56	2.32	14.82
CapEx	136,121	2.89	3.73	0.00	0.65	1.60	3.54	21.03
R&D	138,169	1.35	2.62	0.00	0.00	0.00	1.72	14.23
log(Asset)	138,208	6.84	1.92	−1.62	5.54	6.83	8.13	13.65
PPE	134,158	0.25	0.24	0.00	0.07	0.16	0.37	0.89
Book Leverage	130,244	0.24	0.23	0.00	0.03	0.21	0.37	1.01
log(No_Analysts)	139,959	1.83	0.89	0.00	1.39	1.95	2.48	3.93
Institution %	135,383	0.67	0.27	0.00	0.51	0.75	0.89	1.00
Institution HHI	134,985	0.10	0.13	0.01	0.04	0.05	0.09	1.00
ROA	136,881	0.06	0.23	−0.96	0.03	0.11	0.17	0.46
log(Employment) (annual)	38,917	1.45	1.29	0.00	0.34	1.12	2.24	7.74
External data								
Disaster dummy	139,959	0.05	0.22	0.00	0.00	0.00	0.00	1.00
CO_2 Intensity (annual)	2,774	4.12	7.97	0.00	0.23	0.97	4.08	52.93
I(Green patents) (annual)	39,505	0.08	0.27	0.00	0.00	0.00	0.00	1.00
Green patents ratio (annual)	12,664	0.04	0.14	0.00	0.00	0.00	0.00	1.00
MSCI CCI	17,304	56.44	66.62	0.00	0.00	33.00	94.90	594.00
RepRisk Environmental Score	40,925	2.15	4.89	0.00	0.00	0.00	0.00	31.51
Refinitiv Environmental Score	49,351	47.39	21.70	6.51	29.97	43.20	64.19	97.82
Firm-level measures constructed from alternative data								
Transition Risk MDA	108,714	2.82	8.54	0.00	0.00	0.00	1.39	95.20
Transition Risk RF	89,999	2.16	8.96	0.00	0.00	0.00	0.00	108.06
Transition Risk News	139,959	0.01	0.06	0.00	0.00	0.00	0.00	0.67

This table reports the summary statistics of all variables used in the regression analysis. All variables are at the firm-quarter level, except that *log(Employment)*, *CO_2 Intensity* and green-patent-related variables are at the firm-year level. All the climate risk variables, including the acute, chronic, and transition climate risks are explained in Section 2 and the statistics are summarized after winsorization, but before standardization. Table A.1 in the appendix contains detailed definitions of all variables.

We use publicly available company news as another source of textual data that we can use to construct firms' climate risk measures. We obtain such data from RavenPack, which provides a comprehensive sample of firm-specific news stories from Dow Jones Newswires.[10] To identify news stories about specific firms, we use relevance scores from RavenPack; these scores range from 0 to 100, capturing how closely the underlying news is related to a particular company. We identify relevant news stories for a given firm by requiring the relevance score to be 75 or above, as recommended by RavenPack.[11] We also exclude repeated news using the event novelty score provided by RavenPack so that our data capture only fresh news about a

10 News include *The Wall Street Journal*, *Barron's*, *MarketWatch*, all major PR newswires and regulatory feeds. This data have been frequently used in the literature (e.g., Kelley and Tetlock 2017; Jiang, Li, and Wang 2021).

11 We also experimented with a relevance score of 50 to retrieve RavenPack data, and our results are robust to this variation.

company. Finally, we use the same transition risk dictionary to determine whether a specific news story about a given firm is related to transition risk.

2.4 Other external firm data

To analyze the firm-level response to climate risk through green innovation, we obtain patent data from the Global Corporate Patent data set.[12] We follow Cohen, Gurun, and Nguyen (2020) and Haščič and Migotto (2015) and classify green patents as those containing environment-related technologies, such as emissions abatement technologies, renewable energy, and energy storage. The patent data are available for U.S. firms from 2002 through 2017. We calculate the number of green patents produced by each firm in a given year and define two measures to capture the intensive and extensive margins of firms' green innovation activities: (1) an indicator that equals one if a firm has been granted at least one green patent in a given year, and zero otherwise and (2) the ratio of green patents to the total number of patents granted to the firm in that year. The first measure is available for all public firms, while the second measure is available only for firms that had at least one patent granted in a given year.

We obtain several external data sets to validate the new climate risk measures. The first data set contains natural disaster data from the Spatial Hazard Events and Losses Database (SHELDUS) that has been used in the economics literature (e.g., Barrot and Sauvagnat 2016) to examine the effects of natural disasters. These data record the counties, beginning/end dates, event names, main causes of damage (e.g., flooding, hurricanes), and the estimated economic losses. We match these data with our sample using firms' headquarters locations, and we use the natural disasters as an external benchmark for validating our physical risk measures.

Our second external benchmark comprises several external ESG index or ratings. These scores measure how well a company manages ESG risks and opportunities based on information published in news coverage and/or corporate disclosures, such as sustainability reports and corporate websites, surveys, and information provided by other stakeholders, such as regulatory agencies and industry associations (e.g., Berg, Koelbel, and Rigobon 2022; Christensen, Serafeim, and Sikochi 2021). We obtain ratings from three sources (MSCI, RepRisk, and Refinitiv), and these ratings include overall scores as well as three individual scores (environmental, social, and governance) at the monthly or annual level. We use the MSCI CCI—a climate change theme score that is directly comparable to our climate risk exposure measures—as the main external benchmark. We note that the environmental components of ESG ratings provided by rating agencies focus on environmental risk that is entangled with, but different from, climate risk.

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[12] This data set is available at https://patents.darden.virginia.edu/. Bena et al. (2017) use the data to study the effects of foreign institutional ownership on innovation output.

Nevertheless, we conduct supplemental validation exercises using the RepRisk or Refinitiv Environmental Scores.[13]

Our third external benchmark consists of CO_2 emissions data from the EPA's Greenhouse Gas Reporting Program (GHGRP) as an additional benchmark for our transition risk measure. Since October 2009, the GHGRP program has mandated that sources that emit 25,000 metric tons or more of CO_2 greenhouse gases per year must report their emissions, and the data are made publicly available on an annual basis starting in 2010 at the plant level; and these data include plant identity, geographic location, parent company, industry (NAICS), and greenhouse gas emissions. Following Bartram, Hou, and Kim (2021), we obtain plant-level emissions data from the EPA and match them with firm-level data from Compustat based on the names of parent companies.

3. Measuring Climate Risk at the Firm Level

3.1 Constructing climate dictionaries

We follow the recent literature that exploits textual information in earnings call data to identify risks (e.g., Hassan et al. 2019, 2023, 2020) to construct our firm-level climate risk measures. We must overcome several challenges in applying the textual analysis method to the construction of climate risk measures.

First, as pointed out by Giglio, Kelly, and Stroebel (2021), when studying climate risk and its impact on underlying assets, it is important to note the several categories of climate risks and that these distinct risks often do not materialize at the same time. Broadly speaking, climate-related risks can be classified into two major categories: (1) physical risks, which are related to the physical impacts of climate events, and are either acute (e.g., droughts, floods, extreme precipitation and wildfires) or chronic (e.g., rising temperatures and an accelerating loss of biodiversity), and (2) transition risks, which are caused by not responding to climate change and improving how businesses operate as society moves toward adopting sustainable practices (i.e., low-carbon manufacturing). Transition risks are primarily influenced by policies and regulations and by societal expectations and market pressure. Given the multifaceted nature of climate risk, it is challenging to create a single measure that captures all aspects of a firm's climate risk exposure. Instead, using a dictionary-based approach, we measure three climate-related risks separately: (1) acute physical risk, (2) chronic physical risk, and (3) transition risk. Given the complexity and multifaceted nature of climate issues and the importance of generating replicable results, we believe, for several reasons, that the dictionary approach is a better choice in this context than ML methods. First, ML methods

13 RepRisk, as one of the few ESG ratings not subject to green-washing bias, relies entirely on *negative* news coverage by *external* sources (Berg, Koelbel, and Rigobon (2022)). It has been widely used in the literature (e.g., Li and Wu 2020; Godfrey et al. 2020; Bansal, Wu, and Yaron 2021; Houston and Shan 2022).

are not as transparent as the dictionary approach because many ML algorithms function as black-box models. Second, ML methods are sensitive to initial inputs and parameter choices. Third, the accuracy of ML predictions depends heavily on constructing a large, representative training data set that is not readily available in the context of complex and multifaceted climate issues.

Second, unlike using preexisting training libraries (as in, e.g., political or accounting textbooks), developing climate-related keywords requires considerable human effort. We detect two important issues once we apply a set of commonly known weather or climate keywords to a large set of transcripts. First, a significant number of false positive cases will arise in which keywords are used to describe issues that are entirely unrelated to the climate (e.g., "business climate," "public cloud," "economic storm"). A second issue is that weather and climate irregularities are commonly expressed using combinations of contrasting keywords (e.g., "warm winter," "unseasonably cold," "cool summer"). If we rely on a dictionary that consists entirely of unigrams, it is unlikely that we can include unigrams, such as "winter" or "warm," thus generating many false negatives. We address these issues by manually constructing a hybrid dictionary consisting of both unigrams and bigrams (adjacent two-word combinations) to reduce both false positives and false negatives.

Specifically, our method builds on the premise that no algorithm understands the context of a human conversation better than human beings do.[14] We start our dictionaries with a list of unigrams that we extract from the following sources: (a) disaster "incident-type" indications in the Disaster Declarations Summary of Federal Emergency Management Agency (FEMA), (b) Wikipedia's list of severe weather phenomena,[15] and (c) additional seed words that we added manually, namely, "temperature," "cold," "unseasonable," and so on. We use this list to obtain all bigrams that contain at least one of the unigrams from the entire sample of earnings call transcripts. We then manually screen, for each unigram, the top-500 associated bigrams. If the top-500 associated bigrams are unambiguously used in the context of climate-related conversations, we then include the corresponding unigrams in the unigram dictionary. If not, we include the top-500 associated bigrams in the bigram library pending further screening. To reduce the incidence of false negatives, we supplement the bigram library with climate-related bigrams extracted from additional sources: (a) white papers and reports on climate issues mentioned by Engle et al. (2020), (b) news articles posted by The Weather Channel, and (c) an undergraduate textbook on meteorology (Ahrens 2008). Lastly, we screen the library through many iterations to eliminate false positives and include false negatives.

14 See, for example, studies based on the most advanced conversational AI algorithm, such as Google Meena (Adiwardana et al. 2020) and Facebook BlenderBot (Roller et al. 2020; Xu, Szlam, and Weston 2021).

15 See https://en.wikipedia.org/wiki/List_of_severe_weather_phenomena.

We distinguish between climate risk and other risks in building our dictionaries. First, companies may discuss their climate topics that are related to changes in energy prices, but the latter not exclusively related to climate risk. To ensure that our climate risk measures are not driven by energy prices, our climate dictionaries do not contain any keywords related to energy prices or costs.[16] Instead, we construct a firm-specific, time-varying energy-price exposure index and include it as a control variable in our main analysis. Furthermore, companies' environmental responsibility and greenhouse gas emissions efforts are likely correlated, but not equivalent. We thus remove any keywords on general environmental risk (e.g., air pollution, environmental issues, EPA, sulfur dioxide) from the climate dictionaries.

Our final dictionaries consist of 37 unigrams and 1,649 bigrams: the acute physical risk dictionary contains 21 unigrams and 350 bigrams; the chronic physical risk dictionary contains 16 unigrams and 977 bigrams; and the transition risk dictionary includes 322 bigrams. The majority of the dictionaries consist of bigrams, reflecting our deliberate effort to achieve accurate text identification and quantification, as prior research shows that text classification accuracy improves when applying bigrams of words as opposed to unigrams (e.g., Tan, Wang, and Lee 2002; Bekkerman and Allan 2004).

3.2 Measuring climate risk

Next, we construct our firm-level climate risk measures using these dictionaries. Specifically, we first decompose each of the earnings call transcripts into a list of unigrams/bigrams. Because acute or chronic physical risks are often brought up when short-term climate or weather events are reported in news headlines (e.g., *hurricane*, *wildfire*, and *warm winter*), we require their respective keywords to appear in the vicinity (± 1 sentence) of at least one risk synonym to ensure that firms are indeed exposed to climate risks (similar to Hassan et al. 2019). Simply mentioning a well-publicized weather/climate event without explicitly mapping to a firm's risk profile could reflect a desire for attention or shifting of blame, which does not contribute to our physical climate risk measures. We divide the frequency of these occurrences by the length of the transcript, and then multiply the quotient by 10^4 to reduce the number of decimals. In essence, these measures capture the proportion of a conversation in which acute or chronic weather/climate events as well as a firm's risk exposure are jointly discussed.

Transition risk differs from physical climate risk in that it relates to policies and regulations, technological improvements, and evolving climate patterns. Unlike physical risks, transition risk may not materialize in the short run and thus does not pose immediate threats or introduce any uncertainty to a firm's business operations. As a result, we measure transition risk exposure

16 We exclude keywords such as "energy cost," "energy costs," "fuel bill," "fuel cost," "fuel costs," "fuel expense," "fuel expenses," "gas cost," "gas costs," "wind cost," and "wind costs."

based on discussions of the keywords in our transition risk dictionary only, without requiring these discussions to appear near a risk keyword. Moreover, firms exhibit varying perceptions of and attitudes toward climate risk, with some discussing and addressing transition risk more proactively than others. With this in mind, we develop an additional measure that captures a firm's proactiveness when discussing transition risk. To achieve this, we analyze verbs that appear near (within ±1 sentences of) discussions of transition risk keywords in earnings calls, and manually identify a list of 30 verbs that suggest more proactive attitudes when discussing climate issues.[17] Using proactive verbs, we separately identify our transition risk measures with and without proactiveness.

