# Hedging Climate Change Risk: A Real-time Market Response Approach


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## Abstract

We present a novel methodology for constructing portfolios designed to hedge economic and financial risks arising from climate change. By linking time-stamped conference call transcripts with high-frequency stock price data at the conversation level, we identify a company's dynamic exposure to climate change risks based on real-time stock price movements during climate-related discussions. Our proposed portfolio strategy involves taking long positions in stocks with positive market responses to climate conversations and short positions in stocks with negative market responses. This portfolio appreciates in value during periods with negative aggregate climate news shocks. Compared to portfolios constructed using existing alternative methods, our real-time market response-based portfolios demonstrate superior out-of-sample hedge performance. A key advantage of the real-time market response approach is its ability to extract valuable information from the timing of when the market deems climate-related issues material enough for discussion in conferences and the magnitude of market response to such conversations. Additionally, we showcase the versatility of our approach by successfully constructing hedge portfolios for political risk and pandemic risk.



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## 1. Introduction

Climate change stands as one of the paramount challenges of our era. Beyond its wide-ranging social implications, both the physical effects of climate change and the regulatory efforts to slow carbon emissions possess the potential to significantly disrupt economic activities (Litterman et al., 2020). In light of increasing investor awareness about the economic and financial vulnerabilities linked to climate change, there is a rising demand for financial products to hedge these risks. However, a shortage of available instruments tailored to hedge against these risks has been observed (see Krueger et al., 2020; Giglio, Kelly & Stroebel, 2021; Stroebel & Wurgler, 2021). A nascent field of research suggests that investors can construct portfolios by purchasing stocks that stand to gain and selling those that stand to lose in the event of a climate risk materialization (Engle et al., 2020). Such a long-short portfolio is poised to appreciate in value when climate risks manifest, thus providing a valuable hedge against climate risk. However, dynamically discerning each stock's exposure to climate risk proves challenging, primarily due to the rapidly changing nature of a firm's vulnerability to climate change. In this paper, we introduce a novel methodology that identifies a company's dynamic exposure to climate change risks based on high-frequency real-time stock price movements during climate-related discussions in conference calls.

The key to constructing the hedging portfolio is successfully identifying assets with positive and negative climate change risk exposures. Existing hedging strategies employ two primary approaches. The first, a "narrative" approach, involves selecting long and short positions based on industry classifications (e.g., clean vs. dirty industries) or ESG scores, as seen in Engle et al. (2020), Pastor et al. (2021), and Hoepner et al. (2018). However, this approach faces two main challenges. Firstly, industry classification and ESG scores are inherently noisy, because many firms operate across multiple industries and exhibit varying climate exposures within the same industry, and there is wide disagreement among ESG rating providers on assigning ESG scores to the same firm (Berg et al., 2022). Secondly, a firm's climate change risk exposure can change rapidly over time. For instance, traditional "brown" firms may transition into "green" firms within a short timeframe by investing in clean technologies. However, industry classification and ESG scores adjust slowly and cannot capture these swift changes in climate risk exposure.

The second approach involves a "mimicking portfolio" approach, as introduced by Lamont (2001), where climate risk series are projected onto a set of asset returns using time-series data. This method requires investors to estimate each asset's "Beta" to systematic climate risk and sort assets based on these estimated "Betas." Similar to the narrative approach, the mimicking portfolio approach encounters two key challenges. Firstly, Beta estimates inherently contain noise (Campbell eta al., 2001; Cosemans et al., 2016).[1] Secondly, the mimicking portfolio approach heavily relies on time-series data and learning from past climate risk realizations to determine how assets perform during climate shocks. Consequently, estimated "Betas" cannot capture rapid changes in firms' climate risk exposure. In summary, both the "narrative" approach and the "mimicking portfolio" approach grapple with measurement challenges along two intertwined dimensions: noise and slow adjustment to evolving economic realities. In this paper, we introduce a novel methodology designed to address both of these challenges simultaneously.

Our approach is based on two fundamental pillars: the examination of climate change risk discussions during conference calls and the real-time market reactions to such discussions. We begin by assembling a dataset encompassing all US firms with time-stamped conference call transcripts retrieved from Refinitiv spanning the years 2017 to 2021. Subsequently, we categorize the Q&A sessions of these conference calls into conversations held between corporate managers and specific analysts, deriving 318,031 conversations from 47,792 conference calls. Employing Natural Language Processing (NLP) techniques, we pinpoint conversations where climate risk constitutes a primary focus. Following this identification process, we align these time-stamped conversations with high-frequency stock price data sourced from the TAQ database, allowing us to detect real-time market responses to discussions on climate

[1] For example, Campbell, Lettau, Malkiel, and Xu (2001) note that “firm-specific betas ... are difficult to estimate and may well be unstable over time.”

risk. We identify 8,640 earnings calls with at least one climate-related conversation from 2,255 unique firms.

We operationalize this real-time conversation approach by constructing long-short portfolios that purchase and short sell stocks in the top and bottom deciles of real-time market responses to climate conversations in the past 4 quarters, respectively. We rebalance these portfolios at a quarterly frequency. The anticipated outcome is that this portfolio will exhibit a price increase when aggregate climate risk materializes. Our methodology harnesses precise real-time market responses to climate-related conversations, reducing susceptibility to the measurement noise in industry classifications and ESG scores, as well as the estimation imprecision associated with "Betas." Moreover, our approach is rooted in the timing of financial market recognition of a firm's significant climate exposure, as evidenced by discussions in conference calls. This enables us to align with the moment when the market acknowledges the importance of a firm's climate exposure, allowing for more adaptive adjustments to evolving economic conditions compared to existing measures.

We observe a growing number of stocks with climate risk exposures over time, indicating an increasing awareness of this risk in the financial market. At the start of our sample period, there is an average of 300 firms engaged in climate change risk-related conversations per quarter, which rises to approximately 600 by the end of our sample period. Interestingly, there is a nearly equal distribution of stocks with positive and negative exposures in almost every quarter. There are also several noteworthy patterns that emerge by looking at which stocks are bought or sold. Firstly, our portfolio stocks span a wide range of industries. Secondly, in our baseline hedging portfolio, which maintains between 150 and 250 stocks throughout our sample period, there is a substantial amount of turnover. More specifically, we replace roughly one third of our hedging portfolio stocks every quarter. These frequent turnovers in the portfolio indicate that firms' exposure to climate risk can change rapidly over time, likely due to technological advancements, shifts in production methods, and evolving regulatory policies. Our methodology effectively captures these swift changes in economic reality.

In line with established practices in the literature (Engle et al., 2020), we evaluate the hedging performance of our portfolios by calculating out-of-sample correlations between monthly portfolio returns and various measures of aggregate climate shocks spanning the period from 2017Q4 to 2022Q1. We consider a range of aggregate climate shock measures as hedge targets, drawing from the expanding body of literature that constructs different time series of news related to physical and regulatory climate risks. Rather than selecting a single preferred climate risk series, we assess the portfolio performance against measures constructed by Engle et al. (2020), Faccini et al. (2021), Ardia et al. (2020), Kelly (2021), Boykoff et al. (2023), and Giglio et al. (2023), as well as attention to climate risk, quantified through Google searches. Our findings indicate that our baseline hedge portfolio consistently achieves an out-of-sample correlation of nearly 20% or more with the majority of the climate shock series, with some reaching maximum correlations close to 30%. This performance substantially surpasses the "narrative" and "mimicking-portfolio" approaches documented in Engle et al. (2020) and Alekseev et al. (2023), and is similar to the quantity based approach proposed by Alekseev et al. (2023). Our baseline results confirm the notion that real-time market responses to climate risk conversations contain valuable information for identifying firms' time-varying exposure to aggregate climate news shocks and effectively hedging against such shocks.

Next, we enhance our baseline approach by incorporating insights from the investor attention and information processing literature. Specifically, our methodology relies on real-time market responses to climate-related conversations and is critically dependent on the speed at which investors process and react to these conversations during conference calls. Should investors exhibit limited attention and experience delays in processing this information, our approach may fail to capture their responses adequately. On the other hand, if investors do not perceive climate-related conversations as significant, any stock price fluctuations during these discussions might be attributed to noise or reactions to other information (e.g., information from previous conversations), potentially undermining the performance of our approach. Therefore, our approach is expected to perform more effectively when investors devote greater attention to climate-related issues.

To implement this insight, we leverage geographically localized extreme heat events and natural disasters, which previous research has demonstrated to impact beliefs and attention regarding aggregate climate risk (see, e.g., Egan & Mullin, 2012; Deryugina, 2013; Joireman et al., 2010; Li et al., 2011; Fownes & Allred, 2019; Sisco et al., 2017). We consider instances of extreme temperatures (relative to historical patterns) and natural disasters, such as hurricanes, floods, and wildfires, within a county. On average, we identify 126 firms affected by extreme temperature events and 218 firms affected by natural disasters in a given quarter. These events are likely to draw investors' attention to climate-related issues for companies located in the affected counties. Consequently, market responses to climate risk topics during conference calls of these affected firms are more likely to capture investors' reactions to the companies' climate-related issues. Building on this rationale, we expand our hedging portfolio by incorporating all stocks from companies that have experienced climate risk events in the previous quarter and have climate-related conversations during the current quarter's conference calls. We maintain long (short) positions in stocks that exhibit positive (negative) price movements during climate risk-related conversations in these companies. Our expanded hedging portfolio consistently achieves an even higher out-of-sample correlation above our baseline portfolio of nearly 30% or more with the majority of the climate shock series, with some reaching maximum correlations close to 50%.

The central objective of our paper is to employ our real-time market response approach to create portfolios designed to hedge against the occurrence of climate risk events. This application aligns naturally with our methodology because climate risks have only recently come under the spotlight of investor attention. Consequently, there is a scarcity of financial instruments tailored to hedge against such risks, and insufficient time-series data to enable investors to accurately estimate the climate risk exposures of various assets solely based on price data. Nevertheless, our approach can, in principle, be extended to hedge against any emerging macro-level systematic risk series that firms frequently address in their conference calls. To illustrate the versatility of our approach, we apply it to two such systematic risks: political risk and pandemic risk. In line with our findings regarding the hedging of climate risks, we demonstrate that real-time market responses to conference call conversations concerning political and pandemic risks empower us to construct portfolios that effectively hedge the impact of the corresponding macro-level shocks.

Our study contributes to the expanding body of literature that investigates the interplay between climate change and asset markets (see Giglio, Kelly, and Stroebel 2021 for an extensive review). Within the realm of equity markets, Bolton and Kacperczyk (2021) and Hsu et al. (2022) have demonstrated that firms with high carbon emissions and significant pollution are valued at a discount. Barnett (2020) has illustrated that heightened prospects of future climate policy actions result in lower equity prices for firms carrying substantial exposure to climate policy risk. Moreover, Choi et al. (2020) have reported that stocks of carbon-intensive firms exhibit underperformance during periods of unusually warm weather, likely attributed to the increased attention of investors toward climate risks during such periods. Other studies have identified the pricing of climate risk in various other asset classes, including real estate markets (Baldauf et al., 2020; Bakkensen and Barrage, 2022; Bernstein et al., 2019; Giglio, Maggiori, Rao, Stroebel, and Weber 2021; Murfin and Spiegel, 2020), and municipal bond markets (Painter 2020; Goldsmith-Pinkham et al., 2021; Acharya et al., 2022). Of particular relevance to our research focus, Engle et al. (2020) have shown that the stocks of firms with higher (lower) ESG scores tend to experience higher (lower) returns when negative news regarding climate change emerges, and thus can be employed to construct long-short portfolios to hedge against adverse climate change news.