Applying the above-mentioned procedures, we construct three separate firm-level climate risk measures: (1) acute physical climate risk, (2) chronic physical climate risk, and (3) transition risk. We decompose the transition risk measure into proactive and nonproactive components. All are available at the firm-quarter level.

4. Properties of Firm-Level Climate Risk Measures

In this section, we provide some preliminary validation using the underlying keywords, present our climate risk measures, and examine their time-series and cross-sectional properties.

4.1 Top keywords

In our first validation exercise, we examine the top keywords—unigrams or bigrams—used to construct the climate risk measures, rank-ordered by the frequency of mentions and frequency weight at the transcript level and report the results in Table 2.[18] The results, reported in columns 1–3, show that *hurricanes* and *hurricane* are the most frequently mentioned acute climate unigrams in the proximity of risk synonyms. The keywords *storms*, *drought*, *flooding*, and *wildfire(s)* are also frequently discussed in earnings calls, trending up in the later few years of our sample period. Columns 4–6 report that *weather* is the single-most commonly discussed chronic climate keyword appearing near risk synonyms. It is followed by words referencing specific weather conditions, such as *temperatures* or *snow*. These keywords clearly confirm that our measures accurately capture acute and chronic climate risks.

[17] The complete list of the proactive verbs includes *achieve, acquire, add, announce, build, change, create, develop, enhance, evaluate, expand, generate, grow, hedge, help, improve, increase, initiate, integrate, invest, make, prepare, produce, purchase, rebuild, reduce, replace, respond, restructure* and *spend.*

[18] The frequency weight of each bigram or unigram, denoted as *fweight*, is calculated by dividing the frequency of its occurrences by the length of the transcript, multiplying the quotient by 10^4 to reduce the number of decimals, and summing the values across all transcripts. The average length of earnings call transcripts in our sample is approximately 4,200 words before cleaning and 2,440 words after cleaning, which is consistent with the literature (e.g., Chen, Nagar, and Schoenfeld 2018).

Table 2
Top climate-related keywords

Physical climate risk						Transition climate risk		
Acute risk			Chronic risk					
Bigram/ Unigram	Freq	fweight $= \frac{Freq_{b,P}}{B_P} \times 10^4$	Bigram/ Unigram	Freq	fweight $= \frac{Freq_{b,P}}{B_P} \times 10^4$	Bigram/ Unigram	Freq	fweight $= \frac{Freq_{b,P}}{B_P} \times 10^4$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
hurricane	1560	6371.9	weather	6154	26342.7	energy efficiency	7738	32512.0
hurricanes	552	2243.5	temperatures	122	596.0	renewable energy	6663	29104.3
storms	409	1622.7	the snow	75	299.4	the solar	6623	28819.0
drought	294	1177.2	high water	72	266.2	clean energy	5117	21372.2
flooding	185	728.7	heating season	49	260.4	alternative energy	4160	18367.0
the flood	108	440.6	precipitation	46	252.1	superior energy	3354	12482.7
wildfire	110	356.4	wind season	60	237.1	higher energy	2806	11273.8
windstorm	75	333.8	the ice	57	216.7	new energy	2503	10878.1
wildfires	54	201.6	mild winter	48	188.8	the renewable	2389	10564.8
storm losses	30	155.4	snowfall	42	186.8	the ecosystem	2590	10036.0
severe winter	33	134.0	rainfall	42	175.4	energy management	2156	8861.2
storm related	31	132.5	degree days	34	173.9	energy efficient	2171	8459.6
wind storm	28	125.0	normal winter	36	170.7	the carbon	2243	8414.0
the floods	24	102.0	winter conditions	43	170.5	green energy	2224	8303.4
storm activity	25	100.8	warm winter	36	161.0	wind energy	1893	7817.5
storm costs	21	86.8	rains	34	138.0	the climate	1926	7300.8
water flood	22	82.4	cold winter	33	126.4	fuel efficiency	1874	6730.5
polar vortex	22	76.8	hot summer	30	124.9	shale gas	1655	6350.9
storm season	14	69.7	unseasonably warm	24	110.1	lower energy	1553	6290.3
storm damage	10	64.4	the fog	28	107.4	fuel efficient	1592	5925.9
droughts	14	57.4	harsh winter	27	103.5	energy technologies	1643	5883.5
tropical storm	13	55.3	unseasonably cold	19	99.6	solar power	1344	5836.2
snowstorms	13	52.6	the clouds	23	96.7	alternative fuel	1301	5776.1
snowstorm	12	50.1	the warmest	13	74.5	wind farm	1283	5696.7
winter storm	14	50.1	early winter	13	74.1	fuel economy	1586	5487.9
hailstorm	11	49.6	cool summer	13	72.3	the co2	1479	5476.3
extreme cold	11	48.1	cold season	17	70.9	solar cell	1170	5457.9
extremely cold	10	40.0	the rain	16	64.7	gas drilling	1286	4947.8
storm cost	11	39.0	wind hail	11	63.2	energy future	1214	4715.9
the volcano	11	38.3	the winds	17	62.8	solar projects	1076	4667.6

This table lists the top-30 unigrams or bigrams in each category of $ClimateRisk_{i,t}$ measures, ranked by *fweight*. To calculate the *fweight* for acute and chronic climate risk measures, we first identify the frequency of mentions of individual unigrams and bigram b in proximity to risk synonyms ($Freq_{b,P}$). We then divide this frequency by the length of the transcript P (B_P), multiply the quotient by 10^4, and sum the resultant values across all transcripts in our sample. The calculation of *fweight* in the case of transition climate risk is the same except that we do not require the mention of the unigrams and bigrams to be in the proximity of risk synonyms, which leads to higher *Freq* and *fweight* for that specific category.

Unlike physical climate keywords, words that indicate transition risk are more evenly distributed across many keywords. Among the most frequently appearing are *energy efficiency*, *renewable energy*, *solar*, *clean energy*, and *alternative energy*. In addition to these words, *superior energy*, *higher energy*, *new energy*, *the renewable*, and *the ecosystem* are also discussed frequently. Clearly, these keywords accurately signify discussions of transition climate risk. The calculation of *fweight* in the case of transition climate risk is similar, but we do not require the key unigrams and bigrams to appear in proximity to risk synonyms, which leads to higher average frequencies and *fweights*. Table IA.7 compares the frequency of climate-related bigrams and unigrams with political-risk-related bigrams from a previous study Hassan et al. (2019) and top climate keywords from another study Sautner et al. (2023). It includes the number of earnings calls and the number of firms that mentioned each of the climate-related words besides their frequency and fweight. Our results show that the frequency of top climate-related bigrams is much higher (about 1,600 times) than that of the top political-risk-related bigrams (e.g., the constitution) in Hassan et al. (2019), and similar to that of top climate keywords in Sautner et al. (2023). Internet Appendix B provides further details.

4.2 Summary statistics

The newly constructed climate risk measures are summarized in Table 1, in which we cap them at the 99th percentile to limit outlier values. Among all 4,719 firms in our sample, 18.0%, 27.2%, and 61.8% show at least one quarter with a positive value for the acute, chronic, and transition climate risk measures, respectively.[19] When we divide these measures by the respective standard deviations (SDs), the three standardized climate risk measures have average values of 0.098, 0.159, and 0.256, respectively. The correlation between the two physical risk measures is about 0.100, suggesting that the two are somewhat related. In contrast, their correlations with the transition risk measure are 0.021 and 0.033, respectively, clearly indicating the distinction between physical and transition risk measures. Conditional only on the presence of firms with at least one positive transition risk value, 23.9% of the firm-quarters are identified as being associated with some proactive keywords when transition risk is discussed.

[19] Internet Appendix B provides more information on the frequency and distribution of climate risk discussions in earnings calls, both on an absolute and relative scale. We focus on the transition risk measure, which is the main focus of our paper. The 61.8% of sample firms (or 2,918) that have at least one quarter with a positive value of the transition risk measure correspond to 20.4% of the firm-quarters and 34.7% of the firm-years that have positive values in transition risk. These shares of positive values have increased over time, with 37% of the firm-years having positive values in transition risk in 2017-2018. Figure IA.1 presents the distribution of the standardized transition risk measure, either by firm-quarters in panels A and C or by firm-years in panels B and D. Panels A and B are based on data in all years, and panels C and D are based on data in the most recent 2 years, 2017–2018, in our sample.

4.3 Time-series patterns

We now shift to examining the properties of the constructed measures to provide face validation based on time-series and cross-sectional variations. Figure 1 plots the averages of the climate risk measures over time. In panel A, the acute risk series spikes six times over the past 17 years. We identify the corresponding topics discussed in the conference calls that contribute to the increases in climate risk and label each spike. For example, the spike that occurs in 2005 reflects the catastrophic and long-lasting effect of *Hurricane Katrina*, which flooded the New Orleans area. In contrast, the chronic risk series has remained flat over the past two decades with spikes only between 2012 and 2014. The most commonly discussed keywords during the period was *abnormal weather*.

Panel B plots the time series for the transition climate risk measure, which shows a steady increase from the start of the sample period through 2008Q3 with a gradual retreat to its 2005 level since then. The downtrend in the recent decade has matched well with that of U.S. greenhouse gas emissions. We observe several local spikes, in 2006, 2008, 2011, and 2015, all of which are driven by more frequent discussion of *energy efficiency* and *renewable energy*. Panel C plots the average transition risk measures with and without proactive keywords, divided by their corresponding SDs. The two time series have diverged increasingly since 2008, with firms with proactive responses displaying much lower transition risk than their 2008 levels.

4.4 Industry variations

Industries differ inherently in their exposure to climate risk, so we examine industry variations in our climate risk measures. We regress different climate risk measures on industry dummies, while controlling for time and state fixed effects. Figure 2 plots the coefficients for the NAICS two-digit dummies. The reference industry is other services (NAICS 81).

Panel A shows that utilities face the highest acute physical climate risk among all industries, followed by agriculture, mining, transportation, and construction. A significant portion of the business activities in these industries take place outdoors and thus are subject to disruptions caused by natural disasters. Panel B displays similar patterns, but with a few exceptions. While utilities continue to exhibit high chronic physical climate risk (the second-highest across industries), arts and recreation faces the highest chronic climate risk with agriculture facing the third highest. The industry variations we observe mostly conform to the industry-level exposure to both acute and chronic climate risk.

Panel C shows even wider variations in transition risk than with the physical climate risk measures. Utilities and transportation are subject to significantly higher transition risk than other industries, while service industries face significantly lower transition risk. Panel D displays the industry variations in the proactive transition risk measures. Utilities firms are more likely than

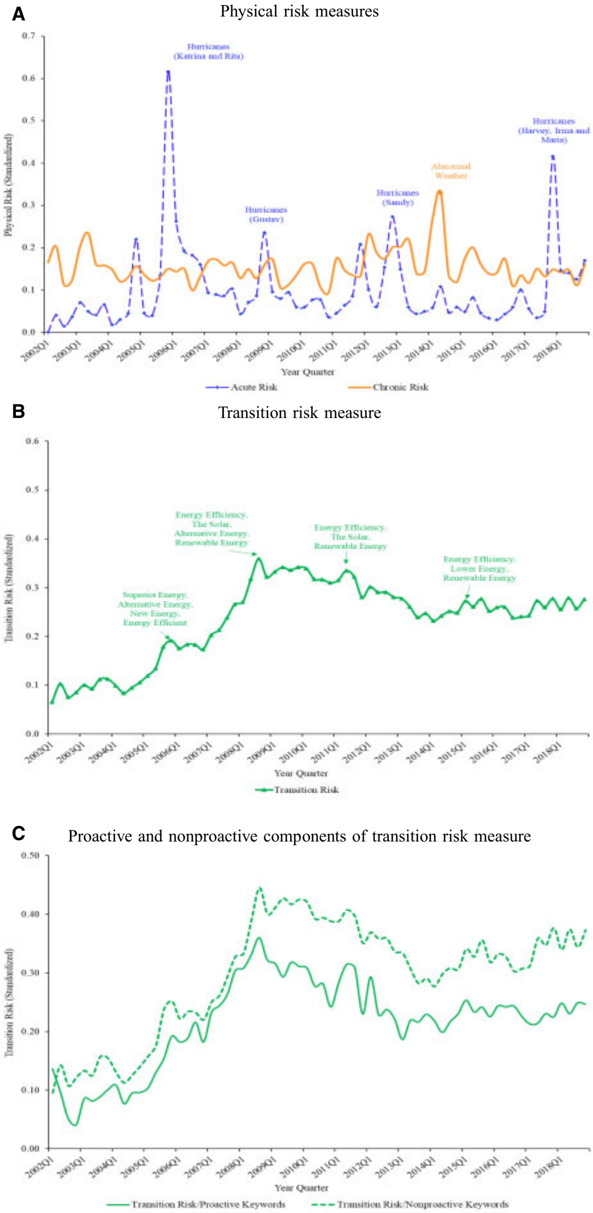


Figure 1
Firm-level ClimateRisk$_{i,t}$
These panels report the average of firm-level $ClimateRisk_{i,t}$ over time. Panels A and B show the time-series average of firm-level *acute risk*, *chronic risk*, and *transition risk* (divided by its SD in the time series), respectively. We label each spike with the corresponding topics discussed in the conference calls which contribute to the increase in each type of climate risk. Panel C plots the time-series average of proactive and nonproactive components of transition risk, divided by their corresponding SDs, based on a subsample of firms with positive transition risk.

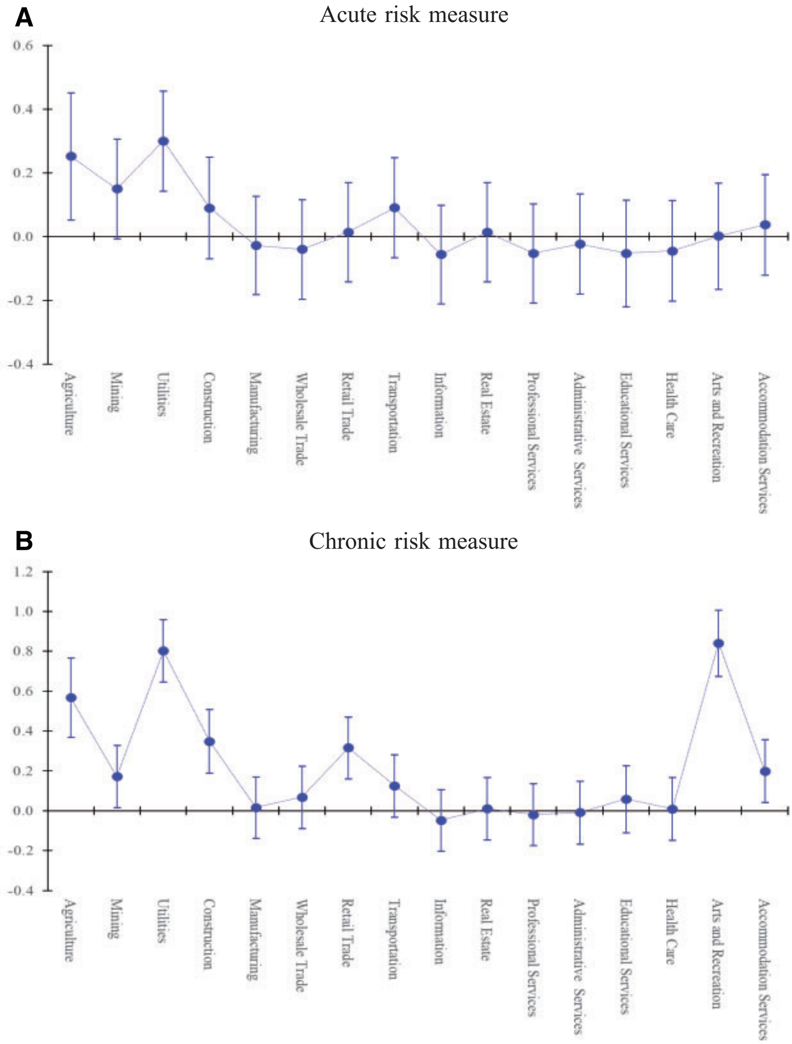
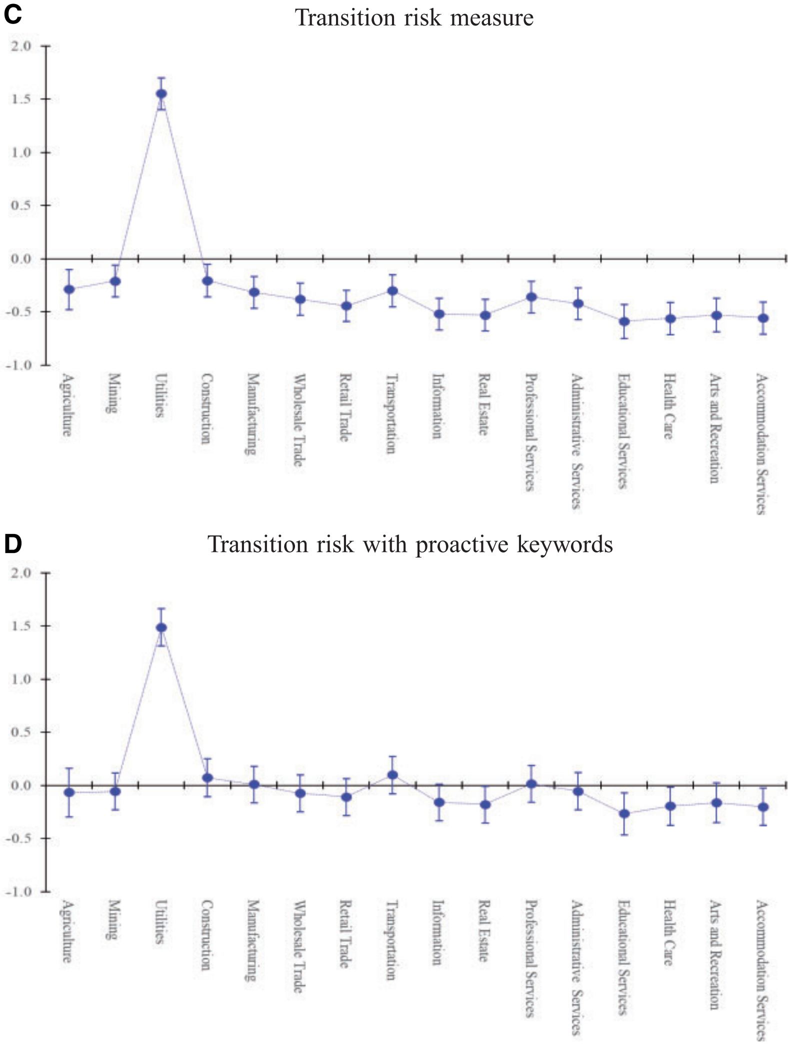


Figure 2
Industry variations in ClimateRisk$_{i,t}$
These panels plot the coefficients for industry (NAICS two-digit) fixed effects and their corresponding 95% interval from regressions of acute climate risk (panel A), chronic climate risk (panel D), transition risk (panel C), and the proactive transition risk (panel D). Time and state fixed effects are controlled in each regression. The reference industry is other services (NAICS 81).

other firms to use proactive keywords when their management teams discuss transition risk topics. In contrast, firms that operate in mining, information, and real estate are less likely to use proactive keywords on such occasions. The observed patterns match well with the broader industry-level exposure to climate regulatory risk.

Figure 2
(Continued)



4.5 Firm-level variations

In Table 3, we report excerpts of the transcripts with the highest $ClimateRisk_{i,t}$. The transcripts indicating the highest acute climate risk are those of the two largest utility companies in California: Edison International and PG&E Corporation, which have been linked to some of California's deadliest wildfires. Relatedly, the chronic risk measure captures discussions of both abnormal weather and variability in weather conditions. The transcript

Table 3
Excerpts in transcripts with highest climate risks

Firm	Date	Climate risk	Value	Keywords	Text surrounding the keywords
Edison International	Oct. 30, 2018	Acute risk	40.00	Wildfire; Uncertainty	We also have the flexibility at these entities to obtain both short and long-term debt while we continue to evaluate options as we work through uncertainty around the wildfire liability and cost recovery.
PG&E Corp	Nov. 5, 2018	Acute risk	39.85	Wildfire; Risks	Our expanded Community Wildfire Safety Program was established after the 2017 wildfires to implement additional precautionary measures intended to reduce or further reduce wildfire risks.
Patriot Transportation	Nov. 30, 2017	Acute risk	35.63	Hurricane; Unpredictable	Hurricane Irma more directly impacted our operations as the state of Florida shut down for 2 or 3 days. This type of business is generally less productive with long lines, unpredictable traffic patterns and other negative occurrences leading to inefficient utilization of our equipment.
Sotherly Hotels Inc	Nov. 8, 2016	Acute risk	32.40	Hurricane; Unsure	Heading into that markets' high winter season we are unsure what the effects may be. The impact of hurricane Matthew on our portfolio in early October was significant.
Talos Petroleum LLC	Nov. 5, 2008	Acute risk	29.00	Storm; Risk	We're also actively engaged in a program of accelerated idle well abandonment to mitigate the ongoing risk of future storms.
Suburban Propane Partners	Nov. 15, 2018	Chronic risk	77.72	Weather; Variability	While the heating season presented some extreme weather variability, average temperatures across our service territories were 8% cooler than the prior year.
Sport Chalet Inc	Feb. 6, 2013	Chronic risk	63.22	Unseasonably warm; Uncertainty	Unseasonably warm and dry weather coming on top of a bad winter sports season last year, combined with our customers' general economic uncertainty along with our desire to be less promotional, all contributed to the slight decrease in comparable store sales.
Idacorp Inc	Feb. 18, 2016	Chronic risk	61.79	Precipitation; Chance	According to the National Oceanic Atmospheric Administration, in March through May, we are looking at about a 33% to 40% chance of above-normal precipitation in the southern portion of our service area and normal precipitation levels in the northern portion.
CH Energy Group inc	Apr. 24, 2002	Chronic risk	52.52	Weather; Risk	A certain amount of variation from normal, either above or below normal degree days was a variation or risk that we retained. Then there was a wider range where we would be compensated if weather were warmer than normal.
Southern Company Gas	Oct. 30, 2013	Chronic risk	51.63	Weather; Unpredictable	Given where you see the rates today, when you're coming up for the 2014 expirations, do you expect – doesn't seem to have been much movement in the market. Is there anything out there that you think might have a significant impact, other than unpredictable weather?
CDTI Advanced Materials Inc	Aug. 11, 2011	Transition risk	464.9	Emission Reductions	Looking at the domestic growth opportunities, we think that the economic recovery, although a little bumpy, is spurring growth in our business and with our distributor network. Additionally, states such as California continue to demonstrate their commitment for on-road diesel emission reductions through innovative programs to drive early adoption by truck operators.
New Jersey Resources Corp	May. 4, 2018	Transition risk	298.2	Clean Energy	I talked about our strategy to provide our customers with reliable, affordable and clean energy services. To execute that strategy, we remain focused on natural gas, energy efficiency, and clean energy investments.
Magnetek Inc.	May. 9, 2012	Transition risk	267.5	Renewable Energy	Some of the growth we experienced in our served industrial markets was offset by lower sales in renewable energy, namely, wind inverters, which declined by more than $3 million year over year to about $2.4 million in the quarter.
Lime Energy Co	Aug. 12, 2009	Transition risk	267.2	Energy Efficiency	This counterbalance truly reflects the underlying strength of our business model and supports our efforts to date in the rapid deployment of tailored energy efficiency solutions to the public and utility marketplaces.
Enel X North America Inc	Aug. 7, 2008	Transition risk	256.7	Clean Energy	Various factors, ranging from unprecedented regulatory support for clean energy solutions, to rising fuel and construction costs, have made the value proposition of our scalable solutions stronger and more important than ever.

The table presents the excerpts in the earnings call transcripts with the highest acute, chronic and transition climate risks, respectively. The values of climate risk measures are ranked before winsorization. For acute and chronic climate risks, we report the corresponding climate-related keywords and risk synonyms. For transition climate risk, we report only the climate-related keywords.

indicating the highest chronic climate risk comes from Suburban Propane Partners, a utility company that offers propane primarily for heating.

The transcript indicating the highest transition climate risk is that of CDTI Advanced Materials, a company that provides solutions to automotive emissions control markets in the United States. On August 11, 2011, the company discussed "states such as California continue to demonstrate their commitment for on-road diesel emission reductions through innovative programs to drive early adoption by truck operators." The other transcripts indicating the highest transition climate risk come from New Jersey Resources Corp, Magnetek Inc., and Lime Energy Co, all of which provide clean or renewable energy services.

5. External Validation

In this section, we conduct a variety of validation tests using external benchmarks to show that our climate risk measures indeed quantify firm-level variations in exposure to climate risks.

5.1 Validating the physical risk measure

We first examine whether local natural disasters correlate with changes in our two physical climate risk measures for the affected firms. Following the literature, we match natural disaster data from SHELDUS with our firm-quarter sample. We then relate local natural disaster events to firms' physical climate risk measures using the following specification:

$$ClimateRisk_{i,t+1} = \sum_{p=0}^{3} \beta_p \cdot Z_{c,t-p} + \gamma \cdot X_{i,t-1} + \zeta_{i,t} + \epsilon_{i,t}, \quad (1)$$

where $Z_{c,t-p}$ is a natural disaster event in the county where a firm's headquarters is located, and time p ranges from 0 to 3 across columns; $X_{i,t-1}$ represents firm-level attributes, such as total assets lagged by one quarter; $\zeta_{i,t}$ refers industry-by-quarter fixed effects that we use to account for time-varying heterogeneity across industries.[20]

Panel A of Table 4 reports the results. The results in columns 1 and 2 indicate that natural disasters in quarter t motivate executives to discuss physical climate risk in quarter t+1. The presence of local natural disasters is associated with a significant 0.085-SD increase in the within-industry-time acute climate risk measure in the subsequent quarter. The effect is statistically significant only in quarter t, not in previous quarters. Similarly, columns 3 and 4 suggest that natural disasters in the preceding quarter are associated with a 0.036-SD increase in the within-industry-time chronic climate risk in the current

[20] We exclude the firms in the energy industry in our regression, mainly due to the confounding impact of natural disasters on energy usage.