The most closely related study to ours is the concurrent work by Alekseev et al. (2023). They combine data on the geographic location and trading behaviors of mutual fund managers with data on the occurrence of localized extreme weather events to investigate which industries mutual fund managers disproportionately buy or sell following such events. Their research demonstrates that portfolios that take long positions in industries that mutual fund managers are more likely to buy after localized extreme weather events (and short those industries that managers are more likely to sell) can effectively hedge against the arrival of national climate news. While Alekseev et al. (2023) leverage rich cross-sectional mutual fund trading responses to local climate shocks to predict how investors will reallocate their capital in response to aggregate climate news shocks, we present an alternative and complementary approach. Our method relies on a different source of information to identify firms' time-varying exposure to climate news shocks: specifically, when managers discuss climate-related topics with analysts and how significantly the market reacts to these conversations in real time. Our approach offers distinct advantages. As demonstrated with political risk and pandemic risk, it can be applied to hedge any macro-level risk that is substantial enough to be discussed in a significant number of firms' conference calls. This approach does not necessitate such risks having a "localized version." Furthermore, our approach is well-suited for hedging rapidly evolving risks since it doesn't require investors to have a clear understanding of the risk. Instead, it simply requires investors' reaction to discussions of such risks in conference calls in the recent past year to have a strong correlation with how investors respond to the same risks in the present.

Our research also contributes to the emerging literature exploring the impact of risk exposure disclosure on asset prices. On the theoretical front, Heinle, Smith, and Verrecchia (2018) delve into the consequences of risk-exposure disclosure on asset prices by reducing investors' perceptions of the uncertainty surrounding a firm's risk. Schmalz and Zhuk (2019) demonstrate that investor learning about firms' risk exposures through earnings results in increased volatility during downturns and skewness in returns. Smith (2022) investigates how risk disclosure influences information acquisition and the feedback loop from prices to investment decisions. More closely related to our work, Smith (2023) illustrates that, in the presence of short-sale constraints, climate risk disclosure can enhance the effectiveness of financial markets in facilitating risk sharing. This enhancement can be attributed to the critical role of precise knowledge about firms' climate exposures in enabling investors to construct efficient climate hedging portfolios. On the empirical front, Smith and So (2022) measure the presence and timing of information related to risk, while Lyle et al. (2023) document that risk exposure disclosure reduces the uncertainty surrounding firm risk. To the best of our knowledge, our study provides the first empirical methodology and evidence on how investors can leverage firms' voluntary disclosures in conference calls to construct climate hedging portfolios.

## 2. Conceptual Underpinning

### 2.1. Climate Change Risk and Asset Prices

In a broad sense, climate risks can be categorized into physical risks and transition risks (Giglio et al., 2021). Physical risks stem directly from climate change impacts on economic activities and thus change firm value. For instance, the potential harm from rising sea levels to companies' facilities near coastlines, leading to property value depreciation, represents a physical climate risk. Extreme temperatures can hurt the value of companies reliant on energy-intensive processes, such as those in the manufacturing or energy sectors, because these companies face operational challenges and increased costs when extreme temperatures strain energy infrastructure or disrupt supply chains. On the other hand, transition risks encompass various effects on firms' operations and business models due to potential shifts toward a low-carbon economy. Transition risks encompass regulatory changes, technological advancements, and shifts in consumer and investor preferences away from high-carbon activities. Although physical and transition risks may not materialize simultaneously, they often exhibit correlation and may even move in opposite directions. For instance, the implementation of a carbon tax, representing a negative transition risk, could decrease the likelihood of future negative realizations of physical climate risks.

Different companies may experience divergent impacts from climate risks—transition and physical risks can create winners and losers in asset markets. For instance, in the context of water scarcity, companies heavily reliant on water-intensive operations, such as those in agriculture or certain manufacturing industries, may face increased costs or disruptions due to water scarcity, negatively impacting their value. Conversely, companies specializing in water-efficient technologies or alternative water sources may experience increased demand and value as they offer solutions to mitigate the impact of water scarcity. Using carbon taxes as an example of climate transition risk, firms heavily dependent on fossil fuels and high carbon emissions, such as traditional coal or oil companies, might see a decline in their value due to increased costs and reduced profitability as a result of the carbon tax. In contrast, companies investing in renewable energy sources or offering energy-efficient technologies may experience an increase in value, as their operations align with the goals of the climate-related policy and may even benefit from incentives or subsidies promoting cleaner practices.

Survey evidence supports the diverse risk exposures among investors. Krueger et al. (2020) reveal that among investment professionals, regulatory and technological risks hold somewhat greater significance than physical risks. Notably, a majority of respondents anticipate that regulatory climate risks are presently important, whereas physical risks are generally perceived to gain prominence over more extended time frames. Strengthening this viewpoint, Stroebel and Wurgler (2021) report a consensus among finance academics, professionals, regulators, and policymakers that regulatory risks stand out as the primary climate risk for investors and firms over the next five years, with a shift towards physical risks becoming the predominant concern over the next thirty years.

Climate risk exposure manifests in numbers: prior research extensively documents the pervasive impact of exposure to climate-related risks on firm value, implying a tight connection between investor wealth and climate risk exposure. An early study by Matsumura, Prakash, and Vera-Munoz (2014) reveals an association between higher emissions and lower firm values. Similarly, Chava (2014) establishes that firms with elevated carbon emissions experience a higher cost of capital. More recently, Ilhan, Sautner, and Vilkov (2021) demonstrate that carbon emission risk is reflected in out-of-the-money put option prices. Hsu, Li, and Tsou (2023) develop and test a model indicating that highly polluting firms are more vulnerable to environmental regulation risk, commanding higher average returns. Garvey, Iyer, and Nash (2018) analyze the effect of changes in direct emissions on stock returns, while Bolton and Kacperczyk (2021) find a significantly positive effect of carbon emissions on U.S. firms' stock returns for both direct and indirect carbon emissions.

Given the widespread evidence regarding the relationship between climate change and firm value, a pertinent inquiry arises: how can investors, firms, employees, and other stakeholders hedge against climate-related risks? In the following section, we demonstrate that understanding the empirical relationship between climate change and firm value also offers actionable insights on utilizing financial markets to hedge climate risks.

## 2. Hedging Demand and Hedging Target

As the awareness of climate change risks increases, stakeholders seek to safeguard their investments and operations against potential losses. For investors, effective climate risk hedging not only shields portfolios from downside impacts but also aligns with evolving environmental, social, and governance (ESG) considerations. Firms, on the other hand, aim to secure their long-term viability by mitigating the financial fallout from climate-related disruptions, ensuring operational resilience, and positioning themselves as sustainable entities in response to evolving market expectations and regulatory environments. In essence, the desire to hedge climate change risk is rooted in the pursuit of financial stability, sustainability, and resilience in the face of an increasingly uncertain climate landscape.

However, due to the long run and nondiversifiable characteristics of climate risk, traditional futures or insurance contracts, where one party commits to compensating the other in the event of a climate-related disaster, face significant implementation challenges. The inherent difficulty lies in finding a counterparty capable of credibly guaranteeing payouts over the extended time frame and unpredictability associated with climate events that might unfold over decades. Given these constraints, investors are constrained to rely on self-insurance against climate risk. Engle et al. (2020) propose an innovative approach inspired by the logic of Black & Scholes (1973) and Merton (1973), suggesting that a dynamic hedging strategy can approximate the function of an infeasible contract directly paying off in the face of a future climate disaster. Rather than acquiring a security with a direct payoff in such an event, investors can construct portfolios designed to offset short-term returns influenced by climate change news over the holding period. By hedging, period by period, the innovations in news about long-run climate change, an investor can ultimately hedge her long-run exposure to climate risk. Although this portfolio may exhibit a lower Sharpe ratio in the short run compared to the Markowitz mean-variance efficient portfolio, the dynamic hedging approach is positioned to compensate investors for potential losses stemming from the realization of climate risk in the long run.

To measure news about long-run climate risk for use as an effective hedge target, Engle et al. (2020) construct a climate news index derived from coverage of climate change in The Wall Street Journal (WSJ). This methodology is grounded in the premise that events containing pertinent information on changes in climate risk are likely to be covered by newspapers, with newspapers serving as a direct source for investors to update their subjective probabilities of climate risks. The topics covered by newspapers that may carry relevant information span a wide spectrum, including extreme weather events (e.g., floods, hurricanes, droughts, wildfires, extreme temperatures), physical changes to the planet (e.g., sea level changes, glacial melting, ocean temperatures), regulatory discussions, technical progress in alternative fuel delivery, and the price of fossil fuels. The frequency of climate news coverage steadily increases over time and experiences spikes around notable global climate events. Engle et al. (2020) interpret the escalating coverage of climate-related topics as the emergence of adverse news regarding future climate change. They validate this approach by supplementing their WSJ-based analysis with additional sentiment-based examinations of climate coverage in newspapers.

Building upon the groundwork laid by Engle et al. (2020), subsequent research has generated diverse climate news series reflecting various climate risks. In this study, we adopt a neutral stance on the optimal hedge target, recognizing that the most suitable choice depends on individual investors' distinct risk exposures. For instance, institutional investors heavily invested in sectors susceptible to physical climate risks, such as coastal real estate or agriculture, may prioritize safeguarding against value depreciation linked to extreme weather events. Investors concentrating on the energy sector might opt to hedge against transition risks, particularly if their portfolios involve fossil fuel-dependent companies facing potential value declines from regulatory shifts or evolving consumer preferences. Consequently, the motivations for climate risk hedging can significantly differ among investors, shaped by their portfolio composition, investment goals, and ethical principles. Following the methodology of Alekseev et al. (2023), we evaluate the efficacy of our approach in hedging various types of climate news shocks, considering a comprehensive array of measures detailed in the subsequent section.

## 3. Hedge Portfolio

With the climate news shocks at hand as hedge targets, the next step is to systematically identify stocks that exhibit positive or negative responses when (negative) news about climate change emerges. The underlying strategy is to strategically hold or overweight stocks that appreciate in value with the occurrence of (negative) climate change news, while shorting or underweighting stocks that depreciate in such circumstances. By building a portfolio that emphasizes stocks performing well during adverse climate news, investors position themselves to capitalize on future instances of negative climate-related developments. The continual adjustment of this portfolio based on evolving information regarding the association between climate news and stock returns leads to a portfolio that is long on climate change winners and short on losers. To dynamically identify firms experiencing value increases or decreases in response to climate change news, Engle et al. (2020) adopt a "narrative approach" by using the E-component in ESG-Scores, reflective of a firm's environmental friendliness, as proxies for climate risk exposures. The hedge portfolio prioritizes firms with high E-Scores and reduces exposure to those with low E-Scores, with relative weights dynamically updated as more data on the interplay among E-Scores, climate news, and asset prices become available. Engle et al. (2020) demonstrate an out-of-sample correlation of 20% between the hedge portfolio's return and innovations in the WSJ climate change news index.

Recent research by Alekseev et al. (2023) introduces an innovative methodology for constructing hedge portfolios, leveraging insights from mutual fund managers' trading decisions. This approach capitalizes on the correlation between extreme local weather events, such as periods of intense heat or drought, and shifts in individuals' perceptions of climate change severity. Their study focuses on identifying industries that mutual fund managers disproportionately buy or sell in the aftermath of such extreme local weather events. Although the individual trading responses may not significantly impact equilibrium prices, they offer valuable insights into market-wide trading behavior in anticipation of yet-to-be-observed climate-related news. The authors provide compelling evidence that portfolios adopting long positions in industries preferred by mutual fund managers following extreme weather events, coupled with short positions in industries they are predisposed to sell, significantly outperform alternative strategies like the "narrative approach" in effectively hedging against diverse national climate news series.

Our methodology for constructing a climate risk hedge portfolio is grounded in two key components: an analysis of climate change risk discussions during conference calls and the real-time market reactions to these discussions. The subsequent section outlines the details of our sample construction process.

## 3. Sample Construction

### 3.1. Time-stamped Conference Call Transcripts

We obtain earnings call transcripts along with their associated time stamps from Refinitiv Workspace. This platform is recognized for its comprehensive coverage of transcripts related to earnings, guidance, mergers and acquisitions, and other corporate conference calls involving a global cohort of over 7,200 companies. The reason for obtaining earnings call transcripts from this platform is the feature of synchronizing textual content with corresponding audio components through the embedding of beginning and ending time stamps for each paragraph. Refinitiv highlights that the time stamps are generated through a collaborative process involving both automated recognition and human oversight. To validate the data's reliability, we conduct a manual verification on a substantial sample. The results demonstrate time disparities of less than one second, providing robust affirmation of the consistency and reliability of the dataset. An example of the transcript data is in Appendix A.