Table 4
Validating firm's climate risk measures

A. Correlations between physical risk measures and natural disaster data

Dep var	Acute Risk$_{i,t+1}$		Chronic Risk$_{i,t+1}$	
	(1)	(2)	(3)	(4)
Natural Disaster$_{c,t}$	0.0849***	0.0851***	0.0353***	0.0363***
	(4.353)	(4.374)	(2.754)	(2.876)
Natural Disaster$_{c,t-1}$		0.0041		−0.0038
		(0.354)		(−0.287)
Natural Disaster$_{c,t-2}$		−0.0145		−0.0170
		(−1.326)		(−1.600)
Natural Disaster$_{c,t-3}$		0.0045		0.0004
		(0.384)		(0.028)
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes	Yes
Industry × Time	Yes	Yes	Yes	Yes
N	133,434	133,434	133,434	133,434
Adj. R^2	.020	.021	.043	.052

B. Correlations between transition risk measures and MSCI CCI

Dep Var	Transition Risk$_{i,t}$		
	All (1)	Proactive (2)	Nonproactive (3)
MSCI CCI$_{i,t}$	0.0512***	0.0446***	0.0468***
	(3.461)	(3.062)	(3.154)
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes
Industry × Time	Yes	Yes	Yes
N	15,747	15,747	15,747
Adj. R^2	.268	.142	.262

C. Correlations between transition risk and CO_2 intensity

Dep Var	CO_2 Intensity$_{i,t+h}$				
	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$
			Specification (1)		
Transition Risk$_{i,t}$	0.4531**	0.5363**	0.4671**	0.5420***	0.6939***
	(2.033)	(2.104)	(2.639)	(3.164)	(3.416)
N	2,529	2,422	2,312	2,202	2,095
Adj. R^2	.174	.245	.0944	.161	.178
			Specification (2)		
Transition Risk/Nonproactive$_{i,t}$	0.3061	0.3579*	0.4082***	0.4449***	0.6449***
	(1.662)	(1.852)	(3.563)	(2.849)	(4.186)
Transition Risk/Proactive$_{i,t}$	0.1758	0.2188	0.0689	0.1210	0.0609
	(1.497)	(1.403)	(0.431)	(0.667)	(0.393)
N	2,529	2,422	2,312	2,202	2,095
Adj. R^2	.174	.180	.0939	.0779	.178
F-test	0.1303	0.1457	0.3393*	0.3239*	0.584***
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes
Industry × Time	Yes	Yes	Yes	Yes	Yes

This table reports the validation results of our firm-level climate risk measures. In panel A, we regress the acute and chronic climate risk measures (standardized) on the occurrence of natural disasters in lagged periods. *Natural disaster* is a dummy variable that equals one if there is a natural disaster in the county where a firm was headquartered in a given quarter, zero otherwise. Columns 1 and 2 use the acute climate risk as the dependent variable, and columns 3 and 4 use the chronic climate risk as the dependent variable. Firm-level control variables (i.e., Firm attributes) include *log(Asset)*, *CapEx*, *PPE*, *Book Leverage*, *log(No_analysts)*, *Institution %*, and *Institution HHI*, all lagged by one quarter. In panel B, we regress transition risk measures on MSCI CCI. Column 1 presents the results of the regressions using the overall transition risk as the dependent variable. Columns 2 and 3 report the results using the proactive and nonproactive components of the transition risk measure as the dependent variable, respectively. Firm attributes that are controlled in panel B include *log(Asset)*, *CapEx*, *PPE*, *Book leverage*, and *ROA (%)*. Panel C shows the results of regressing CO_2 intensity in different lead periods on different transition risk measures (standardized): transition risk in Specification (1) and two decomposed transition risk measures in Specification (2). Lagged *log(Asset)* is controlled in all columns of both specifications of panel C. Industry by time fixed effects are included in all three panels. Table A.1 in the appendix defines all variables in detail. The standard errors are clustered at the firm level and t-statistics are shown in parentheses. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

quarter. Overall, our physical climate risk measures capture variations in a firm's exposure to local natural disasters, a key driver of physical climate risks.

5.2 Validating the transition risk measure

5.2.1 Correlations with ESG scores. We start our validation of the transition risk measure with the MSCI CCI. We use MSCI rather than other ESG databases for two reasons. First, it is arguably one of the best-accepted ESG data vendors among practitioners and academia (e.g., Engle et al. 2020; Serafeim and Yoon 2023). As the leading global provider of financial indexes, MSCI has successfully incorporated its ESG ratings into a wide range of investment products. Second, CCI is a climate change theme score, which is more closely related to our transition climate risk exposure measures.[21]

To compare the two measures, we first compare the coverage of the two measures. It's worth noting that the CCI is only available after 2013 and maintains the same value if not updated, while our earnings-call based measures have been available since 2002 and are only applied to the quarter of earnings calls. Figure IA.2 in Internet Appendix B plots the number of unique public firms for each year of our transition risk measure and the MSCI CCI measure. We can see that even during the years when the two data sets overlap, our measure adds substantial coverage beyond the MSCI data, as demonstrated by the green bars. Specifically, for each year from 2013 to 2018, our measure on average provides coverage of transition risk to an additional 952 firms with nonmissing values and 480 firms with positive values. Over the same period, on average, about 225 firms each year in the MSCI CCI data set do not have earnings conference calls and are thus not covered in our sample.

We then match the CCI data with our sample, resulting in a small panel of 15,995 firm-quarters. Panel A of Figure 3 displays the scatterplot between our transition climate risk measure and the CCI, showing a positive and significant correlation between the two series. We formalize the correlation test by regressing $ClimateRisk_{i,t}$ on the CCI following a specification that is similar to Equation (1). We report the results in panel B of Table 4. The results in column 1indicate a positive correlation between the two series, which is significant at 1%, suggesting that a one-SD increase in the CCI is associated with a 0.051-SD contemporaneous increase in the transition climate risk. In columns 2 and 3, we document similar results using proactive and nonproactive components of the transition risk measure as the dependent variables, with both coefficients being statistically significant at the 1% level. This set of results provides evidence that our transition risk measure is positively correlated with the CCI within the same industry and time.

[21] Following Equation (1), we also run regressions of $ClimateRisk_{i,t}$ on either RepRisk or Refinitiv environmental scores as well their overall ESG scores. The results, untabulated in the version, show that our transition risk measure is positively correlated with the environmental component of ESG scores, but not with their social and governance components.

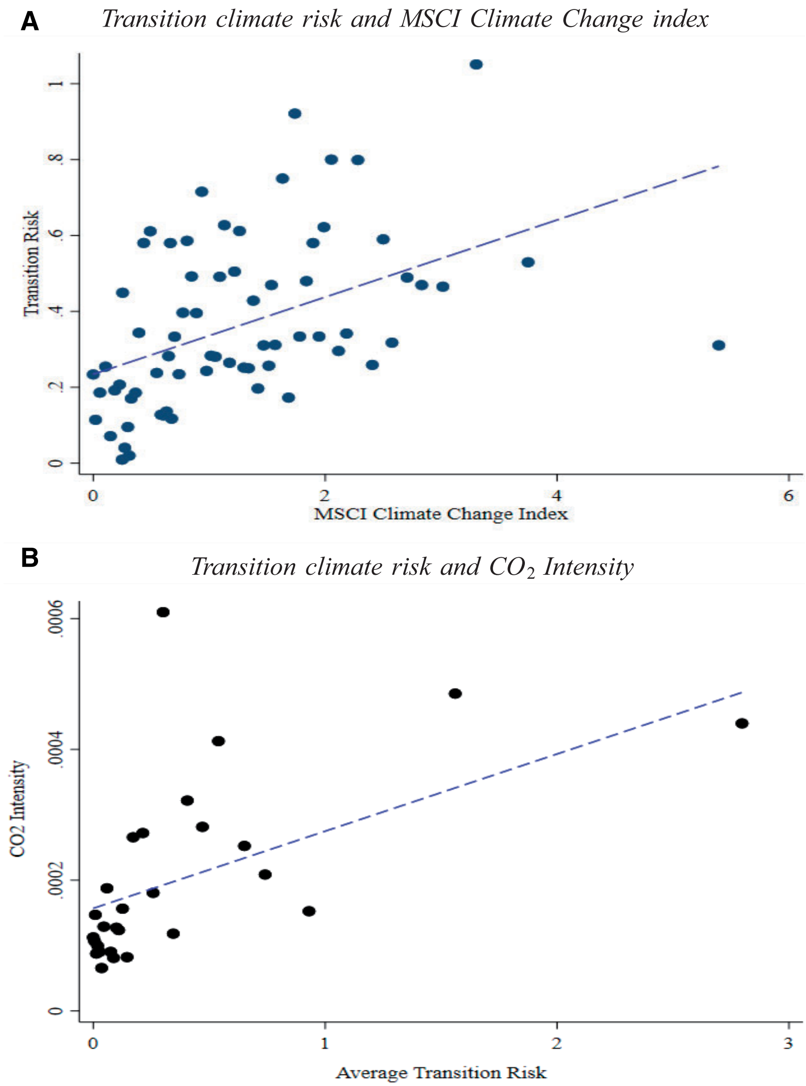


Figure 3
Scatterplots of transition climate risk and external measures
The panels describe the correlation between the transition climate risk and two external measures. Panel A presents the (binned) scatterplot between transition climate risk and MSCI CCI for firms that have both measures available. Panel B illustrates the (binned) scatterplot of the average transition climate risk and the direct CO_2 intensity at NAICS six-digit level for the manufacturing sector, sourced from Shapiro (2021).

Overall, we believe that our transition risk measure is highly complementary to these ESG scores, with several additional benefits. First, our measure is available for a large sample of public firms in the United States over a long sample period starting in 2002, while ESG scores in the CCI are available after

2012. Second, for the same reason, our measure is less subject to selection bias. Third, our measure is more timely and thus can be better used to inform real-time decisions.

5.2.2 Transition risk and CO_2 intensity. In our final validation, we examine how well our transition risk measures correlate with a firm's carbon intensity. Recent studies use carbon intensity (carbon emissions scaled by total assets) to estimate the effects of a firm's exposure to climate risks, especially policy and regulatory risks (e.g., Bolton and Kacperczyk 2021a,b). We also examine whether and how firms that are identified with proactive keywords in earnings calls manage their emissions in reality compared with how others do when facing similar transition risks.

Panel B of Figure 3 presents a scatterplot of transition risk and direct CO_2 intensity at the NAICS six-digit level for the manufacturing sector, sourced from Shapiro (2021).[22] We find a strong and positive correlation between the two, with a correlation coefficient of 0.19, which is significant at the 1% level, providing some validation that our transition risk measure captures variations in carbon intensity. We then formalize the test by regressing a firm's CO_2 intensity obtained from GHGRP on the transition risk measures as follows:

$$Y_{i,t+k} = \beta \cdot TransitionRisk_{i,t} + \gamma \cdot X_{i,t-1} + \zeta_{i,t} + \epsilon_{i,t}, \tag{2}$$

where $Y_{i,t+k}$ is the firm's CO_2 intensity in year $t+k$ (k ranges from 1 to 5); $X_{i,t-1}$ includes the firm's total assets lagged by one year. We include industry-by-year fixed effects in the analysis to account for time-varying heterogeneity across industries. Our sample covers 762 firms for which both series are available, mainly firms operating in the manufacturing, mining, energy, and transportation sectors from 2010 to 2018.

We report the results in panel C of Table 4. In specification (1), we find a positive and significant correlation between the transition risk measure and the firm's CO_2 intensity from year $t+1$ onward, with the magnitude increasing over time. A one-SD increase in the transition risk measure is associated with an increase in CO_2 intensity of 0.4531 basis points (which is significant at the 5% level) in year $t+1$ and of 0.6939 basis points (which is significant at the 1% level) in year $t+5$. In Specification (2), where we separate the transition risk measure into proactive and nonproactive components, we find a positive and significant coefficient for the nonproactive component from year $t+2$ onward, not on the proactive component, and the differences are significant at the 10% or lower level. The contrast suggests that, while firms that face higher transition risk and adopt nonproactive responses are associated with higher future CO_2 emissions, those that face higher transition risk but adopt proactive responses

[22] Direct CO_2 intensity is measured as average emissions per \$1 of output by each industry in 2007 by Shapiro (2021).

are not. In essence, our transition climate risk measures are predictive of the firm's future carbon emissions.[23]

6. Explaining Climate Risk Measures

In this section, we analyze the relative contributions of aggregate, sectoral, and firm-level variations as well as firm-level characteristics to the new climate risk measures.

6.1 Variance decomposition

We first conduct a variance decomposition analysis—calculating how much of the variation in each of the three climate risk measures is accounted for by firm-level characteristics and various sets of fixed effects. In panel A of Table 5, we report R^2 values from a variety of specifications that explain the climate risk measures. These results indicate that time + state + industries, together, can explain only 2%, 3.4% and 12.4% of the variations in the acute, chronic, and transition risk measures, respectively. Adding interactions between state, industry, and time all help increase the explanatory power of the model, but to a limited extent. Nevertheless, even with the strictest specification, where we control for county-by-time and industry-by-time fixed effects, the model explains less than 12.5% of the variations in any of the climate risk measures, leaving more than 87% attributable to firm-level or other idiosyncratic factors. This result suggests that, unlike natural disaster data or marketwide news about long-run climate risk used by Engle et al. (2020), the majority of variations in our three climate risk measures occur at the firm level.

When we add firm and time fixed effects, the model captures 9.7%, 20.9%, and 65.7% of the variations in the three climate risk measures, respectively. Further adding firm-level attributes and interaction between industry and time or state and time offers some additional power in predicting the two physical risk measures, but not the transition risk measure. This result suggests that our climate risk measures capture both cross-firm differences and within-firm variations in climate risk exposure. For example, the transition risk measure for Sempra Texas Holdings increases to 184.97 in Q3 2013 from 11.10 in Q1 2006.

6.2 Correlations with firm characteristics

Panel B of Table 5 presents the results of regressions relating climate risk measures to a list of important firm-level attributes, all lagged by one quarter, to

[23] We also regress the transition climate risk measures on CO_2 intensity in the contemporaneous and previous quarters following the specification in Equation (1) to explore the two-way relationship in an exercise that is similar to Granger Causality test. The results, reported in Table IA.1 in the Internet Appendix, suggest that the relationship between our transition climate risk and CO_2 intensity runs only one way, with transition climate risk measures significantly predicting the firm's CO_2 emissions in the future, but not in the opposite direction.

Table 5
Characteristics of climate risk measures

A. Variance decomposition

	Dep Var					
	Acute $\text{Risk}_{i,t}$		Chronic $\text{Risk}_{i,t}$		Transition Climate $\text{Risk}_{i,t}$	
Model specification	Adj. R^2	Δ	Adj. R^2	Δ	Adj. R^2	Δ
Time	.009		.001		.005	
Time + State	.015	.015	.008	.008	.018	.018
Time + County	.025	.025	.040	.040	.073	.073
Time + NAICS2	.016	.016	.030	.030	.118	.118
Time + NAICS3	.026	.026	.043	.043	.161	.161
Time + NAICS4	.028	.028	.075	.075	.199	.199
Time + State + NAICS2	.020	.020	.034	.034	.124	.124
State + NAICS2 × Time	.028	.012	.042	.012	.136	.018
State × Time + NAICS2	.037	.021	.037	.007	.118	.000
State × Time + NAICS2 × Time	.042	.026	.045	.015	.130	.012
County × Time + NAICS2 × Time	.063	.047	.064	.034	.121	.003
Firm + Time	.080	.064	.200	.170	.655	.537
Firm + Time + Firm Attributes	.080	.064	.200	.170	.655	.537
Firm + Time + Firm Attributes + NAICS2 × Time	.088	.072	.209	.179	.673	.555
Firm + Time + Firm Attributes + State × Time	.097	.081	.209	.179	.657	.539
Residual	.903		.791		.343	

B. Firm characteristics of climate risk measures

Dep Var	Physical $\text{Risk}_{i,t}$		Transition $\text{Risk}_{i,t}$	
	Acute (1)	Chronic (2)	All (3)	Proactive (4)
$\log(\text{Asset})_{i,t-1}$	0.0074**	0.0055	0.0138**	0.0104***
	(2.147)	(0.992)	(1.982)	(2.989)
$\text{CapEx}_{i,t-1}$	−0.0011	−0.0025	−0.0008	0.0007
	(−0.845)	(−1.184)	(−0.314)	(0.480)
$\text{PPE}_{i,t-1}$	0.1204***	0.1410***	0.2768***	0.0943**
	(4.687)	(2.907)	(2.773)	(1.976)
Book $\text{Leverage}_{i,t-1}$	−0.0095	0.0194	−0.1163***	−0.0328*
	(−0.463)	(0.578)	(−3.318)	(−1.819)
$\log(\text{No\_Analysts})_{i,t-1}$	−0.0094	−0.0455***	−0.0135	−0.0218***
	(−1.463)	(−3.414)	(−0.854)	(−3.190)
$\text{Institution\%}_{i,t-1}$	0.0304*	−0.0028	−0.0767	−0.0122
	(1.680)	(−0.067)	(−1.132)	(−0.498)
Institution $\text{HHI}_{i,t-1}$	0.0133	−0.0724	0.0413	0.0239
	(0.444)	(−1.240)	(0.430)	(0.553)
Transition $\text{Risk}_{i,t}$				0.5858***
				(11.711)
Industry × Time FE	Yes	Yes	Yes	Yes
N	124,682	124,682	124,682	124,682
Adj. R^2	.0243	.0419	.129	.386

Panel A reports the results on the adjusted R^2 from a projection of $ClimateRisk_{i,t}$ on various sets of fixed effects. Column 1 reports the adjusted R^2 of the regressions with acute climate risk as the dependent variable and different sets of fixed effects as the independent variables. In column 2, we report the change/improvement in adjusted R^2 relative to a benchmark. The benchmark for regressions in the first block is zero (no fixed effects). The benchmark for regressions in the second and third blocks is the fourth row in the first block (Time + NAICS2 fixed effects). We repeat the analysis in columns 3 and 4 with chronic climate risk as the dependent variable, and in columns 5 and 6 with transition climate risk as the dependent variable. Panel B presents regressions of acute risk, chronic risk, all transition risk, and proactive transition risk on a variety of lagged deterministic variables. Industry by time fixed effects are included in all regressions in panel B. Standard errors are clustered at the firm level. t-statistics are shown in parentheses. $*p<.1$; $**p<.05$; $***p<.01$.

better understand what types of firms tend to have higher values in the climate risk measures that we constructed. We control for industry-by-time fixed effects to account for time-varying heterogeneity across industries. Among all the variables, the first set is related to a firm's physical exposure to climate risk. We find an overall positive relationship between the firm's physical assets and the climate risk measures: the coefficients for PPE and total assets are positive and significant in most regressions. The results suggest that firms that hold more physical assets tend to face higher climate risk exposure.

A second set measures the firm's financial leverage. We find it to be negatively correlated with the transition risk, but not with the two physical risk measures, suggesting that highly leveraged firms tend to be associated with lower transition risk exposure. This evidence is consistent with the evidence documented by Ginglinger and Moreau (2023), who find that firms with greater climate risk have lower leverage even after controlling for firm characteristics known to determine leverage.[24]

The final set of measures included in our regressions capture external characteristics of firms, such as the number of analysts covering the firm and institutional ownership. These measures could be correlated with how climate issues are discussed in earnings calls. We find a negative relationship between the number of analysts and our climate risk measures, with one measure being statistically significant. This suggests that firms are less likely to discuss climate-related topics during earnings conference calls when a large number of analysts cover the firm. This could be because with higher analyst coverage, ample information already may be available regarding the firm's climate exposure, leading to less need for discussion during earnings calls. We do not find a significant correlation between institutional ownership and our climate risk measures.

Lastly, we analyze the correlations between the proactive component of the transition risk measure and firm-level attributes, controlling for transition risk itself. Our results show that firms that carry low leverage, hold more physical assets, and are followed by fewer analysts tend to respond more proactively to rising climate risk.

7. Do Capital Markets Price Climate Risks?

7.1 Baseline results

The pricing of climate risks in financial markets is a key issue in the climate finance literature, as highlighted by recent studies (Giglio, Kelly, and Stroebel 2021; Stroebel and Wurgler 2021). In particular, regulatory risk associated with transition risk is viewed as a top climate risk over the next 5–30 years. In this section, we aim to investigate whether transition risk is priced in stock

[24] They conclude that their results are consistent with the hypothesis that climate risk reduces leverage via larger expected distress costs and higher operating costs.

markets. To measure a firm's valuation, we use Tobin's q, which is the ratio of a firm's market value to the replacement value of its physical assets. Tobin's q has been widely used in the literature for this purpose, as it captures the value of intangible assets in addition to physical capital. This measure is high (low) when the firm has more (less) valuable intangible assets, which makes it well-suited for our analysis of the predictable effects of a firm's transition risk on its value. Specifically, we estimate the following regression specification:

$$Tobin's\ q_{i,t+k} = \beta \cdot TransitionRisk_{i,t} + \gamma \cdot X_{i,t-1} + \zeta_{j,t} + \epsilon_{i,t}, \tag{3}$$

where the dependent variable is Tobin's q in quarter $t+k$ ($k=1,3,5$); $TransitionRisk_{i,t}$ is the main explanatory variable; $X_{i,t-1}$ includes the firm's assets, CapEx, PPE, book leverage, ROA, and energy price exposure that we constructed using the earnings call data. We also include industry-by-quarter fixed effects to account for both observable and unobservable time-varying heterogeneity across industries.

In panel A of Table 6, we present the baseline results based on the entire sample, where in each column we report the results of a regression of Tobin's q over various lead times k (1, 3 and 5). For columns 1–3 we use $TransitionRisk_{i,t}$ as the main explanatory variable. All coefficients for $TransitionRisk_{i,t}$ are negative and significant at the 1% level. For instance, the results in column 1 suggest that a one-SD increase in the transition risk measure is associated with about a 0.0389—1.9% of the mean—decrease in Tobin's q in the next quarter.[25] Also, the magnitude of the coefficient increases slightly when we use Tobin's q as the dependent variable over a longer horizon ($k=3,5$), suggesting that there is no reversal in the estimated pricing effect. Therefore, our results in this table suggest that transition risk has been priced in equity markets.

For columns 4–6 we include proactive and nonproactive components of our transition risk measures as the main explanatory variables. We also include the firm-level $Action\ Index$ as additional control, which captures the overall proactiveness of firms that do not face high transition risk. This measure is calculated as the total frequency of mentions of proactive verbs in an entire transcript (except those that fall within ±1 sentences of climate-related discussions), divided by the length of the transcript. Interestingly, we find that, while the coefficient for nonproactive transition risk is negative and significant, that on proactive measure is nonsignificant. The difference between the two

[25] The estimate is comparable to those in several papers in the literature that estimate the pricing effect of carbon emissions. For example, Matsumura, Prakash, and Vera-Munoz (2014) estimate that an increase of carbon emissions from the 25th to 75th percentile is associated with 4.2% decrease in the market value of equity (calculated as number of shares outstanding multiplied by year-end stock price). Both Bolton and Kacperczyk (2021b) and Chava (2014) estimate a significant carbon premium, by 2.85% of stock returns per one-standard-deviation change in total emission levels in each country and 1.04% of expected cost of equity for U.S. firms that have higher net environmental concerns, respectively.

Table 6
Pricing of climate risk

A. All years

Dep Var	Tobin's $q_{i,t+h}$					
	$h=1$ (1)	$h=3$ (2)	$h=5$ (3)	$h=1$ (4)	$h=3$ (5)	$h=5$ (6)
Transition risk$_{i,t}$	−0.0389***	−0.0404***	−0.0418***			
	(−3.828)	(−3.978)	(−4.179)			
Transition risk/Nonproactive$_{i,t}$				−0.0416***	−0.0407***	−0.0405***
				(−4.764)	(−4.466)	(−4.719)
Transition risk/Proactive$_{i,t}$				0.0047	0.0005	−0.0024
				(0.618)	(0.081)	(−0.326)
Energy Price Exposure$_{i,t}$	−0.0634***	−0.0577***	−0.0547***	−0.0601***	−0.0545***	−0.0517***
	(−5.814)	(−5.382)	(−5.059)	(−5.503)	(−5.077)	(−4.784)
Action Index$_{i,t}$				−0.0583***	−0.0520***	−0.0462***
				(−4.458)	(−3.941)	(−3.455)
Firm attributes$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	111,691	104,442	97,470	111,691	104,442	97,470
Adj. R^2	.182	.210	.171	.218	.211	.210
F-test				−0.0463***	−0.0412***	−0.0381***

B. Transition risk by different periods

Dep var	Tobin's $q_{i,t+1}$			
Sample	Year ≤ 2009 (1)	Year ≥ 2010 (2)	Year ≤ 2009 (3)	Year ≥ 2010 (4)
Transition Risk$_{i,t}$	−0.0041	−0.0571***		
	(−0.305)	(−4.911)		
Transition Risk/Nonproactive$_{i,t}$			−0.0151	−0.0548***
			(−1.412)	(−5.234)
Transition Risk/Proactive$_{i,t}$			0.0174	−0.0045
			(1.461)	(−0.537)
Energy Price Exposure$_{i,t}$	−0.0554***	−0.0742***	−0.0527***	−0.0706***
	(−3.729)	(−5.920)	(−3.546)	(−5.607)
Action Index$_{i,t}$			−0.0426***	−0.0702***
			(−3.013)	(−3.883)
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes
N	50,706	60,985	50,706	60,985
Adj. R^2	.180	.183	.181	.185

This table presents results from firm level regressions testing the relation between our transition climate risk measures (standardized) and Tobin's q. Panel A reports the results from regression analysis of firm's Tobin's q in different lead time periods (*t+1*, *t+3*, and *t+5*) on the lagged transition climate risk (in quarter *t*). In columns 1–3, the key explanatory variable is the overall transition risk measure. In columns 4–6, we decompose the transition risk measure into proactive and nonproactive components and add *Action Index* as an additional control variable. In panel B, we separately examine the relationship between Tobin's q and lagged transition climate risk in two subsample periods: 2002–2009 and 2010–2018. In both panels, all specifications include time-varying firm-level control variables, including lagged (i.e., *t*-1) *log(Asset)*, *CapEx*, *PPE*, *Book Leverage*, and *ROA (%)*. Industry (NAICS three-digit) by quarter fixed effects are also included in all tests. We exclude the firms in finance and utility sectors in this analysis. Table A.1 in the appendix contains detailed definitions of all variables. Standard errors are double clustered at the firm and quarter levels. *t*-statistics are shown in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

coefficients is statistically different from zero at the 1% level. This result suggests that equity markets appear to discount firms that do not actively manage their transition risk, but not those that are proactive in addressing the risk. This finding is also consistent with our earlier evidence that the nonproactive transition risk measure is associated with higher CO_2 emissions intensity, while the proactive transition risk measure is not.[26]

7.2 Subsample analysis: Before and after 2010

In this section, we investigate whether there are any time-series variations in the pricing effects of climate risk. The pricing of climate risks is likely to change substantially over time, as noted by Giglio, Kelly, and Stroebel (2021), and the rise in investor attention to climate risk is a relatively recent phenomenon. Some global events play a crucial role in shaping societal expectations and perceptions of climate change, as several studies have shown. For instance, Engle et al. (2020) report that the intensity of climate news coverage peaked in December 2009 when the UN Climate Change Conference in Copenhagen announced a U.S.-backed climate deal with pledges to meet certain emissions reduction targets. Moreover, in January 2010, the SEC issued its first guidance to public firms on existing SEC disclosure requirements as they apply to climate change issues.[27] To examine how the pricing of climate risk evolves over time, we conduct the analysis again after splitting the sample into observations made before and after 2010.

In panel B of Table 6, we present the results of this analysis, in which we focus on Tobin's q in $t+1$ as the dependent variable. Based on the results in column 1, the coefficient for $TransitionRisk_{i,t}$ is close to zero and not significant in the early period ($\leq$ 2009), but turns negative and significant in the late period ($\geq$ 2010) with a much larger magnitude, suggesting that a firm's climate risk is priced by the capital market with a significant discount in recent years. The contrast between the results in columns 1 and 2 underscores the importance of rising investor attention as conjectured by Giglio, Kelly, and Stroebel (2021) as well as various climate-related initiatives and regulations that were implemented around that time.[28] In columns 3 and 4, we report the results obtained when we decompose transition risk into proactive and nonproactive components. We find that it is the nonproactive component that primarily drives the negative relationship between transition risk and market valuation in the late period. The coefficient for the proactive transition climate risk measure is not statistically significant in the early or late periods. Consistent with the evidence reported in panel A, there is a significant

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[26] To address the potential concern that there are a large number of zero values in the climate risk measures, we also conduct a set of zero-inflated regressions in which we control for a dummy variable that equals one if the transition risk measure is positive and zero otherwise. The results in panel A of Table IA.2 in the Internet Appendix show that the coefficients for the continuous transition climate measures are very similar in magnitude and statistical significance to those in Table 6, while the coefficient for the dummy variable is not statistically significant.