As outlined by Cao, Flake, and Liu (2023), an inherent challenge in the real-time analysis of granular conference data is the discrepancy between the relative time assigned to each textual component within a transcript and the absolute real-world time. This issue arises due to the common practice of starting audio files from the first word of the operator, often with a delay, leading to a misalignment between transcripts and the scheduled conference starting time. To address this, following the approach recommended by Cao, Flake, and Liu (2023), we adjust (push back) the relative time stamp by 90 seconds.

This correction is based on our manual examination of 40 conferences, indicating that audio files typically commence approximately 90 seconds after the scheduled time. Our unit of observation is at the conversation level, delineated by the exchange of dialogues between a specific analyst and managers, each with a defined starting and ending time for alignment with intraday data.

### 3.2. Real-time Market Reaction to Conference Conversations

Our intraday price and quote data are obtained from the NYSE Trade and Quote (TAQ) database. Earnings calls held during regular trading hours are matching with the trading information available within the TAQ database. However, approximately half of our sample's earnings calls take place after trading hours, making the corresponding trading data inaccessible. For these instances, we match the calls with quote data, as per the findings of Grégoire and Martineau (2021) that highlight the predominant reflection of earnings surprises in price changes through quotes rather than trades, which suggests the feasibility of using quote data to measure market reaction.

We clean our intraday trading price data following methodologies established in prior literature (Barndorff-Nielsen et al., 2009; Bollerslev et al., 2016; Bollerslev et al., 2020). Details are provided in Appendix A. Additionally, the cleaning process for quote data from the TAQ database follows the steps set by Grégoire and Martineau (2021). Bid-ask spreads can have significant difference, which generate noise rather than information. For example, bid prices may reach as low as \$0.01, while ask prices can soar to \$199,999. To address this concern, we selectively retain quote data where the bid-ask difference, relative to the mid-quote value, remains below 20%. This filtering process ensures the reliability of our data by mitigating extreme fluctuations (Grégoire and Martineau, 2021).

We start with 47,792 earnings call transcripts with 318,031 conversations, ranging from January 2017 to December 2021. To identify conversations related to climate change risks, we employ a method based on four sets of climate change bigrams, as developed by Sautner (2023).[2] We provide two examples

[2] Sautner (2023) introduced an innovative method for creating four distinct sets of climate change bigrams within earnings calls. The first set encompasses broadly defined aspects of climate change, while the remaining three measures are dedicated to specific

of climate related conversations in Appendix B. The first example involves AptarGroup, Inc. (Aptar), a manufacturer of consumer dispensing packaging and drug delivery devices. The conservation discusses plastic beverage packaging and Aptar’s plan to create more sustainable plastic packaging. It generated a positive market reaction (5.55%). In the second example, analysts are concerned about setbacks in Livent’s partnership and investments in Nemaska Lithium, a producer of lithium. In addition, low Lithium prices and Livent’s unprofitability generated further negative market reactions ( -8.72%).

This process results in a sample comprising 21,380 climate related conversations from 13,378 transcripts. To ensure the quality of our data and to focus on discussions where climate change is the primary topic, we exclude conversations that are either less than one minute or exceed ten minutes in duration, thereby eliminating outliers. Additionally, we filter out conversations that lack trading or quote information or have zero market reactions. In cases where a single conference transcript contains multiple conversations related to climate change, we calculate the average market reaction to gauge the climate change risk exposure for that particular earnings call. The final sample consists of 8,640 earnings calls with at least one climate-related conversation from 2,255 unique firms.

### 3.3. Extreme Temperature and Natural Disaster Data

Data on extreme heat events and natural disasters are obtained from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and PRISM Climate Group. We first identify extreme heat events following Alekseev et al. (2023), which has three different criteria. The first criterion captures whether there were any fatalities or injuries attributed to extreme heat within a county using data from SHELDUS. The second criterion for extreme heat events is based on crop indemnity payments and utilizes data collected by the U.S. Department of Agriculture, with a version managed by SHELDUS. The third criterion involves the examination of temperature data obtained from the PRISM Climate Group. More specifically, we identify extreme heat county-months where the maximum temperature exceeds the county's

climate change "topics." These specific topics include opportunities, physical shocks (such as sea level rise), and regulatory shocks (including carbon taxes and cap and trade markets). In total, there are 9,641 unique bigrams, exemplified by terms like "opportunity wind" and "money coal".

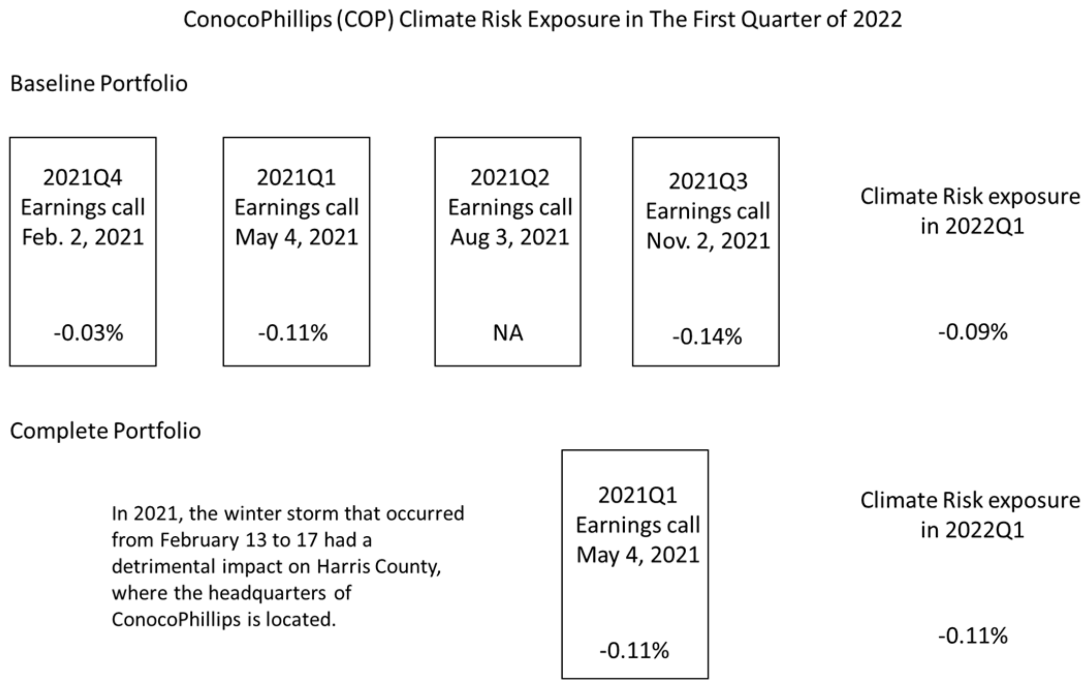
ten-year historical average maximum for the same month by at least 4 degrees Celsius (7.2 degrees Fahrenheit). In addition to extreme heat events, we incorporate 13 other types of natural disasters from the SHELDUS database, including wind, severe storms/thunderstorms, flooding, winter weather, hail, tornadoes, lightning, drought, hurricanes/tropical storms, wildfires, coastal events, fog, and tsunami/seiche occurrences. This dataset consists of 11,657 natural disaster events spanning 3,114 counties over the period from 2017 to 2021.

## 4. Hedging Portfolio Construction

Our approach to constructing climate risk hedge portfolios relies on the idea that market reactions to climate-related conversations serve as a suitable proxy for a firm's climate risk exposure. We form two portfolios: a baseline portfolio, solely based on conference conversations, and a refined "complete" portfolio that leverages local climate shocks drawing market attention to climate-related topics for local firms. In the baseline portfolio, we assess a firm's risk exposure in a given quarter by considering market reactions to climate change-related conversations in the preceding four quarters. For example, when determining ConocoPhillips' climate risk exposure in the first quarter of 2022, we average market reactions to climate-related conversations in ConocoPhillips' earnings calls over the past four quarters, which were -0.03%, missing, -0.11%, and -0.14%, respectively. Since no climate-related conversations occurred in the 2021Q2 earnings call, we utilize the average market reaction of -0.09% (the average of -0.03%, -0.11%, and -0.14%) as a measure of ConocoPhillips' climate risk exposure in 2022Q1.

We operationalize this real-time conversation approach by constructing long-short portfolios that purchase and short sell stocks in the top and bottom deciles of real-time market responses to climate conversations in the past 4 quarters, respectively. We rebalance these portfolios at a quarterly frequency. We also examine other long-short thresholds, such as top and bottom 20% and 30%.

Exhibit 1: Climate Risk Exposure Measurement




Our methodology relies on real-time market responses to climate-related conversations, and its effectiveness is contingent on how swiftly investors process and react during conference calls. If investors exhibit limited attention and experience delays in processing this information, our approach may inadequately capture their responses. Borrowing insights from the investor attention literature, we posit that when a county undergoes a climate-related event, market reactions in the subsequent earnings calls of firms headquartered in that county more accurately mirror their risk exposures to climate challenges. For example, during a severe winter storm affecting Harris County, where ConocoPhillips is headquartered, between February 13 and 17, 2021, we anticipate heightened investor attention on climate change-related conversations in the upcoming 2021Q1 earnings call. This renders the market reaction in this call a more precise proxy for the risk exposure in the first quarter of 2022. In cases where no natural disaster events occurred in the preceding four quarters, we continue to use the average exposure, as in the baseline portfolio.

To construct the complete portfolio, we expand our baseline portfolio by incorporating all stocks from companies that have experienced climate risk events in the previous quarter and have climate-related conversations during the current quarter's conference calls. We maintain long (short) positions in stocks that exhibit positive (negative) price movements during climate risk-related conversations in these companies.

## 5. Climate Risk Hedge Targets

Climate change encompasses a spectrum of risks that are imperfectly correlated, including physical threats such as extreme weather and climate transition risks such as the uncertain risk of adjustment toward carbon neutrality (Bolton and Kacperczyk, 2023). To capture these risks, recent literature has adopted a news-based approach to construct a time series that captures news about climate risks. The intuition is that events containing relevant information about shifts in climate change are likely to be covered in news outlets, including newspapers and Television programs. We build on the insights of Engle et al. (2020), which argue that to hedge against a slow-moving long-term risk such as climate change, a hedge can be constructed as a sequence of short-live hedges against *news* about future realizations of these risks. This approach has been adopted in a number of recent studies, for example, Stecula and Merkley (2019), Ardia et al. (2020), Alekseev et al. (2023), and Giglio et al. (2023). Following Alekseev et al. (2023), we remain agnostic of the choice of hedge target by gathering a broad range of measures proposed in the recent literature that overlaps with the time series of our transcript data. For a given climate change news series, we use the AR (1) innovation as the hedge target (Engel et al., 2020; Alekseev et al., 2023). The list of climate change news series is described in Appendix C. The first four series (TV, NEWS, GOOGLE, and NYT) span our entire sample period and, therefore, are the main set of series we use in constructing the hedging targets.

## 6. Evaluation of Hedge Portfolios

In this section, we evaluate the hedging performance of our portfolios. We start by examining several notable patterns. First, Table 1 reveals a growing number of stocks with climate risk exposures over time, signaling an increasing awareness of this risk in the financial market. In Column 2 (after filtering out extremely lengthy and short conversations), we find that at the onset of our sample period, there is an average of 300 firms engaged in climate change risk-related conversations per quarter, which rises to approximately 600 by the end of our sample period. Notably, Columns 3 and 4 highlight an almost equal distribution of stocks with positive and negative exposures in nearly every quarter.