[27] Further details on the SEC's Interpretive Release can be found at https://www.sec.gov/news/press/2010/2010-15.htm.

[28] We acknowledge that it is difficult to identify the exact source of the change in the pricing effect of transition risk. Several factors could be at play, such as shifts in investor attention and changes in climate-related policies and regulations.

difference in the pricing effects of proactive and nonproactive transition risk components.

7.3 Horse-race analysis

We perform additional analyses to assess the robustness of our results regarding the pricing effects of climate risk. First, we carry out a horse-race analysis between our transition risk measure and various alternative measures. These competing measures include: (1) a transition risk measure constructed using SEC filings data; (2) a transition risk measure constructed using firm-related news data; (3) external ESG scores; and (4) climate exposure measures from Sautner et al. (2023). In addition, we also perform sensitivity analysis regarding regression specifications and strategic disclosure considerations.

7.3.1 Transition risk measures constructed using SEC filings data. We construct the first set of alternative measures using Management Discussion and Analysis (MD&A) and Risk Factors (RF) sections in the 10-K/10-Q filings, respectively. We apply the same climate dictionaries to the filings data to construct $TransitionRiskMDA_{i,t}$ and $TransitionRiskRF_{i,t}$. In panel A of Table 7, we present the results of a horse-race analysis in which we regress Tobin's q, in $t+1$ or $t+5$, on both our transition risk measure and one of the two alternative transition risk measures in each regression.[29] The results in columns 1–4 show that the coefficients for our transition risk measure remain negative and significant, while those on the alternative transition climate risk measures are not statistically significantly different from zero except for in column 3, where the coefficient for $TransitionriskRF_{i,t}$ is less than half of that on our transition risk measure. We note that, compared with the earnings call data, one major drawback of using the Risk Factors section is that it contains only information about the risk factors themselves, with no discussion of how a company addresses or responds to those risks. In columns 5–8, we report the results of an analysis where we decompose transition risk into proactive and nonproactive components. We continue to find that the discount on our transition risk measure is driven primarily by its nonproactive component, which is also negative and significant at the 1% level in all columns, after controlling for competing measures.

7.3.2 Transition risk measure constructed using firm-related news data. The second alternative measure is constructed using firm-related news data. $TransitionRisk\ News_{i,t}$ is the ratio between the number of news articles related to a firm's transition climate risk exposure and the number of all news articles related to the company. We construct this measure by applying the same transition risk dictionary to the firm-related news data. Panel B of Table 7

[29] Table IA.3 in the Internet Appendix presents the correlation of these alternative measures.

Table 7
Alternative transition risk measures

A. Alternative transition risk measures from SEC filings data

Dep Var	Tobin's $q_{i,t+h}$							
	$h=1$ (1)	$h=5$ (2)	$h=1$ (3)	$h=5$ (4)	$h=1$ (5)	$h=5$ (6)	$h=1$ (7)	$h=5$ (8)
Transition Risk$_{i,t}$	−0.0373***	−0.0425***	−0.0351***	−0.0422***				
	(−3.524)	(−4.141)	(−3.181)	(−4.035)				
Transition Risk/Nonproactive$_{i,t}$					−0.0384***	−0.0398***	−0.0370***	−0.0388***
					(−4.126)	(−4.414)	(−3.828)	(−4.221)
Transition Risk/Proactive$_{i,t}$					0.0019	−0.0047	0.0033	−0.0062
					(0.215)	(−0.579)	(0.342)	(−0.721)
Transition Risk MDA$_{i,t}$	−0.0102	−0.0062			−0.0122	−0.0076		
	(−0.491)	(−0.296)			(−0.585)	(−0.366)		
Transition Risk RF$_{i,t}$			−0.0161**	−0.0111			−0.0157**	−0.0108
			(−2.553)	(−1.590)			(−2.502)	(−1.557)
Energy Price Exposure$_{i,t}$	−0.0592***	−0.0511***	−0.0582***	−0.0494***	−0.0559***	−0.0483***	−0.0549***	−0.0462***
	(−5.494)	(−4.661)	(−5.030)	(−4.236)	(−5.185)	(−4.402)	(−4.729)	(−3.956)
Action Index$_{i,t}$					−0.0560***	−0.0427***	−0.0614***	−0.0487***
					(−4.086)	(−3.073)	(−4.023)	(−3.114)
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	89,308	79,141	72,095	62,792	89,308	79,141	72,095	62,792
Adj. R^2	.186	.176	.188	.183	.187	.177	.190	.184
F-test					−0.0403***	−0.0351***	−0.0403***	−0.0326***

(*Continued*)

Table 7
(Continued)

B. Alternative transition risk measures from news data

Dep Var	Tobin's $q_{i,t+h}$							
	$h=1$	$h=5$	$h=1$	$h=5$	$h=1$	$h=5$	$h=1$	$h=5$
Climate News Restriction	Relevance $\geq$ 75				Relevance $\geq$ 50			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Transition Risk$_{i,t}$	−0.0370***	−0.0389***			−0.0425***	−0.0446***		
	(−3.403)	(−3.628)			(−3.937)	(−4.201)		
Transition Risk/Nonproactive$_{i,t}$			−0.0398***	−0.0375***			−0.0452***	−0.0432***
			(−4.163)	(−4.040)			(−4.772)	(−4.768)
Transition Risk/Proactive$_{i,t}$			0.0046	−0.0026			0.0047	−0.0024
			(0.601)	(−0.349)			(0.621)	(−0.328)
Transition Risk News$_{i,t}$	−0.0051	−0.0074	−0.0047	−0.0074	0.0094	0.0071	0.0095	0.0069
	(−0.514)	(−0.770)	(−0.481)	(−0.776)	(0.814)	(0.641)	(0.819)	(0.630)
Energy Price Exposure$_{i,t}$	−0.0630***	−0.0540***	−0.0596***	−0.0510***	−0.0642***	−0.0553***	−0.0608***	−0.0523***
	(−5.857)	(−5.056)	(−5.547)	(−4.781)	(−5.999)	(−5.218)	(−5.689)	(−4.944)
Action Index$_{i,t}$			−0.0583***	−0.0462***			−0.0583***	−0.0462***
			(−4.458)	(−3.455)			(−4.454)	(−3.452)
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	111,691	97,470	111,691	97,470	111,691	97,470	111,691	97,470
Adj. R^2	.182	.171	.183	.172	.182	.171	.183	.172
F-test			−0.0444***	−0.0349***			−0.0499***	−0.0408***

(*Continued*)

Table 7
(Continued)

C. MSCI CCI

Dep Var	Tobin's $q_{i,t+h}$							
	$h=1$		$h=5$		$h=1$		$h=5$	
	Overlapped Sample							
Sample	Yes	No	Yes	No	Yes	No	Yes	No
Coverage	13%	87%	13%	87%	13%	87%	13%	87%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Transition Risk$_{i,t}$	−0.0567***	−0.0325***	−0.0445**	−0.0377***				
	(−3.501)	(−2.991)	(−2.680)	(−3.642)				
Transition Risk/Nonproactive$_{i,t}$					−0.0618***	−0.0346***	−0.0401**	−0.0366***
					(−3.773)	(−3.919)	(−2.463)	(−4.312)
Transition Risk/Proactive$_{i,t}$					0.0151	0.0031	−0.0100	−0.0021
					(0.999)	(0.387)	(−0.669)	(−0.265)
MSCI CCI$_{i,t}$	−0.1703***		−0.1706***		−0.1661***		−0.1685***	
	(−3.066)		(−3.015)		(−3.031)		(−2.995)	
Energy Price Exposure$_{i,t}$	−0.0564**	−0.0601***	−0.0520*	−0.0516***	−0.0542**	−0.0570***	−0.0496*	−0.0489***
	(−2.182)	(−5.535)	(−1.912)	(−4.866)	(−2.090)	(−5.233)	(−1.812)	(−4.607)
Action Index$_{i,t}$					−0.0453	−0.0541***	−0.0264	−0.0429***
					(−1.171)	(−4.174)	(−0.689)	(−3.252)
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes	Ye	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,564	97,814	10,614	86,561	13,564	97,814	10,614	86,561
Adj. R^2	.212	.182	.203	.172	.213	.183	.203	.172
F-test					−0.0769**	−0.0377***	−0.0301	−0.0345**

(*Continued*)

Table 7
(Continued)

D. Measures from Sautner et al. (2023)

	Tobin's $q_{i,t+h}$					
	$h=1$	$h=5$	$h=1$	$h=5$	$h=1$	
Sample	All Years				Year≥2010	Year≥2010
	(1)	(2)	(3)	(4)	(5)	(6)
Transition Risk$_{i,t}$	−0.0385***	−0.0386***			−0.0494***	
	(−3.431)	(−3.363)			(−3.854)	
Transition Risk/Nonproactive$_{i,t}$			−0.0413***	−0.0391***		−0.0475***
			(−3.838)	(−3.677)		(−4.081)
Transition Risk/Proactive$_{i,t}$			−0.0029	−0.0094		−0.0075
			(−0.361)	(−1.132)		(−0.822)
CCExposure$_{i,t}$	0.0145	0.0026			−0.0122	
	(0.749)	(0.128)			(−0.629)	
CCExposure$^{Phy}_{i,t}$			−0.0027	−0.0039		0.0065
			(−0.252)	(−0.376)		(0.422)
CCExposure$^{Opp}_{i,t}$			0.0216	0.0146		0.0055
			(1.574)	(1.094)		(0.346)
CCExposure$^{Reg}_{i,t}$			0.0075	0.0041		−0.0216*
			(0.397)	(0.200)		(−1.690)
Energy Price Exposure$_{i,t}$	−0.1012***	−0.0888***	−0.0979***	−0.0857***	−0.1159***	−0.1120***
	(−7.904)	(−7.028)	(−7.680)	(−6.844)	(−7.534)	(−7.285)
Action Index$_{i,t}$			−0.0513***	−0.0450***		−0.0595***
			(−3.820)	(−3.274)		(−3.352)
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	124,444	109,730	124,444	109,730	71,224	71,224
Adj. R^2	.151	.149	.152	.150	.159	.161
F-test			−0.0384**	−0.0297*		−0.0400

This table presents the horse-race test results when we regress Tobin's q in different lead time periods on both our transition risk measures using earnings call transcript data and other transition risk measures constructed from alternative data source. In panel A, the alternative transition risk measures are the measure based on the MD&A section of SEC filings (columns 1–2, 5–6) and the measure based on the Risk Factors section of SEC filings (columns 3 and 4, 7 and 8), respectively. The alternative risk measures in Panel B are constructed from company news data from RavenPack database. *Transition risk news* is equal to the number of news articles related to the firm's transition climate risk exposure divided by the number of all news articles related to the company. In column 1 to column 4, the news articles are filtered by relevance score higher than 75. According to RavenPack, Values above 75 are considered significantly relevant. Column 5 to column 8 present the results when we change the relevance cutoff to 50. In Panel C, the alternative transition risk measure is the MSCI CCI. Column 1, 3, 5, and 7 present the regression results on the overlapped sample (13% of our sample). Column 2, 4, 6, and 8 present the results on the other part of our sample (87% of our sample) that is not covered in MSCI CCI. In panel D, we use the climate exposure measures from Sautner et al. (2023). Specifically, *CCExposure* is the relative frequency with which bigrams related to climate change occur in the transcripts of earnings calls. $CCExposure^{Phy}$ is the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of earnings calls. $CCExposure^{Opp}$ is the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of earnings calls. $CCExposure^{Reg}$ is the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of earnings calls. Lagged firm attributes (*log(Asset)*, *CapEx*, *PPE*, *Book Leverage*, and *ROA (%)*) and industry by quarter fixed effects are included in all tests of each panel. Table A.1 in the appendix contains detailed definitions of all variables. Standard errors are double clustered at the firm and quarter levels. *t*-statistics are shown in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

reports the horse-race results. The results in columns 1 and 2 show that the coefficient of our transition risk measure remains negative and significant at the 1% level in all specifications, while the coefficient for $Transitionrisknews_{i,t}$ is not significant, suggesting that there is no relationship between the fraction of firm-specific news that involves climate issues and Tobin's q. The results in columns 3 and 4 are very similar when we replace the transition risk measure by its proactive and nonproactive components. The significant price discount associated with transition risk is driven by firms that do not undertake proactive responses, while the coefficient for $Transitionrisknews_{i,t}$ remains nonsignificant. In columns 5–8, we repeat the above analysis using 50 as the relevance score cutoff in RavenPack and find almost the same results. This set of results suggests that our transition risk measure contains valuable information not already available in other public sources.

7.3.3 MSCI Climate Change index. The third alternative measure of climate risk is MSCI's CCI. In panel C of Table 7, we report the horse-race results. In all specifications, the coefficients of our transition risk measure and its nonproactive component are negative and significant at the 5% or lower level, confirming that the estimated price discount indicated in Table 6 is robust in the horse race against the CCI. The coefficient for the CCI measure is also negative and significant at the 1% level, suggesting that firms with higher climate change scores are also priced at a significant discount in the stock market. The coexistence of the two competing measures also suggests that they complement each other in capturing firms' climate risk exposure.[30]

7.3.4 Climate risk measures from Sautner et al. (2023). Our final horse-race test uses the climate change exposure measures developed by Sautner et al. (2023) based on an ML approach as the competing measure. Panel D of Table 7 reports the results. We find that the coefficients for our transition risk measure and its nonproactive component are negative and significant at the 1% level, while those on their climate exposure measures are not statistically significant from zero, as shown in columns 1–4. This pattern persists when we focus on recent years (2010 or later), as Sautner et al. (2023) show a strong correlation between their measures and Tobin's q using only the data from more recent years. There, we find the coefficient for their regulatory climate exposure measure ($CCExposure^{Reg}$) to be marginally significant and small in magnitude compared with that on our transition climate risk measure.