There are also several noteworthy patterns that emerge by looking at which stocks are bought or sold. Table 2A and 2B indicate that our portfolio stocks span a diverse range of industries. In Table 3A and 3B, we analyze the decomposition of our baseline and complete portfolios, respectively. The baseline hedging portfolio, maintaining between 150 and 250 stocks throughout our sample period, exhibits significant turnover, with around one-third of stocks being replaced each quarter. This high turnover underscores the dynamic nature of firms' exposure to climate risk, influenced by factors such as technological advancements, shifts in production methods, evolving regulatory policies, and changing consumer and investor preferences. Our methodology adeptly captures these rapid changes in economic reality, a pattern also evident in the complete portfolio (Table 3B).

As a criterion for assessing hedging performance, we compare out-of-sample correlations between hedging portfolio returns and AR(1) innovations to various climate news series for each month in our testing period (2017Q4-2022Q1). Table 4 presents these correlations, where each row represents a distinct hedge portfolio, such as the 10% portfolio that involves sorting stocks based on their exposure to climate change risk and taking long (short) positions in the top (bottom) decile. Each column corresponds to a different climate news series, all coded so that higher values denote negative climate news. As a result, positive correlations indicate successful hedges. The same information is depicted in Figures 1 and 2, where each point in the dot plot represents the out-of-sample correlation coefficient of a hedge portfolio return with a climate news series. The various colors represent different news series, with the first four (TV, NEWS, GOOGLE, and NYT) spanning our entire sample period, while the remaining columns in Table 4 and the second panel in Figures 1 and 2 pertain to hedge targets covering specific periods within our sample.

Our portfolios emerge as robust hedges for the Boykoff et al.(2023)'s TV index and NEWS index, GOOGLE climate-risk search index, and Giglio et al.(2023)'s New York Time index, with the long-short portfolio of the top and bottom deciles (P10%) being the best performer. The results underscore the consistent out-of-sample correlation of nearly 20% or more achieved by our baseline hedge portfolio with the majority of climate shock series, with some correlations approaching maximum values of around 30%. This level of performance markedly surpasses the "narrative" and "mimicking-portfolio" approaches documented in Engle et al. (2020) and Alekseev et al. (2023), and aligns closely with the quantity-based approach proposed by Alekseev et al. (2023). These findings suggest that our real-time market response based portfolios effectively hedge a spectrum of climate risks, encompassing both physical and transition risks. As our approach is not tailored to specific climate targets, its robust performance across various measures implies an effective hedge against a shared, common component of climate risks considered in our analysis.

Transitioning to our expanded "complete" hedging portfolio presented in Panel b of Table 4 and Figure 2, we observe consistently higher out-of-sample correlations compared to our baseline portfolio, surpassing 30% or more with some reaching maximum correlations approaching 50%. The long-short portfolio of the top and bottom deciles (P10%) remains the most effective, boasting superior performance and requiring minimal trading costs. Both the baseline and complete portfolios exhibit similar proficiency in hedging various other climate news shocks (as shown in the remaining columns of Table 4 and Panel b of Figures 1 and 2). However, we caution that these results are derived from a specific segment of our overall sample period.

Our “complete” portfolio includes all stocks that have encountered either a heat shock or a natural disaster shock in their headquarters county in the preceding quarter and engage in climate-related discussions during the current quarter's earnings calls. The inclusiveness of this approach prompts the question: should we consider all these firms, or would it be more beneficial to include solely the top and bottom deciles of firms based on their stock price responses to climate conversations? Table 5 provides an overview of the quarterly count of stocks affected by extreme temperatures and natural disasters, ranging between 200 and 450. To assess hedging performance within this "shocked" stock sample, we formulate hedge portfolios exclusively based on these stocks. Specifically, we progressively broaden the portfolio by incorporating the top and bottom 10%, 20%, and 30% of stocks based on the magnitude of their stock return responses to climate conversations. The outcomes are detailed in Table 6. Across various climate-related news series, the hedge performance of the larger portfolio (P30%) consistently yields superior results. This observation implies that climate shocks significantly amplify investor attention to climate discussions during earnings calls, and even mild stock price reactions to such discussions encompass substantial information regarding the stock's exposure to climate risk.

In our final analysis, we explore the extent to which common factors, specifically the three and five Fama-French factors, contribute to the return correlations of the hedge portfolios. To examine the factor loadings, we run regressions of the hedge portfolio excess returns on the returns of the market and Fama-French factors. The results, presented in Tables 7, reveal that a few portfolios exhibit a significant loading on the market, but none demonstrate a significant loading on any of the Fama-French factors. In addition, the time-series variation in the Fama-French factors captures, on average, less than 10% of the variation in the hedge portfolios. These results suggest that a common loading on the Fama-French factors is not the primary driver of the high return correlations observed across the different hedge portfolios.

## 7. Hedging Other Emerging Risks

The primary aim of our paper is to utilize our real-time market response approach for constructing portfolios aimed at hedging against climate risk events. Although our methodology naturally aligns with this application, it holds the potential to be extended to hedge against any emerging macro-level systematic risk series frequently addressed by firms in their conference calls. To showcase the adaptability of our approach, we briefly explore two alternative applications: political risk and pandemic risk. We identify conversations related to political risks and epidemic diseases using the methodology developed by Hassan et al. (2020) and Hassan et al. (2023), respectively. In essence, we identify these conversations by locating words or bigrams found in the dictionaries provided on the authors' website.[3] Our analysis yields a total of

[3] https://github.com/mschwedeler/firmlevelrisk

32,620 earnings call conversations related to political risks from 2017 to 2021 and 8,574 earnings calls with conversations pertinent to epidemic diseases specifically from 2020 to 2021. The hedge target for political risk comes from the Newspaper-based Economic Policy Uncertainty index (EPU), while the hedge target for pandemic risk comes from the newspaper-based infectious disease equity market volatility tracker developed by Baker, Bloom, David, and Kost (2019). Details of these hedge targets are included in Appendix C.

As depicted in Figure 2, consistent with our findings regarding the hedging of climate risks, we demonstrate that real-time market responses to conference call conversations concerning political and pandemic risks empower us to construct portfolios that effectively hedge the impact of the corresponding macro-level shocks. Further details on the performance of our portfolios in hedging political and pandemic risk are provided in the Online Appendix.

**8. Conclusion**

We present a novel methodology designed to construct portfolios that effectively hedge against economic and financial risks stemming from climate change. Our strategy capitalizes on real-time market responses to climate change-related discussions during conference calls. Through the integration of time-stamped conference call transcripts with high-frequency stock price data at the conversation level, we discern a company's dynamic exposure to climate change risks, relying on real-time stock price movements during climate-related conversations. The proposed portfolio strategy entails taking long positions in stocks with positive market responses to climate conversations and short positions in those with negative market responses. This portfolio exhibits appreciation in value during periods characterized by negative aggregate climate news shocks. Notably, our real-time market response-based portfolios demonstrate superior out-of-sample hedge performance when compared to portfolios constructed using existing alternative methods.

A distinctive advantage of the real-time market response approach lies in its capacity to extract valuable information from the timing when the market deems climate-related issues material enough for discussion in conferences, coupled with the magnitude of market response to such conversations. To illustrate the versatility of this approach, we successfully construct hedge portfolios for political risk and pandemic risk. We acknowledge the potential for future research to delve into a more comprehensive investigation of how our approach can be extended to hedge against other emerging systematic risks.

Our approach and findings bear significant policy and practical implications. Globally, and notably in the United States, there is a growing emphasis on climate-related disclosure by businesses. The U.S. Securities and Exchange Commission has recently proposed a rule mandating public companies to report their greenhouse gas (GHG) emissions, aligning with similar initiatives in the European Union (EU) and the United Kingdom.[4] Beyond the rationale of providing investors with information on material risks and exerting pressure on firms to reduce emissions (Greenstone et al., 2023), our research indicates an additional, perhaps less recognized, benefit of climate disclosure—enabling investors to proactively hedge climate change risk by dynamically revealing firms' exposure to such risks.

In practice, there is a prevalent concern among investors regarding insufficient disclosure by portfolio firms, impeding the construction of suitable hedging instruments. For instance, Ilhan, Krueger, Sautner, and Starks (2023) provide survey evidence revealing that a majority of global institutional investors "consider climate risk reporting to be at least as important as financial reporting, with almost one-third considering it more important." Additionally, Krueger, Sautner, and Starks (2020) present survey findings suggesting that "many market participants, including institutional investors, find climate risks difficult to price and hedge, possibly because of their systematic nature, a lack of disclosure by portfolio firms, and challenges in finding suitable hedging instruments." Our approach addresses this concern by providing investors with an effective hedging instrument based on firms' voluntary disclosure in conference calls.

[4] See https://www.sec.gov/news/press-release/2022-46, and https://www.sec.gov/files/33-11042-fact-sheet.pdf.

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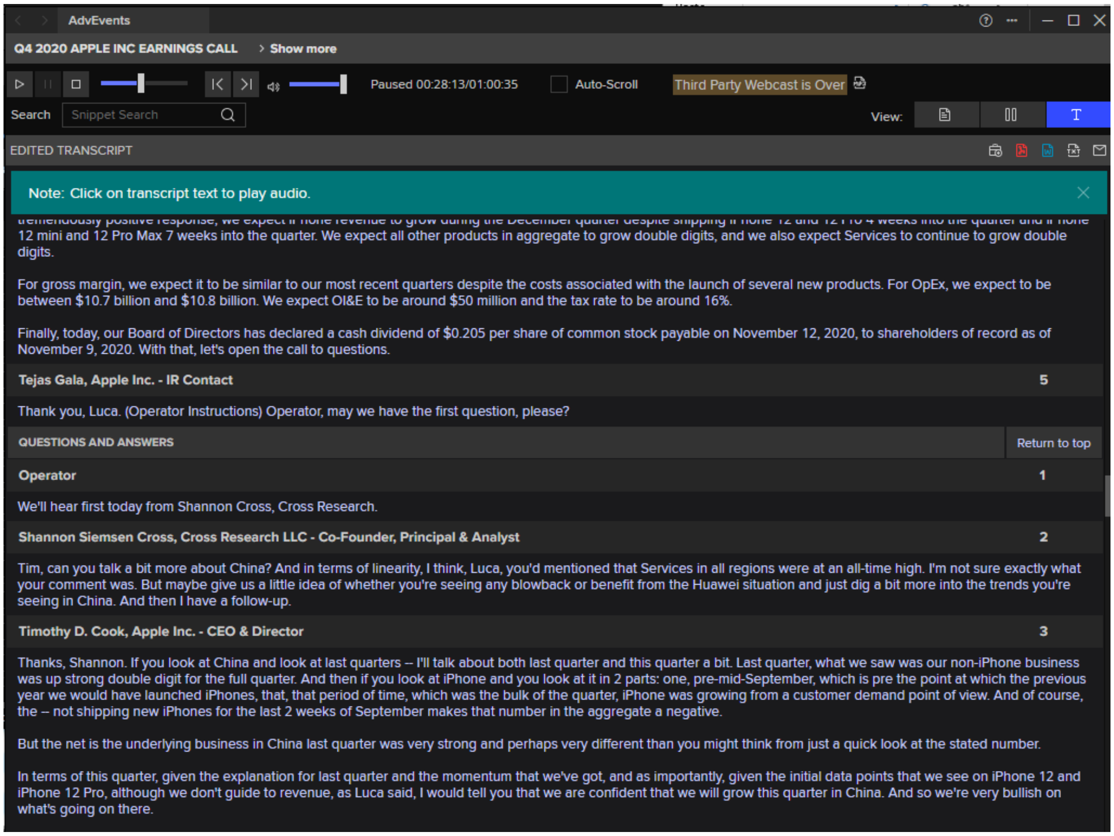
## Appendix A1. Retrieving Time-stamped Conference Call Transcripts

The following figure shows the typical format of transcripts in Refinitiv Workspace. Each sentence is marked with a time stamp relative to the audio file. When you click a sentence, the corresponding part of the audio file will be played.



## Appendix A2. Cleaning the TAQ Data

To clean the TAQ data, we begin the removal of entries satisfying at least one of the following criteria: 1) prices that are equal to or less than zero; trade sizes that are equal to or less than zero; 2) corrected trades (i.e., trades flagged with a Correction Indicator, CORR, other than 0, 1, or 2); 3) an abnormal sale condition (i.e., trades for which the Sale Condition, COND, has a letter code other than @, ∗, E, F, @E, @F, ∗E, or ∗F). Following this initial filtration, we assign singular values to each variable for every second. In instances where one or multiple transactions occur within the same second, we derive the sum of volumes, aggregate trade counts, and the volume-weighted average price for that temporal interval. In cases where no transactions transpire within a given second, we assign zero values to both volume and trade counts. Regarding the volume-weighted average price, we employ the most proximate entry from the preceding second.

## Appendix B. Examples of Climate Conversations

### Example 1: AptarGroup, Inc.

AptarGroup, Inc. (Aptar) is a manufacturer of consumer dispensing packaging and drug delivery devices. This conservation discusses plastic beverage packaging and Aptar's plan to create more sustainable plastic packaging. It generated a positive market reaction (5.55%).

*George Leon Staphos, BofA Merrill Lynch, Research Division - MD and Co-Sector Head in Equity Research*

I guess, the first question I had was on beverage trends and kind of a two-part. One, the -- in china, you've been managing against this issue now for probably, I don't know, 1.5 years. When should we, if it's possible to discern anniversary that beverage closure issue in china? When will the comps turn flat to positive at least in terms of that issue? And relatedly, what are your customers saying more broadly about their **use of plastic for beverages**, from water to -- in everything else, energy drinks, et cetera?

*Stephan B. Tanda, AptarGroup, Inc. - President, CEO & Director*

On the first topic or question, you're being very kind with the term managing. That's the reality.

*George Leon Staphos, BofA Merrill Lynch, Research Division - MD and Co-Sector Head in Equity Research*

That's how we are, stephan.

*Stephan B. Tanda, AptarGroup, Inc. - President, CEO & Director*

Yes. The china beverage customer is -- constitutes a very good business, but we have very limited visibility both on the end-user demand as well as on the customer orders. So I've called the anniversary before, so I'm not going to do it, again, since I've been wrong. I'll bet that this business, it will continue to surprise both on the upside and on the downside, and it just depends which quarters you compare. And the fourth quarter was kind of a perfect storm, next quarter might be the opposite. And I cannot give you a better answer, unfortunately. Now on your second question, the big debate or the big question with bottled water is really the flat top caps, how can you eliminate the screwing off the caps throwing away, because those single caps are one of the highest volume items that ends up in the sea. So that drives people more to the sports cap closures, that drives more to the solutions where the cap stays with the bottle and, hopefully, also the flip lid product that we are discussing with customers and our technology is already in the market that in some countries with that, again where the **lid stays with the bottle and gets recycled with the bottle**. I mean, the overall theme here is really all about circularity. **Plastic is a very good energy-efficient product, but it needs to come back, it can't be a one-way street**.

*George Leon Staphos, BofA Merrill Lynch, Research Division - MD and Co-Sector Head in Equity Research*

So that's helpful, Stephan. So from your customer standpoint and from what they're hearing from the consumer, the bigger issue is on the cap on the one hand, which presumably that's **an opportunity and you can solve that**, and **less on the actual use of plastic as long as it's recyclable and returnable and your customers are comfortable that, that will be resolved**.

*Stephan B. Tanda, AptarGroup, Inc. - President, CEO & Director*

**Yes**. And you see initiatives around having them to pay a fee that you get returned when you return the bottle, as has been standard in places like Germany for a long time.

*George Leon Staphos, BofA Merrill Lynch, Research Division - MD and Co-Sector Head in Equity Research*

Okay. My last 2 questions, and I'll turn it over. Can you talk us about -- this is because of the real good comparison the other segments within pharma, it kind of stands out. But injectables, was the 5% core growth, which would be better than most of the other sectors that I look at period and packaging, but was it in line with what you were expecting? How were trends in injectables playing out relative your expectations? And then I'm not sure I heard and perhaps you're not in a position to provide, but did you comment on how much cash outlay there will be this year for the transformation, both in terms of cash cost for redundancies and capital?

*Stephan B. Tanda, AptarGroup, Inc. - President, CEO & Director*

On the injectable market, this is certainly in line though with market demand, market demand is even a little bit higher to be perfectly honest. We are -- that's one of the areas where we have service issues from a capacity point of view. So -- but that certainly continues to be a very interesting area with good growth prospects. Now I'll turn it to bob.

*Robert W. Kuhn, AptarGroup, Inc. - Executive VP, CFO & Secretary*

And George, you were looking at 2019 for the cash outlays for transformation?

*George Leon Staphos, BofA Merrill Lynch, Research Division - MD and Co-Sector Head in Equity Research*

Yes. Both, if you can, redundancy and other costs and then capital associated with it.

*Robert W. Kuhn, AptarGroup, Inc. - Executive VP, CFO & Secretary*

Sure. So in total, it's around $40 million is what we're anticipating for 2019.

## Example 2: Livent Corporation

Analysts are concerned about setbacks in Livent's partnership and investments in Nemaska Lithium, a producer of lithium. In addition, low Lithium prices and Livent's unprofitability generated further negative market reactions ( -8.72%).

*Joel Jackson, BMO Capital Markets Equity Research* - *Director of Fertilizer Research & Analyst*

Paul, you know what I know the Nemaska story quite intimately, unfortunately.

*Paul W. Graves, Livent Corporation - President, CEO & Director*

You do. You do.

*Joel Jackson, BMO Capital Markets Equity Research* - *Director of Fertilizer Research & Analyst*

I do. I've been there. So obviously, you had a claim against them. You got the stake somewhat in lieu of that claim. I understand. Is this basically go back to the drawing board and say, "okay, **the original hydromet plant, we don't think that works**. We're going to go back with at all optionality here. Maybe we'll do just like a chinese conversion plant there, soda ash, sulfuric acid, do new environmental studies, go right back to the beginning, put the plant in whabouchi, not shawinigan. Like I mean, is that the way to think about it? This is a totally, let's go back to scratch, go back to square one, see any good value out of it?

*Paul W. Graves, Livent Corporation - President, CEO & Director*

Not quite square one. Look, I don't think, for one moment, that what Nemaska did was all entirely useless. I think they actually did a lot of really good work, and they've made some valuable investments in there. **But I think Nemaska had a couple of issues behind it,** frankly, Joel. Well, let's 3, to be blunt. The first issue, I think, that they had was the financing structure, clearly, and that's what drove them into this position. I think the second is that -- and maybe linked to that is they allowed themselves to be overambitious as to what that mine was actually capable of in terms of production. And so they ended with a mine plan that was creating higher capital spend and a whole bunch of issues with regard to its functional capabilities to operate reliably as a mine, particularly in that relatively harsh environment up there. And then the third area was the entire strategy with regard to the chemical conversion plant. I don't, for one minute, think the hydromet capability of technology is not something that could work. It could. We absolutely would love it to work if we can make it work. **But we have to get confident that it is going to operate at an operating cost that makes sense. It's certainly more capital-intensive, but it does have some pretty significant environmental benefits.** I would also say, just to give you an idea as to the challenges, as to that process, **it almost certainly doesn't feel like the location that they've selected for it is actually going to work for it for a whole bunch of geological and engineering reasons.** And so it may be that unless we change the technology, the plant couldn't even shoring even if we wanted it to. And so there's a lot of questions that have to be answered. So while it's not quite a blank sheet of paper, it's certainly not taking the existing plan and tweaking it. It will be a much more fundamental reassessment than that.

*Joel Jackson, BMO Capital Markets Equity Research - Director of Fertilizer Research & Analyst*

So Paul, obviously, **lithium prices have been really bad this year**. We're seeing on the cost curve, we're seeing a lot of pain. We're seeing all churn, we see the shift. We're seeing oracle with negative margin. We're seeing Livent that basically nears their earnings in the third quarter here. And so when you look at your business model and what you are -- and at this low -- at the low part of the cycle, **Livent is basically near 0 or losing money**. Does that make you think about https://ir.livent.com/news/news-details/2022/Livent-Announces-Agreement-to-Double-its-Ownership-Stake-in-Nemaska-Lithium-to-50-

Percent/default.aspx, and this next happens, Livent will be better prepared, not better prepared, but better organized, have a better full earnings level at the bottom of the cycle? And what would you do to achieve that? Do you think that's fair?

*Paul W. Graves, Livent Corporation - President, CEO & Director*

Absolutely. Everything you said, yes. **Now, there's only so much you can do, right? The economics of resource extraction and chemical processing, there's only so much we can do**. We are a low-cost producer, but we do have a cost burden of being a public company, right? If we will report it as a segment of a larger organization, we would look a lot healthier than we do today. And so you kind of got to break through all of this and get your head around what it really means if we had a lot of, for example, mark-to-market investments that we're balancing around in a quarter and you could take some extra earnings. There's lots of noise when you try and compare lithium companies to lithium companies. However, you're absolutely right. **It's hard to grow a business like ours with the profitability where it is.** And so we do have to think differently about it. And frankly, Nemaska is one of those. We have been, I admit, nonconventional and somewhat creative with regard to our partnership with Pallinghurst. But it's a source of capital for us and it's allowing us to operate in a wider plane than we otherwise would have to. We would have had to incur some quite significant cost, maybe one-off, maybe longer, if we weren't partners with Pallinghurst. The expectation, over time, with Nemaska is that we increase our ownership stake, and it becomes a fundamental part of our portfolio, giving us resource diversification and giving us a differentiated story to serve different markets. I think there's no doubt, Europe and North America are looking for supply chains that are shorter that allow them to maybe not touch every part of the world before they get to them. And so I think we're taking steps that, in theory at least, position us well for the future, and we'll keep doing that. We'll absolutely keep doing that. But frankly, everything and anything is on the table to make us more cost-efficient, to give us a more differentiated position with customers, and we'll keep doing everything we can.