30 In an additional analysis, we also consider the environmental components of the RepRisk and the Refinitiv ESG scores in a similar horse-race specification. Panel A of Table IA.4 in the Internet Appendix reports the results. We find that the coefficients for our transition risk measure and its nonproactive component remain negative and significant at the 1% level after controlling for the environmental ratings of RepRisk and Refinitiv.

7.4 Controlling for firm fixed effects

Our baseline regressions control for industry-by-time fixed effects, along with firm-level attributes that vary over time. This specification allows us to compare the differential outcomes, such as Tobin's q, between firms that face high and low climate risk within the same industry at a given time. However, it is important to also consider within-firm variations over time to fully understand the impact of climate risk on firms' outcomes. To address this concern, we have experimented with an alternative specification where we control for both firm and industry-by-time fixed effects, which allows us to compare within-firm changes in climate risk and firm outcomes while addressing potential endogeneity issues. The results are reported in Table 8. Panel A uses the change in Tobin's q as the dependent variable and the change in $TransitionRisk_{i,t}$ as the main explanatory variable. Our analysis shows that a higher increase in the transition risk measure is associated with a larger decrease in Tobin's q in the future. The effect is statistically significant at the 10% level or lower after the third quarter (including $t+4$, $t+5$, $t+6,\ldots$), indicating that the stock markets gradually price in the change in transition risk within a given firm.

Panel B focuses on changes in the proactive and nonproactive components of our transition risk measures as the main explanatory variables. The results indicate that only changes in transition risk with nonproactive responses are significantly priced at a discount, while the coefficient for changes in transition risk with proactive responses is negative, but not statistically significant. These findings are consistent with our baseline results in Section 7.1, suggesting that equity markets discount firms that do not actively manage their transition risk, but not those that proactively address the risk.

Overall, our results remain robust after controlling for firm fixed effects and further support the idea that changes in climate risk discussion correlate with changes in Tobin's q.

7.5 Strategic disclosure in earnings calls

Like any other disclosure data, discussions during earnings calls are not immune to selection bias introduced by strategic considerations. For instance, executives may choose to speak about certain aspects of a firm's climate risk exposure while not necessarily answering certain questions brought up by analysts. To address selection concerns regarding earnings calls, we restrict the sample in two ways, such that the particular selection concern is more constrained and repeat the pricing regression to see if our estimates remain robust. In the first exercise, we filter out earnings calls where we detect an extreme tone. The literature on qualitative disclosure has shown that management can strategically determine the tone of textual disclosures to achieve certain outcomes (e.g., Lang and Lundholm 2000; Feldman et al. 2010; Arslan-Ayaydin, Boudt, and Thewissen 2016). In the second exercise, we exclude earnings calls which rank in the top quartile based on the number of "nonanswers" from management during a call, measured using the

Table 8
Pricing of within-firm climate risk

A. Total transition risk

Dep Var	ΔTobin's $q_{i,t+h}$					
	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	$h=5$ (5)	$h=6$ (6)
ΔTransition Risk$_{i,t}$	−0.0003	−0.0025	−0.0030	−0.0053**	−0.0034*	−0.0046**
	(−0.164)	(−1.023)	(−1.177)	(−2.066)	(−1.824)	(−2.127)
Energy Price Exposure$_{i,t}$	0.0008	0.0032	0.0037	0.0030	0.0041	0.0041
	(0.477)	(1.216)	(1.350)	(0.887)	(1.188)	(1.124)
Firm Attributes$_{i,t-1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	110,761	106,830	103,113	99,421	95,929	92,554
Adj. R^2	.103	.188	.311	.301	.392	.427

B. Proactive and nonproactive transition risk

Dep Var	ΔTobin's $q_{i,t+h}$					
	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=4$ (4)	$h=5$ (5)	$h=6$ (6)
ΔTransition Risk/ Nonproactive $_{i,t}$	−0.0009	−0.0026	−0.0035	−0.0046*	−0.0033*	−0.0050**
	(−0.454)	(−1.222)	(−1.571)	(−1.944)	(−1.857)	(−2.137)
ΔTransition Risk/Proactive	0.0010	−0.0002	0.0006	−0.0012	−0.0004	0.0004
	(0.853)	(−0.165)	(0.435)	(−0.872)	(−0.307)	(0.498)
Energy Price Exposure$_{i,t}$	0.0009	0.0035	0.0041	0.0037	0.0050	0.0049
	(0.531)	(1.333)	(1.501)	(1.104)	(1.443)	(1.351)
Action Index$_{i,t}$	−0.0025	−0.0055*	−0.0080**	−0.0123**	−0.0150***	−0.0155***
	(−1.220)	(−1.751)	(−2.004)	(−2.642)	(−3.039)	(−2.934)
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	110,761	106,830	103,113	99,421	95,929	92,554
Adj. R^2	.103	.188	.312	.301	.392	.428

This table presents the results from firm level regressions testing the relation between the change in transition climate risk measures (standardized) and the change in Tobin's q while controlling for firm fixed effects. Panel A reports the results from regression analysis of change in Tobin's q in different lead time periods (*t+1*,*t+2 t+3*, *t+4*, *t+5* and *t+6*) on the lagged change in transition climate risk. The key explanatory variable is the change in transition risk measure from *t*-1 to *t*. In panel B, we decompose the change in transition risk measure into the change in proactive and nonproactive components and add *Action Index* as an additional control variable. In both panels, all specifications include time-varying firm-level control variables, including lagged (i.e., *t*-1) *Tobin's q*, *log(Asset)*, *CapEx*, *PPE*, *Book Leverage*, and *ROA (%)*. Industry (NAICS three-digit) by quarter fixed effects are also included in all tests. We exclude the firms in finance and insurance sector. Table A.1 in the appendix contains detailed definitions of all variables. Standard errors are double clustered at the firm and quarter levels. *t*-statistics are shown in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

latest linguistic analysis method proposed by Gow, Larcker, and Zakolyukina (2021).[31] We report the results of this analysis in Table IA.5. We find that the

[31] This measure is viewed in the literature as a proxy for strategic considerations or corporate disclosure policies. Gow, Larcker, and Zakolyukina (2021) show that analyst questions that have a negative tone, greater uncertainty, and greater complexity, or requests for greater detail are more likely to trigger nonanswers. Performance-related questions tend to be associated with nonanswers, and this association is weaker when performance news is favorable.

price discount associated with high transition risk is still significant based on the restricted samples. Our results suggest that the selection issue is not a major concern for our analysis.

8. Firms' Responses to Climate Risks

In this section, we investigate whether firm-level climate risk exposure affects a firm's real business activities. To do so, we estimate differences in corporate responses associated with high climate risk by running regressions specified in Equation (2), where the dependent variable includes CapEx, R&D expenditures, the fraction of green patents, and employment over horizon $t+k$ ($k>0$). The main explanatory variables are transition risk and its proactive and nonproactive components in t. We control for a firm's total assets as well as industry-by-time fixed effects. In essence, we compare differences in corporate responses between firms that face high and those that face low transition climate risk, as well as between firms with and without proactive responses to transition risk.

8.1 Investment

The theoretical literature has offered mixed predictions regarding investment under uncertainty. While Bernanke (1983), Pindyck (1991), Pindyck and Solimano (1993) and Dixit and Pindyck (1994) predict a decline in investment in times of high uncertainty, other studies, such as Oi (1961), Hartman (1972, 1976), Abel (1983), Roberts and Weitzman (1981), and Bar-Ilan and Strange (1996), predict a positive relationship. Ultimately, how firm-level investment varies with climate risk exposure is an empirical question.

Table 9 presents the results of an analysis using CapEx scaled by total assets as the dependent variable. The results in columns 1–3 indicate a positive, but not significant, coefficient for $ClimateRisk_{i,t}$, suggesting that there is no statistically significant difference in future investment between firms that face high and those that face low transition risk. In columns 4–6, we investigate differences between the responses of firms that do and those that do not respond to climate risk proactively. To do so, we regress the same set of firm-level outcomes on transition risk with and without proactive keywords. We see that the coefficients for two of the transition risk measures are both positive, but only the coefficient for proactive transition risk is statistically significant (at the 1% level), suggesting that firms that proactively respond tend to increase their CapEx following an increase in transition risk. A one-SD increase in transition risk with proactive keywords in t is associated with a 0.046-percentage-point increase in CapEx in $t+1$ and about a 0.06-percentage-point increase in CapEx

Table 9
Predicting the firm's investment

Dep Var	$CapEx_{i,t+h}$					
	$h=1$ (1)	$h=3$ (2)	$h=5$ (3)	$h=1$ (4)	$h=3$ (5)	$h=5$ (6)
$\text{Transition Risk}_{i,t}$	0.0480	0.0498	0.0421			
	(1.460)	(1.499)	(1.256)			
$\text{Transition Risk/Nonproactive}_{i,t}$				0.0236	0.0158	0.0074
				(0.783)	(0.547)	(0.252)
$\text{Transition Risk/Proactive}_{i,t}$				0.0460***	0.0623***	0.0641***
				(2.951)	(3.455)	(3.287)
$\text{Energy Price Exposure}_{i,t}$	0.0896*	0.1120**	0.1186**	0.0867*	0.1030**	0.1136**
	(1.901)	(2.435)	(2.557)	(1.836)	(2.236)	(2.452)
$\text{Action Index}_{i,t}$				0.0058	0.0782***	0.0201
				(0.274)	(3.442)	(0.909)
$\text{Firm Attributes}_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	126,099	118,043	110,313	126,099	118,043	110,313
Adj. R^2	.439	.437	.435	.439	.438	.435
F-test				−0.0224	−0.0465	−0.0567*

This table reports estimates of the regressions of capital expenditures (in different lead time periods) on transition risk. Columns 1–3 shows the results using *Transition risk* as the key explanatory variable. In columns 4–6, we replace transition risk measure with its two components: nonproactive and proactive transition risk, and we add *Action index* as additional control variable. Lagged *log(Asset)* and industry by quarter fixed effects are included in all tests. Table A.1 in the appendix defines all the variables. Standard errors are double clustered at the firm and quarter levels. t-statistics are shown in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

in $t+3$ and $t+5$.[32] The estimates are economically meaningful, representing approximately 1.6%–2.3% of the average investment level. In the bottom row, we report the differences between the two coefficients along with their significance levels based on F-tests, showing that the difference in CapEx between proactive and nonproactive firms, when both face high climate risk, is significant at the 10% level in $t+5$.

8.2 Innovation

To reach net-zero emissions or decarbonization, firms are inevitably required to innovate or change the way they do business. Thus, innovation is a viable and important response for firms facing high transition risk. We consider two measures of innovation: one is R&D expenditure, scaled by assets, the other is the fraction of green patents. In panel A of Table 10, we report the results for R&D expenditures. We find negative and significant coefficients for $ClimateRisk_{i,t}$ in columns 1–3, suggesting high transition risk is associated with lower R&D expenditures. A one-SD increase in transition risk is associated with a 0.0529-

[32] Although not fully reported in this table, our analysis reveals that the coefficients of the firm-level action index (i.e., $Action\ index$) are positive for the five consecutive quarters, with the magnitude varying over time. Specifically, the coefficient is 0.0058 in $t+1$ and increases to 0.0782 in $t+3$ before decreasing to almost zero. While the coefficient is not significant in $t+1$, it becomes statistically significant at the 1% level in $t+2$ and $t+3$, before becoming insignificant thereafter. These results suggest that a higher level of action index, in general, is associated with higher CapEx investments with a two-quarter lag, even for firms that do not face high climate risk.

Table 10
Predicting the firm's other responses

A. R&D expenditures

Dep Var	R&D investment$_{i,t+h}$					
	$h=1$	$h=3$	$h=5$	$h=1$	$h=3$	$h=5$
	(1)	(2)	(3)	(4)	(5)	(6)
Transition Risk$_{i,t}$	−0.0556**	−0.0529**	−0.0565**			
	(−2.393)	(−2.269)	(−2.391)			
Transition Risk/Nonproactive$_{i,t}$				−0.0548***	−0.0550**	−0.0557***
				(−2.697)	(−2.611)	(−2.675)
Transition Risk/Proactive$_{i,t}$				−0.0033	0.0026	−0.0025
				(−0.252)	(0.179)	(−0.167)
Energy Price Exposure$_{i,t}$	−0.1797***	−0.1782***	−0.1741***	−0.1603***	−0.1605***	−0.1561***
	(−7.917)	(−7.756)	(−7.701)	(−7.174)	(−7.107)	(−7.015)
Action Index$_{i,t}$				−0.2684***	−0.2463***	−0.2485***
				(−11.879)	(−10.685)	(−10.758)
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	128,503	119,997	111,971	128,503	119,997	111,971
Adj. R^2	.388	.381	.373	.398	.389	.382
F-test				−0.0515**	−0.0576**	−0.0532**

B. Green patents (annual)

Dep Var	I(Green patents)$_{i,t+h}$				Green patents ratio$_{i,t+h}$			
	$h=1$	$h=2$	$h=1$	$h=2$	$h=1$	$h=2$	$h=1$	$h=2$
Sample	All Firms				Firms with Patents Only			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Transition Risk$_{i,t}$	0.0115	0.0080			0.0321***	0.0331***		
	(1.598)	(1.276)			(3.914)	(3.883)		
Transition Risk/Nonproactive$_{i,t}$			0.0057	0.0014			0.0189**	0.0165*
			(0.804)	(0.200)			(2.252)	(1.836)
Transition Risk/Proactive$_{i,t}$			0.0090**	0.0103**			0.0193**	0.0251***
			(2.396)	(2.168)			(2.959)	(3.395)
Energy Price Exposure$_{i,t}$	0.0373***	0.0352***	0.0359***	0.0340***	0.0207**	0.0231**	0.0188**	0.0208**
	(4.930)	(4.683)	(4.903)	(4.708)	(2.525)	(2.367)	(2.339)	(2.307)
Action Index$_{i,t}$			0.0063	0.0026			−0.0019	−0.0018
			(1.580)	(0.745)			(−0.820)	(−0.908)
Firm Attributes$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	32,713	32,713	32,713	32,713	9,372	8,186	9,372	8,186
Adj. R^2	.199	.193	.192	.193	.103	.110	.109	.122
F-test			−0.0033	−0.0089			−0.0004	−0.0086