## Appendix C. Hedge Target

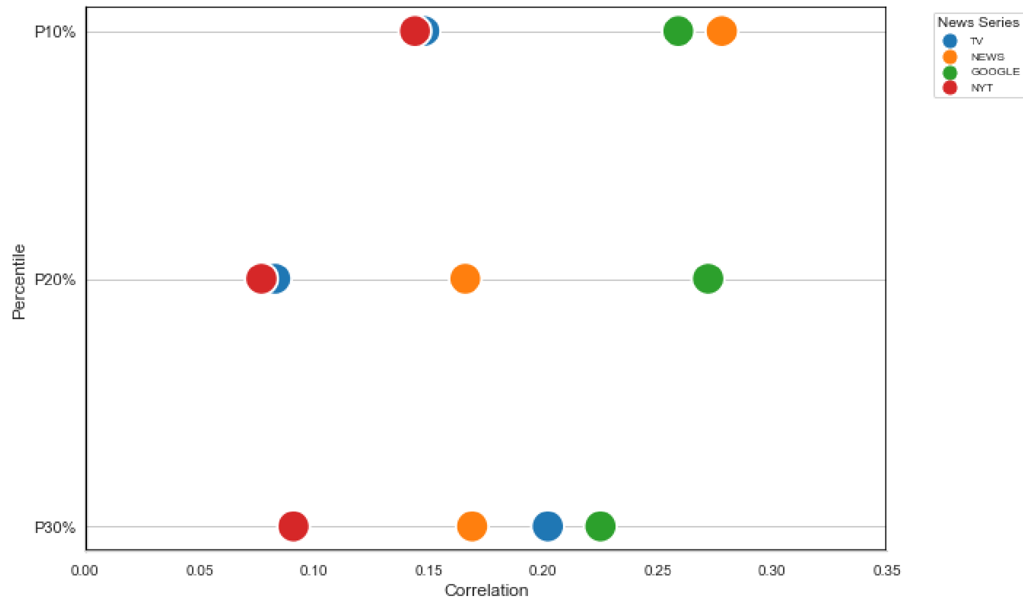
| | |
|---|---|
| TV | This series reflects US Television coverage of climate change or global warming, constructed by the Media And Climate Change Observatory (MeCCO). MeCCO monitors 130 sources (across newspapers, radio, and TV) in 59 countries in seven different regions around the world. The US Television dataset (Boykoff et al., 2023) specifically monitors seven major television stations (ABC, CBS, CNN, FOX, MSNBC, NBC, PBS) for mentions of climate change at a monthly frequency. It measures the attention given to climate change and its related risks, without distinguishing between positive and negative news. This index is available at a monthly frequency between January 2000 and January 2023 (date of download).<br>*Source:* https://scholar.colorado.edu/concern/datasets/z890rv64z |
| NEWS | This series reflects the coverage of climate change news in major US newspapers, including American Public Media, The Associated Press, Los Angeles Times, New York Times, United Press International, USA Today, The Wall Street Journal, and Washington Post. It measures the attention given to climate change and its related risks without distinguishing between positive and negative news. This index is available at a monthly frequency between January 2000 and May 2023 (date of download).<br>*Source:* https://scholar.colorado.edu/concern/datasets/5x21tg924 |
| GOOGLE | This series of climate news reports reflects the level of interest among the general public in the topic of 'climate change' as determined by national Google search trends. It measures the attention given to climate change and its related risks without distinguishing between positive and negative news. The monthly index is constructed between January 2010 to December 2021.<br>*Source: Google* |
| NYT | The NYT climate news, developed by Giglio et al. (2023), captures news related to climate change in the New York Times. It distinguishes between positive and negative news and is constructed as the number of negative climate articles minus the number of positive climate articles on a given day. The daily series is available between January 2000 to December 18, 2022. To obtain monthly data, they are aggregated by calculating the average of the daily series.<br>*Source:* https://www.biodiversityrisk.org/download/ |
| CPU | The climate policy uncertainty index (Gavriilidis, K., 2021) searches for articles related to mentions of climate change policy uncertainties in eight major US newspapers, including Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal. This index is constructed on a monthly basis and is available between January 1987 to August 2022.<br>*Source:* https://www.policyuncertainty.com/climate_uncertainty.html. |
| CHNEG | This is the Crimson Hexagon Negative News (CHNEG) climate news indices created by Engle et al. (2020). This index builds on the proprietary news aggregations from Crimson Hexagon, which covers over 1,000 outlets, including the WSJ, The New York Times, The Washington Post, Reuters, BBC, CNN, and Yahoo News. News is separated into good and bad news, and the index is calculated as the shares of negative climate |

| | |
|---|---|
| | change news. The index is available monthly between July 2008 and May 2018.<br>While Engle et al. (2020) also developed the WSJ index, utilizing climate news coverage in *The Wall Street Journal,* the WSJ index ends in June 2017, before the start of our sample period.<br>*Source: Engle et al. (2020), accessed via*<br>https://pages.stern.nyu.edu/~jstroebe/ |
| MCCC | ABBL (Ardia et al., 2020) expands upon the WSJ index of Engle et al. (2020) by incorporating new media outlets. It also makes a distinction between positive and negative news. The daily index is available between January 2003 and June 2018. To obtain monthly data, they are aggregated by calculating the average of the daily series.<br>*Source: Ardia et al. (2020), accessed via*<br>*https://sentometrics-research.com/download/mccc/* |
| IntSummit<br>GlobWarm<br>NatDis<br>ClimatePolicy | These four indices are obtained from Faccini et al. (2021) climate new indices: international climate summits (IntSummit), global warming (GlobWarm), natural disasters (NatDis), and narrative indices (ClimatePolicy). The first three indices measure the extent of news coverage related to their respective topics. ClimatePolicy is created through a manual process involving the reading and classification of 3,500 articles. IntSummit and ClimatePolicy focus on news regarding transition risk, while GlobWarm and NatDis are more inclined to capture news concerning physical risk. Data is available daily from January 2000 to November 2019. To obtain monthly data, they are aggregated by calculating the average of the daily series.<br>*Source: Faccini et al. (2021), accessed via*<br>*https://sites.google.com/view/george-skiadopoulos/research/selected-publications?authuser=0* |

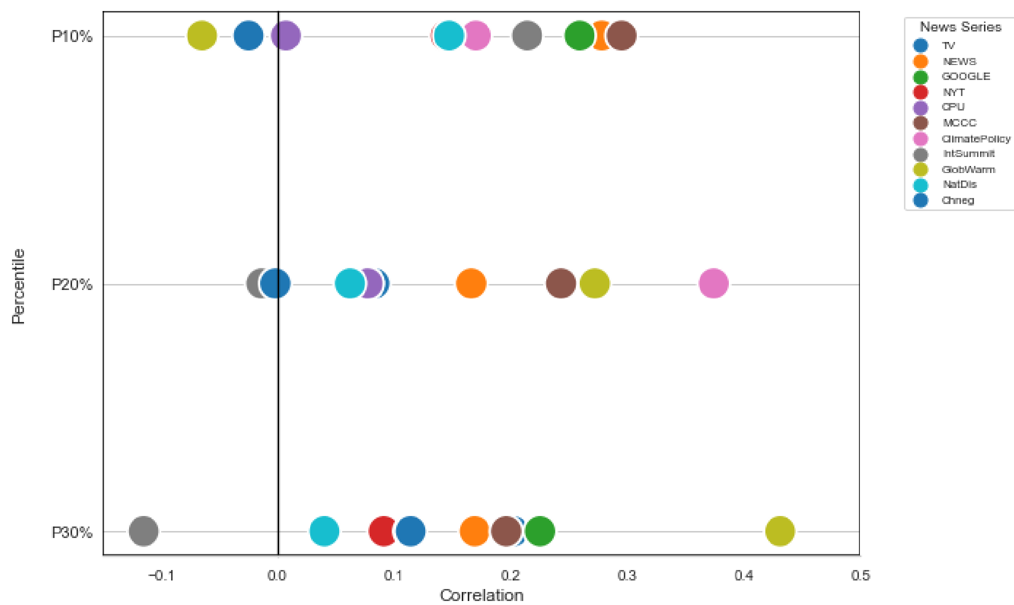
In addition, we use similar methods to hedge against risks related to economic uncertainty and infectious disease.

| | |
|---|---|
| EPU | Newspaper-based economic policy uncertainty developed by developed by Scott R. Baker, Steven J. Davis, and Jeffrey Levy. Data is available monthly from January 1985 to April 2023 (date of download).<br>Source: https://www.policyuncertainty.com/state_epu.html |
| Infection | Newspaper-based infectious disease equity market volatility tracker developed in Baker, Bloom, David, and Kost (2019). Data is available daily from January 1985 to Mary 2023 (date of download). To obtain monthly data, they are aggregated by calculating the average of the daily series.<br>Source: https://www.policyuncertainty.com/infectious_EMV.html |

Figure 1: Climate Change Hedge Performance of Baseline Portfolios



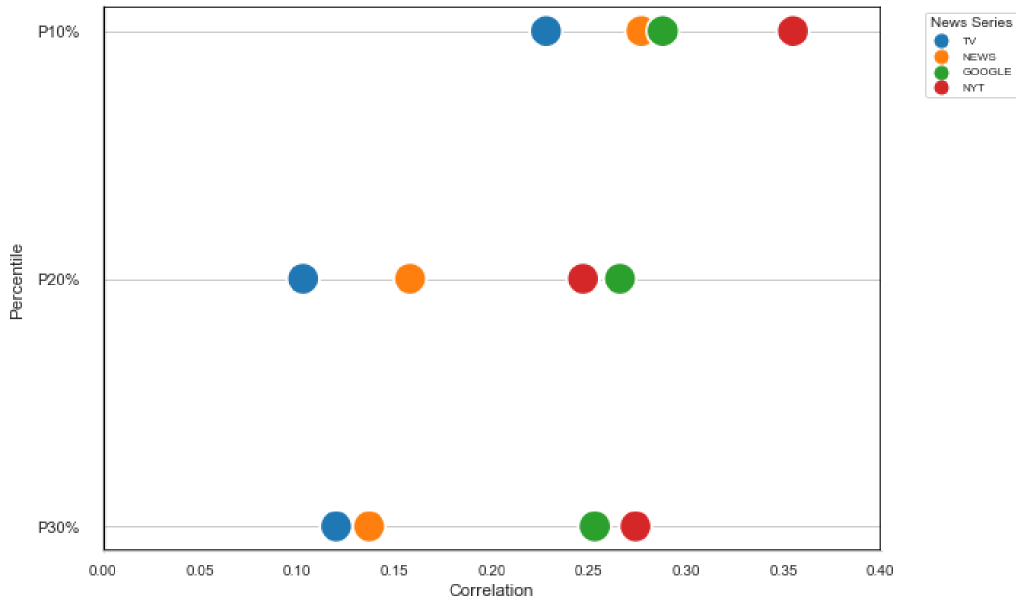

(a) Four main climate news series



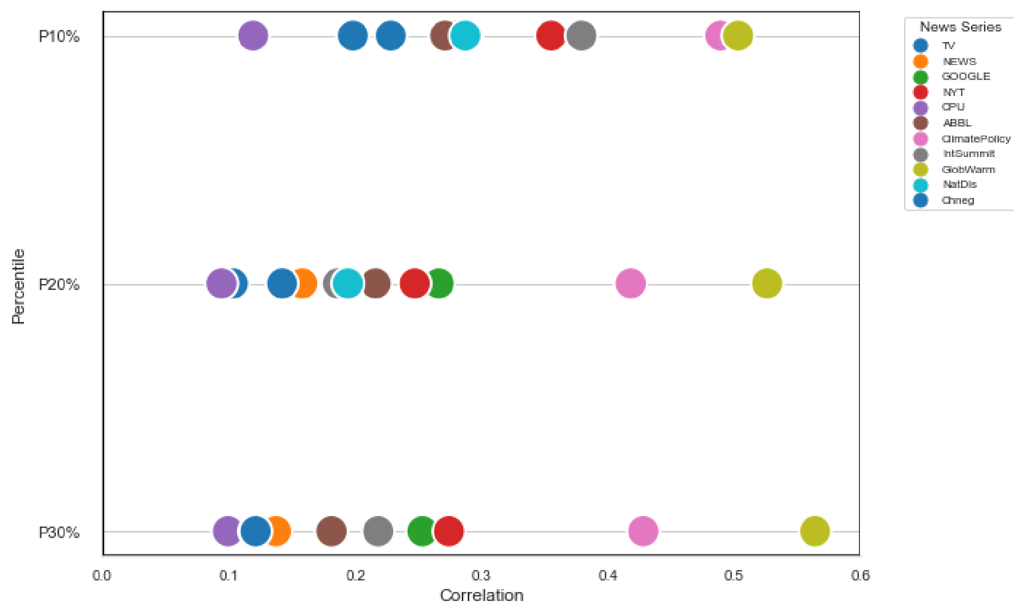

(b) All climate news series

Note: This figure shows the monthly return correlations for climate change baseline hedge portfolios based on percentiles 10%, 20%, and 30% respectively. For climate news series, such as TV, NEWS, GOOGLE, NYT, CPU, and MCCC, the sample period of hedge portfolio is from 2017Q4 to 2022Q1. For climate news series, such as ClimatePolicy, IntSummit, GlobWarm, NatDis, the sample period of hedge portfolio is from 2017Q4 to 2018 Q4. For climate news series, such as Chneg, the sample period of hedge portfolio is from 2017Q4 to 2018 Q2. Different colors represent different groups of climate news series. Panel A presents the hedge performance based on the four primary climate news series. Panel B presents the hedge performance based on all twelve climate news series.

Figure 2: Climate Change Hedge Performance of Complete Portfolios




(a) Four main climate news series




(b) All climate news series

Note: This figure shows the monthly return correlations for climate change complete hedge portfolios based on percentiles 10%, 20%, and 30% respectively. For climate news series, such as TV, NEWS, GOOGLE, NYT, CPU, and MCCC, the sample period of hedge portfolio is from 2017Q4 to 2022Q1. For climate news series, such as ClimatePolicy, IntSummit, GlobWarm, NatDis, the sample period of hedge portfolio is from 2017Q4 to 2018 Q4. For climate news series, such as Chneg, the sample period of hedge portfolio is from 2017Q4 to 2018 Q2. Different colors represent different groups of climate news series. Panel A presents the hedge performance based on the four primary climate news series. Panel B presents the hedge performance based on all twelve climate news series.

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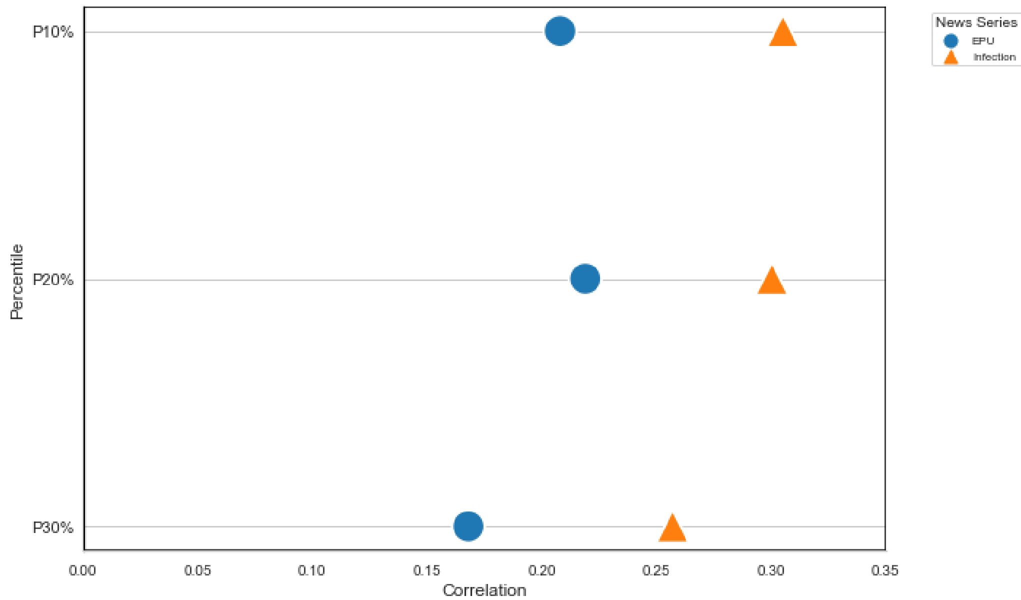
Figure 3: Political Risk and Pandemic Risk Hedge Performance




Note: This figure shows the monthly return correlations for political risk and pandemic risk hedge portfolios based on percentiles 10%, 20%, and 30%, respectively. The sample period of political risk (Pandemic) hedge portfolio is from 2017Q4 (2020Q3) to 2022Q1. Dots in squares present the hedge performance based on the political risk news series. Dots in triangles present the hedge performance based on pandemic news series.

Table 1: Summary Statistics of Climate Change Hedge Portfolios

| Quarter | Climate exposure | Refined climate exposure | Positive climate exposure | Negative climate exposure | Baseline hedging portfolios | Complete hedging portfolios |
|---|---|---|---|---|---|---|
| 2017Q1 | 223 | 153 | 72 | 81 | - | - |
| 2017Q2 | 721 | 461 | 218 | 243 | - | - |
| 2017Q3 | 604 | 396 | 207 | 189 | - | - |
| 2017Q4 | 472 | 210 | 108 | 102 | 151 | 416 |
| 2018Q1 | 466 | 309 | 158 | 151 | 165 | 463 |
| 2018Q2 | 495 | 288 | 155 | 133 | 180 | 515 |
| 2018Q3 | 626 | 392 | 195 | 197 | 157 | 342 |
| 2018Q4 | 676 | 421 | 215 | 206 | 157 | 395 |
| 2019Q1 | 734 | 483 | 256 | 227 | 177 | 436 |
| 2019Q2 | 705 | 453 | 227 | 226 | 200 | 494 |
| 2019Q3 | 738 | 468 | 226 | 242 | 213 | 502 |
| 2019Q4 | 724 | 469 | 250 | 219 | 215 | 486 |
| 2020Q1 | 683 | 464 | 210 | 254 | 219 | 533 |
| 2020Q2 | 314 | 206 | 106 | 100 | 213 | 492 |
| 2020Q3 | 746 | 524 | 262 | 262 | 202 | 461 |
| 2020Q4 | 848 | 586 | 298 | 288 | 209 | 462 |
| 2021Q1 | 941 | 671 | 323 | 348 | 222 | 487 |
| 2021Q2 | 925 | 455 | 239 | 216 | 244 | 544 |
| 2021Q3 | 879 | 610 | 294 | 316 | 249 | 629 |
| 2021Q4 | 858 | 621 | 300 | 321 | 250 | 626 |
| 2022Q1 | - | - | - | - | 255 | 582 |

Note: This table presents summary statistics of climate hedge portfolios by quarter. The sample period of conferences with climate exposure is from 2017 Q1 to 2021 Q4. The sample period of hedge portfolios is from 2017 Q4 to 2022 Q1. Climate exposure represents the number of conferences with at least one conversation related to climate change. Refined climate exposure shows the number of conferences after filtering out extreme and no-response conversations. Extreme conversations are identified as those with a duration of less than/equal to one minute or greater than/equal to ten minutes. No-response conversations are identified as those with zero or missing market response. Positive (Negative) climate exposure indicates the number of conferences with a positive (negative) average market reaction to the climate change conversations. Baseline (Complete) hedge portfolios indicates the number of stocks in the hedge portfolios without (with) consideration of climate shocks.

Table 2A: Industrial Distribution of Baseline Portfolios.

| GICS | Industry | Number of firms | | | |
|---|---|---|---|---|---|
| | | Avg. | Min | Median | Max |
| 1010 | Energy | 11.6 | 6 | 11 | 18 |
| 1510 | Materials | 11.8 | 9 | 11.5 | 15 |
| 2010 | Capital Goods | 26.3 | 18 | 26 | 33 |
| 2020 | Commercial & Professional Services | 11.5 | 7 | 12 | 15 |
| 2030 | Transportation | 4.4 | 1 | 5 | 8 |
| 2510 | Automobiles & Components | 5.8 | 2 | 5.5 | 11 |
| 2520 | Consumer Durables & Apparel | 9.8 | 5 | 10 | 16 |
| 2530 | Consumer Services | 7.1 | 2 | 5.5 | 14 |
| 2550 | Retailing | 8.4 | 2 | 8.5 | 13 |
| 3010 | Food & Staples Retailing | 2.6 | 1 | 2.5 | 4 |
| 3020 | Food, Beverage & Tobacco | 5.9 | 3 | 5 | 12 |
| 3030 | Household & Personal Products | 1.8 | 1 | 1.5 | 5 |
| 3510 | Health Care Equipment & Services | 14.9 | 10 | 15 | 21 |
| 3520 | Pharmaceuticals, Biotechnology & Life Sciences | 12.2 | 3 | 14.5 | 22 |
| 4010 | Banks | 3.6 | 1 | 3.5 | 8 |
| 4020 | Diversified Financials | 9.2 | 4 | 8.5 | 18 |
| 4030 | Insurance | 2.5 | 1 | 2 | 5 |
| 4510 | Software & Services | 15.3 | 6 | 15 | 28 |
| 4520 | Technology Hardware & Equipment | 12.2 | 8 | 12 | 19 |
| 4530 | Semiconductors & Semiconductor Equipment | 11.8 | 7 | 12 | 15 |
| 5010 | Telecommunication Services | 3.4 | 1 | 3 | 5 |
| 5020 | Media & Entertainment | 4.6 | 1 | 5 | 11 |
| 5510 | Utilities | 4.2 | 1 | 4 | 7 |
| 6010 | Real Estate | 3.6 | 1 | 3 | 7 |

Note: This table shows the industrial distribution of baseline climate hedge portfolios. The average, minimum, median, and maximum value of stocks for each industry are at quarterly level. The sample period is between 2017Q4 to 2022Q1.

Table 2B: Industrial Distribution of Complete Portfolios.

| GICS | Industry | Number of firms Avg. | Min | Median | Max |
|---|---|---|---|---|---|
| 1010 | Energy | 44.3 | 26 | 45 | 65 |
| 1510 | Materials | 39.3 | 31 | 37 | 54 |
| 2010 | Capital Goods | 65.1 | 40 | 64 | 93 |
| 2020 | Commercial & Professional Services | 19.8 | 11 | 19.5 | 28 |
| 2030 | Transportation | 12.6 | 8 | 13 | 16 |
| 2510 | Automobiles & Components | 15.2 | 9 | 15 | 20 |
| 2520 | Consumer Durables & Apparel | 15.9 | 11 | 17 | 22 |
| 2530 | Consumer Services | 15.7 | 11 | 14.5 | 23 |
| 2550 | Retailing | 19.1 | 12 | 19 | 24 |
| 3010 | Food & Staples Retailing | 4.8 | 3 | 4 | 8 |
| 3020 | Food, Beverage & Tobacco | 13.3 | 9 | 12 | 21 |
| 3030 | Household & Personal Products | 3.3 | 1 | 3 | 7 |
| 3510 | Health Care Equipment & Services | 21.9 | 15 | 22 | 31 |
| 3520 | Pharmaceuticals, Biotechnology & Life Sciences | 18.6 | 7 | 20 | 30 |
| 4010 | Banks | 16.2 | 11 | 15.5 | 25 |
| 4020 | Diversified Financials | 20.1 | 14 | 20 | 27 |
| 4030 | Insurance | 6.9 | 3 | 6.5 | 12 |
| 4510 | Software & Services | 25.7 | 7 | 29.5 | 42 |
| 4520 | Technology Hardware & Equipment | 25.0 | 15 | 26 | 31 |
| 4530 | Semiconductors & Semiconductor Equipment | 22.9 | 14 | 23.5 | 29 |
| 5010 | Telecommunication Services | 4.7 | 2 | 5 | 8 |
| 5020 | Media & Entertainment | 9.0 | 4 | 9 | 14 |
| 5510 | Utilities | 28.7 | 19 | 28.5 | 40 |
| 6010 | Real Estate | 22.4 | 15 | 22 | 30 |

Note: This table shows the industrial distribution of complete climate hedge portfolios. The average, minimum, median, and maximum value of stocks for each industry are at quarterly level. The sample period is between 2017Q4 to 2022Q1.

Table 3A: Decomposition of Baseline Hedge Portfolios

| Quarter | Incumbent | New entrant | Exit | Positive | Negative | Position change |
|---|---|---|---|---|---|---|
| 2017Q4 | 0 | 151 | 0 | 76 | 75 | 0 |
| 2018Q1 | 142 | 23 | 20 | 83 | 82 | 0 |
| 2018Q2 | 137 | 43 | 9 | 90 | 90 | 4 |
| 2018Q3 | 111 | 46 | 28 | 78 | 79 | 6 |
| 2018Q4 | 89 | 68 | 69 | 76 | 81 | 13 |
| 2019Q1 | 121 | 56 | 68 | 87 | 90 | 16 |
| 2019Q2 | 125 | 75 | 36 | 100 | 100 | 17 |
| 2019Q3 | 156 | 57 | 52 | 107 | 106 | 26 |
| 2019Q4 | 152 | 63 | 44 | 106 | 109 | 28 |
| 2020Q1 | 152 | 67 | 61 | 110 | 109 | 36 |
| 2020Q2 | 149 | 64 | 63 | 108 | 105 | 40 |
| 2020Q3 | 160 | 42 | 70 | 100 | 102 | 37 |
| 2020Q4 | 136 | 73 | 53 | 104 | 105 | 38 |
| 2021Q1 | 141 | 81 | 66 | 111 | 111 | 40 |
| 2021Q2 | 153 | 91 | 68 | 122 | 122 | 51 |
| 2021Q3 | 203 | 46 | 69 | 123 | 126 | 60 |
| 2021Q4 | 167 | 83 | 41 | 123 | 127 | 54 |
| 2022Q1 | 163 | 92 | 82 | 127 | 128 | 54 |

Note: This table displays a decomposition of baseline hedging portfolios by quarter. Incumbent (New entrant) represents the number of stocks that were (were not) held in the last quarter. Exit represents number of stocks were held in the last quarter but are absent in this quarter. Positive (Negative) shows the number of stocks in portfolios with a positive (negative) average market reaction to climate change. Position change indicates the number of stocks in given quarter changed their position in the portfolios. Past four quarters are used to construct quarterly portfolios except for 2017Q4. Three historical quarters are used to construct the portfolios in 2017Q4.