(*Continued*)

Table 10
(Continued)

C. Employment (annual)

Dep Var	log(Employment)$_{i,t+h}$			
	$h=1$	$h=2$	$h=1$	$h=2$
	(1)	(2)	(3)	(4)
Transition risk$_{i,t}$	-0.0195**	−0.0202**		
	(−2.050)	(−2.047)		
Transition risk/nonproactive$_{i,t}$			−0.0188*	−0.0197*
			(−1.731)	(−1.692)
Transition risk/proactive$_{i,t}$			−0.0000	0.0002
			(−0.003)	(0.022)
Energy price exposure$_{i,t}$	0.0032	0.0007	−0.0041	−0.0067
	(0.249)	(0.050)	(−0.325)	(−0.508)
Action index$_{i,t}$			0.0634***	0.0624***
			(6.647)	(6.267)
Firm attributes$_{i,t-1}$	Yes	Yes	Yes	Yes
Industry × Time FE	Yes	Yes	Yes	Yes
N	32,165	30,533	32,165	30,533
Adj. R^2	.776	.771	.778	.773
F-test			−0.0188	−0.0199

In panel A, we regress *R&D Investment* (in *t+1*, *t+3*, *t+5*) on overall transition risk measure (in columns 1-3) and decomposed transition risk measures (in columns 4–6), respectively. In columns 1–4 of panel B, the dependent variable is *I(Green patents)*, a dummy variable equals one if a firm has at least one green patent, and zero otherwise. The sample includes all firms. In columns 5–8 of panel B, the dependent variable is *Green patents ratio*, the number of green patents scaled by the total number of patents in the year. The sample is restricted to the firms with patents. In panel C, the dependent variable is the natural logarithm of the firm's employment level. All specifications include lagged (i.e., *t*-1) *log(Asset)* as the control variable. Industry by quarter fixed effects are included in all tests. Table A.1 in the appendix defines all the variables. Standard errors are double clustered at the firm and quarter levels. *t*-statistics are shown in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

to 0.0565-percentage-point decrease in future R&D expenditures. Again, the coefficients are fairly stable over various horizons of R&D expenditures. The results in columns 4–6 suggest that the negative relationship between transition risk and a firm's future R&D expenditures is significant only for the firms that do not proactively respond, not for proactive firms.

In panel B of Table 10, we report the results of regressions using green patent measures as the dependent variable. The results in columns 1–4 are based on all firms and use an indicator of having at least one green patent as the dependent variable. We find a positive, but not significant, coefficient for $ClimateRisk_{i,t}$ in columns 1 and 2, suggesting that there is no statistically significant difference in future green patents between firms with high and low transition risk. For columns 3 and 4, we investigate differences between the responses of firms that do and those that do not respond to climate risk proactively. We see that the coefficients for two of the transition risk measures are both positive, but only the coefficient for proactive transition risk is statistically significant (at the 5% level), suggesting that firms that proactively respond are more likely to innovate via green patenting when facing high transition risk. A one-SD increase in transition risk with proactive keywords in t is associated with a 0.01-percentage-point increase in the likelihood that a green patent is filed in $t+1$ and 0.01-percentage-point increase in $t+2$. The estimates are economically meaningful, representing approximately 12.5% of the average probability that a green patent is filed.

The results in columns 5–8 are based on patenting firms only, using the ratio of green patents to the total number of patents filed by a firm as the dependent variable. We find positive and significant coefficients (at the 1% level) on $ClimateRisk_{i,t}$ as shown in columns 5 and 6, suggesting that firms that face high transition risk are associated with a higher ratio of green patents. A one-SD increase in transition risk with proactive keywords in t is associated with a 0.0321-percentage-point increase in the ratio of green patents in $t+1$ and a 0.0331-percentage-point increase in $t+2$. The results in columns 7 and 8 show that the coefficients for two of the transition risk measures are both positive and significant, but the coefficient for proactive transition risk is slightly higher and more significant (at the 5% or lower level). A one-SD increase in transition risk with proactive keywords in t is associated with a 0.0251-percentage-point increase in the ratio of green patents in $t+2$.

Given the significant and positive relationship we find between a firm's greenness and their proactiveness in managing transition risk, we conduct further analysis to explore the attributes of proactive firms and their potential differential impact on firm valuation in Internet Appendix C. Starting with firms that have patented green technologies and those that have not but are proactive in their responses to transition risk, we find that green patenting firms are more likely to be proactive in addressing transition risk, while nongreen patenting firms do not show a significant difference in being proactive relative to firms that do not patent. Panel A of Table IA.8 presents the results. Panel B of that table shows that while both types of proactive firms are valued positively by the equity markets, the difference between green proactive firms and those with nonproactive responses is much larger than that between nongreen proactive firms and those with nonproactive responses. Both differences are statistically significant at the 1% level, indicating that the equity markets tend to value green proactive responses to transition risk more than nongreen proactive responses.[33]

8.3 Employment

Another strategy at a firm's disposal for responding to rising climate risk is adjusting employment (e.g., through plant closings, layoffs, or hiring freezes). Layoffs and plant closings have been commonly adopted by executives at public companies to increase productivity, address ongoing risks, and appeal to capital markets. The results, reported in panel C of Table 10, indicate that there is a negative and significant relationship (at the 5% level) between transition risk and the logarithm of the employment level in the following 2 years. A one-SD increase in transition risk is associated with an approximately 0.02-percentage-point decrease in a firm's employment stock. The negative relationship is primarily driven by firms that do not proactively respond. The relationship is not statistically significant for firms that proactively respond.

8.4 Summary

In summary, we find a significantly negative relationship between transition risk and R&D expenditure as well as employment, driven primarily by firms that face high transition risk but do not proactively respond. In contrast, firms that proactively respond increase their total CapEx investment and file more green patents following an increase in their transition risk.[34] These findings, while revealing divergent responses on the part of firms facing high transition risk, may not suggest any causal relationships between the two, because

33 In an additional analysis, we also attempted to separate the proactive firms into two categories: (1) "fixer" firms, which help address their customers' climate risk (e.g., manufacturer of electric planes) and (2) nonfixer firms that face high transition risk (e.g., airline company), using a more general approach that captures a set of keywords in business descriptions. We observe a positive correlation between green patenting firms and fixer firms. Panel C of Table IA.8 shows that fixer firms are more likely to be proactive in managing transition risk. However, after controlling for other firm attributes, the relationship between fixer firms and proactive responses to transition risk becomes statistically insignificant. Panel D of Table IA.8 shows that while both types of proactive firms are not discounted by equity markets, the valuation is slightly larger for fixer proactive firms compared to nonfixer proactive firms, but the difference is not statistically significant at the conventional level.

34 We conduct additional regressions to study the relationship between within-firm variations in climate risk and firm-level outcomes (e.g., CapEx, the fraction of green patents, and employment). We report the results in panels B–D of Table IA.6 in the Internet Appendix. We also show that firms that proactively respond to climate risk increase total CapEx investment while controlling for firm and time fixed effects. The statistical and economic significance of the coefficient for the proactive component of transition risk increase over time. Discussions of proactive management of climate risks are associated with a significant increase in CapEx after quarter $t+1$ instead of immediately in quarter $t+1$, suggesting that these firms take time to put "words" into "actions." We do not, however, find a significant relationship between within-firm variation in transition risk and employment in subsequent years. This is not surprising insofar as the employment variable is very sticky over time.

our constructed measures simply capture transition risk discussions during earnings calls. Instead, our evidence suggests that the new measures capture new and valuable information about business conditions and can be highly predictive of changes in these corporate outcomes.[35]

9. Conclusion

This paper quantifies the presence and materiality of firm-level climate risk exposure. We develop a novel set of firm-level climate risk measures, covering both physical and transition risks, by applying a modified textual analysis method to earnings call transcript data. Most variations in physical climate risk appear to be idiosyncratic factors that may be unrelated to firm-level attributes, while most variations in transition risk can be explained by idiosyncratic factors at the firm level. Using external benchmarks, we find that our three risk measures capture changes in the respective types of climate risk a company faces. As a unique innovation of our study, we also measure firms' proactiveness in addressing climate issues. One key finding of our study is that firms that face higher transition risk, especially those that do not proactively respond, are valued at a discount in the equity market. Horse-race analyses show that our measures offer unique value for studying how capital markets price climate risk, particularly transition risk.

Using several corporate outcomes as dependent variables, we find that firms that face high transition risk significantly decrease their R&D expenditures and employment. This negative relation is primarily driven by firms that do not proactively respond to rising climate risk. Firms that proactively respond to this risk tend to significantly increase their total CapEx investment and file more green patent applications. Thus, firms' attitudes toward climate issues—whether or not proactive— matter significantly in determining how firms respond to rising climate risk.

Our key finding that firms that do not proactively respond to transition risk are valued at a discount underscores the importance of disclosing climate risks in a transparent and comprehensive manner to ensure that investors have access to accurate information and can make informed investment decisions. Our ability to identify variations in firm-level climate risk exposure and responses suggests that when such information is available, investors find it relevant. Indeed, regulators have begun to focus on how best to provide this information to investors. In March 2021, the SEC created a Climate and ESG Task Force to identify climate and ESG-related misconduct. In March 2022, the SEC proposed new rules that require public companies to report climate-related risks and emissions data in registration statements and annual reports.

[35] In panels B–D of Table IA.2 in the Internet Appendix, we present the results from zero-inflated regressions of CapEx, green patents, and employment, respectively. They show that coefficients for the continuous transition risk measures and the dummy variable for nonzero values are both positive and significant.

Appendix

Table A.1
Variable definitions

Variable name	Description	Source
Acute climate risk	The frequency of mentions of the unigrams or bigrams related to the acute climate discussion in the proximity of risk synonyms, divided by the total length of the transcript, and then multiplied by 10^4	StreetEvents
Chronic climate risk	The frequency of mentions of the unigrams or bigrams related to the chronic climate discussion in the proximity of risk synonyms, divided by the total length of the transcript, and then multiplied by 10^4	StreetEvents
Transition climate risk	The frequency of mentions of the unigrams or bigrams related to the transition climate discussion, scaled by the total length of the transcript, and then multiplied by 10^4	StreetEvents
Transition risk/proactive	The frequency of mentions of the unigrams or bigrams related to the transition climate discussion in the proximity of proactive verbs, divided by the total length of the transcript, and then multiplied by 10^4	StreetEvents
Transition risk/nonproactive	The frequency of mentions of the unigrams or bigrams related to the transition climate discussion which are not in the proximity of proactive verbs, divided by the total length of the transcript, and then multiplied by 10^4	StreetEvents
Energy price exposure	The number of sentences that jointly mentions synonyms of "energy" synonyms and "price" (two words not necessarily synonyms for each other), divided by the total number of sentences in the earnings call transcript. Synonyms of "energy" include gas, fuel, oil, and energy. Synonyms of "price" include cost, expense, price, costs, expenses, and prices	StreetEvents
Action index	The frequency of mentions of the "proactive" verbs in the entire transcript (except those near, within ± 1 sentences of, climate-related discussions), divided by the length of the transcript	StreetEvents
Disaster dummy	A dummy variable equal to one if there is a natural disaster in the same county where a firm was headquartered	SHELDUS
CO_2 intensity	Sum of CO_2 emissions of all plants operated by the firm, scaled by the total assets	EPA
Tobin's q	(Total assets + Market value of equity - Book value of equity) / Total assets	Compustat
CapEx	Capital expenditures, scaled by the total assets of the previous quarter end	Compustat
R&D	Research & Development expenditures, scaled by the total assets of the previous quarter end	Compustat
log(Employment) (annual)	Natural logarithm of firm's employment	Compustat
I(Green patents) (annual)	A dummy variable that equals one if a firm has at least one green patent in the year, and zero otherwise. Green patents are identified following the OECD classification	Global Corporate Patent data set
Green patent ratio (annual)	The number of green patents scaled by the total number of patents in the year	Global Corporate Patent data set
log(Asset)	Natural logarithm of firm's total assets.	Compustat
PPE	Property, Plant and Equipment, scaled by total assets of the previous quarter end.	Compustat
Book Leverage	Total debt (= short-term debt + long-term debt), scaled by the total assets.	Compustat
log(No_Analysts)	The natural logarithm of number of analysts covering the firm.	I/B/E/S

(*Continued*)

Table A.1
(*Continued*)

Variable name	Description	Source
Institution %	The percentage of institutional ownership.	Thomson-Reuters Institutional Holdings (13F)
Institution HHI	The Herfindahl–Hirschman Index of institutional ownership.	Thomson-Reuters Institutional Holdings (13F)
ROA	Operating Income Before Depreciation (OIBDPQ), scaled by total assets of the previous quarter end, multiply by 100.	Compustat
Transition Risk MDA	The transition climate risk measure based on the management discussion and analysis section of SEC filings.	10K/10Q
Transition Risk RF	The transition climate risk measure based on the risk factors section of SEC filings.	10K/10Q
Transition Risk News	The number of news articles related to the firm's transition climate risk exposure divided by the total number of news articles related to the firm.	RavenPack
MSCI Climate Change Index (CCI)	The climate change materiality weight × the climate change risk rating. The materiality weight measures the importance of climate change to a firm's financial performance. The climate change risk rating is calculated as (10 - climate change theme score). Climate change theme score is a continuous variable ranging from 0 to 10, with higher value indicating better performance (i.e., lower risk).	MSCI
RepRisk Environmental Score	The environmental component of ESG rating provided by RepRisk.	RepRisk
Refinitiv Environmental Score	The environmental component of ESG score provided by Refinitiv.	Refinitiv

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