Table 3B: Decomposition of Complete Hedge Portfolios

| Quarter | Incumbent | New entrant | Exit | Positive | Negative | Position change |
|---|---|---|---|---|---|---|
| 2017Q4 | 0 | 416 | 0 | 210 | 206 | 0 |
| 2018Q1 | 410 | 53 | 6 | 233 | 230 | 5 |
| 2018Q2 | 430 | 85 | 33 | 261 | 254 | 19 |
| 2018Q3 | 281 | 61 | 234 | 173 | 169 | 45 |
| 2018Q4 | 261 | 134 | 81 | 192 | 203 | 78 |
| 2019Q1 | 348 | 88 | 47 | 209 | 227 | 90 |
| 2019Q2 | 354 | 140 | 82 | 261 | 233 | 112 |
| 2019Q3 | 426 | 76 | 68 | 258 | 244 | 121 |
| 2019Q4 | 372 | 114 | 130 | 242 | 244 | 127 |
| 2020Q1 | 406 | 127 | 80 | 277 | 256 | 154 |
| 2020Q2 | 420 | 72 | 113 | 241 | 251 | 166 |
| 2020Q3 | 412 | 49 | 80 | 223 | 238 | 162 |
| 2020Q4 | 340 | 122 | 121 | 234 | 228 | 164 |
| 2021Q1 | 330 | 157 | 132 | 240 | 247 | 181 |
| 2021Q2 | 406 | 138 | 81 | 270 | 274 | 209 |
| 2021Q3 | 506 | 123 | 38 | 331 | 298 | 263 |
| 2021Q4 | 514 | 112 | 115 | 319 | 307 | 276 |
| 2022Q1 | 464 | 118 | 162 | 292 | 290 | 261 |

Note: This table displays a decomposition of complete hedging portfolios by quarter. Incumbent (New entrant) represents the number of stocks that were (were not) held in the last quarter. Exit represents number of stocks were held in the last quarter but are absent in this quarter. Positive (Negative) shows the number of stocks in portfolios with a positive (negative) average market reaction to climate change. Position change indicates the number of stocks in given quarter changed their position in the portfolios. Past four quarters are used to construct quarterly portfolios except for 2017Q4. Three historical quarters are used to construct the portfolios in 2017Q4.

Table 4: Climate Hedge Performance

Panel A: Climate Hedge Performance of Baseline Portfolios

| Percentile | Correlation | TV | NEWS | GOOGLE | NYT | CPU | ABBL | ClimatePolicy | IntSummit | GlobWarm | NatDis | Chneg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 10% | Pearson | 0.148 | 0.278 | 0.259 | 0.144 | 0.007 | 0.295 | 0.170 | 0.214 | -0.065 | 0.147 | -0.025 |
| 10% | Spearman | 0.122 | 0.315 | 0.317 | 0.119 | 0.011 | 0.231 | 0.104 | 0.004 | 0.021 | 0.200 | 0.119 |
| 20% | Pearson | 0.083 | 0.166 | 0.272 | 0.077 | 0.077 | 0.243 | 0.374 | -0.014 | 0.272 | 0.062 | -0.002 |
| 20% | Spearman | 0.070 | 0.208 | 0.364 | 0.044 | 0.036 | 0.224 | 0.518 | -0.186 | 0.336 | 0.257 | 0.190 |
| 30% | Pearson | 0.202 | 0.169 | 0.225 | 0.091 | 0.113 | 0.196 | 0.114 | -0.115 | 0.431 | 0.040 | 0.114 |
| 30% | Spearman | 0.205 | 0.210 | 0.265 | 0.048 | 0.052 | 0.170 | 0.239 | -0.125 | 0.329 | 0.175 | -0.095 |

Panel B: Climate Hedge Performance of Complete Portfolios

| Percentile | Correlation | TV | NEWS | GOOGLE | NYT | CPU | ABBL | ClimatePolicy | IntSummit | GlobWarm | NatDis | Chneg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 10% | Pearson | 0.228 | 0.277 | 0.288 | 0.355 | 0.119 | 0.271 | 0.489 | 0.379 | 0.503 | 0.287 | 0.198 |
| 10% | Spearman | 0.154 | 0.314 | 0.337 | 0.330 | 0.041 | 0.278 | 0.682 | 0.225 | 0.418 | 0.475 | 0.452 |
| 20% | Pearson | 0.103 | 0.158 | 0.266 | 0.247 | 0.094 | 0.216 | 0.418 | 0.186 | 0.526 | 0.194 | 0.142 |
| 20% | Spearman | 0.050 | 0.200 | 0.321 | 0.250 | 0.054 | 0.226 | 0.546 | 0.079 | 0.429 | 0.357 | 0.381 |
| 30% | Pearson | 0.120 | 0.137 | 0.253 | 0.274 | 0.099 | 0.181 | 0.428 | 0.218 | 0.564 | 0.120 | 0.121 |
| 30% | Spearman | 0.084 | 0.170 | 0.305 | 0.237 | 0.027 | 0.203 | 0.579 | 0.025 | 0.464 | 0.257 | 0.333 |

Note: This table displays the monthly correlations between the returns of climate hedge portfolios and AR(1) innovations of various climate index series. The portfolios are constructed with sorting thresholds set at 10%, 20%, and 30% respectively. All climate index series are coded so that higher numbers indicate negative climate news. Consequently, positive correlation coefficients indicate successful hedges. Panel A (B) shows the climate hedge performance of baseline (complete) portfolios. For climate news series, such as TV, NEWS, GOOGLE, NYT, CPU, and MCCC, the sample period of hedge portfolio is from 2017Q4 to 2022Q1. For climate news series, such as ClimatePolicy, IntSummit, GlobWarm, NatDis, the sample period of hedge portfolio is from 2017Q4 to 2018 Q4. For climate news series, such as Chneg, the sample period of hedge portfolio is from 2017Q4 to 2018 Q2.

Table 5: Summary Statistics of Climate Shocks

| | Heat Shock | | Natural Disaster | |
|---|---|---|---|---|
| Quarter | # County | # Firm | # County | # Firm |
| 2017Q4 | 112 | 257 | 36 | 68 |
| 2018Q1 | 117 | 274 | 37 | 85 |
| 2018Q2 | 121 | 285 | 44 | 114 |
| 2018Q3 | 34 | 93 | 39 | 130 |
| 2018Q4 | 55 | 130 | 55 | 158 |
| 2019Q1 | 55 | 132 | 65 | 179 |
| 2019Q2 | 52 | 120 | 64 | 230 |
| 2019Q3 | 41 | 97 | 66 | 248 |
| 2019Q4 | 20 | 52 | 65 | 273 |
| 2020Q1 | 27 | 58 | 66 | 312 |
| 2020Q2 | 26 | 70 | 63 | 263 |
| 2020Q3 | 27 | 74 | 55 | 231 |
| 2020Q4 | 19 | 49 | 61 | 252 |
| 2021Q1 | 13 | 43 | 68 | 276 |
| 2021Q2 | 27 | 75 | 72 | 286 |
| 2021Q3 | 49 | 124 | 75 | 323 |
| 2021Q4 | 53 | 161 | 71 | 288 |
| 2022Q1 | 51 | 166 | 61 | 216 |

Note: This table displays the summary statistics of climate shocks, including heat shocks and natural disasters. # County presents the number of counties experiencing heat shocks or natural disasters, with at least one firm being impacted. # Firm presents the number of firms impacted by heat shocks or natural disasters. If two types of shocks happen in the same month and same county, we classify corresponding county and firms into group of natural disasters.

Table 6: Climate Hedge Performance of Shock Portfolios

| Percentile | Correlation | TV | NEWS | GOOGLE | NYT | CPU | ABBL | ClimatePolicy | IntSummit | GlobWarm | NatDis | Chneg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 10% | Pearson | 0.138 | 0.251 | 0.155 | 0.080 | 0.120 | 0.135 | 0.556 | 0.312 | 0.428 | 0.151 | -0.340 |
| 10% | Spearman | 0.059 | 0.223 | 0.278 | 0.028 | 0.077 | 0.050 | 0.461 | -0.132 | 0.254 | 0.386 | -0.333 |
| 20% | Pearson | 0.176 | 0.154 | 0.172 | 0.244 | 0.167 | 0.118 | 0.472 | 0.288 | 0.736 | 0.312 | -0.023 |
| 20% | Spearman | 0.106 | 0.156 | 0.337 | 0.216 | 0.130 | 0.122 | 0.511 | 0.157 | 0.586 | 0.343 | -0.119 |
| 30% | Pearson | 0.199 | 0.164 | 0.239 | 0.297 | 0.156 | 0.156 | 0.519 | 0.417 | 0.712 | 0.281 | 0.166 |
| 30% | Spearman | 0.160 | 0.180 | 0.390 | 0.315 | 0.083 | 0.138 | 0.696 | 0.396 | 0.739 | 0.468 | 0.357 |

Note: This table displays the monthly correlations between the returns of climate hedge portfolios and AR(1) innovations of various climate index series. The portfolios are constructed with sorting thresholds set at 10%, 20%, and 30% of stocks that experience climate shocks in the past quarter, respectively. All climate index series are coded so that higher numbers indicate negative climate news. Consequently, positive correlation coefficients indicate successful hedges. For climate news series, such as TV, NEWS, GOOGLE, NYT, CPU, and MCCC, the sample period of hedge portfolio is from 2017Q4 to 2022Q1. For climate news series, such as ClimatePolicy, IntSummit, GlobWarm, NatDis, the sample period of hedge portfolio is from 2017Q4 to 2018 Q4. For climate news series, such as Chneg, the sample period of hedge portfolio is from 2017Q4 to 2018 Q2.

Table 7 Factor Exposures of Hedge Portfolios

Panel A: Factor Exposures of Baseline Portfolios

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | P10% | P20% | P30% | P10% | P20% | P30% |
| Mkt-RF | -0.105 | -0.075** | -0.052 | -0.104 | -0.067 | -0.065 |
| | (0.07) | (0.03) | (0.03) | (0.10) | (0.05) | (0.04) |
| SMB | -0.114 | -0.026 | 0.003 | -0.176 | -0.079 | 0.003 |
| | (0.12) | (0.08) | (0.05) | (0.14) | (0.09) | (0.07) |
| HML | -0.055 | -0.014 | 0.014 | 0.051 | 0.045 | 0.045 |
| | (0.08) | (0.05) | (0.04) | (0.12) | (0.07) | (0.06) |
| RMW | | | | -0.124 | -0.118 | -0.009 |
| | | | | (0.16) | (0.11) | (0.08) |
| CMA | | | | -0.183 | -0.097 | -0.097 |
| | | | | (0.26) | (0.15) | (0.12) |
| Constant | 0.267 | 0.253 | 0.182 | 0.374 | 0.323 | 0.233 |
| | (0.32) | (0.21) | (0.17) | (0.35) | (0.22) | (0.20) |
| Observations | 54 | 54 | 54 | 54 | 54 | 54 |
| R-squared | 0.095 | 0.078 | 0.047 | 0.116 | 0.107 | 0.067 |

Note: This table presents the regression results of monthly returns of the climate hedge portfolios on Fama-French factors. Columns (1) – (3) shows the results for the Fama-French three-factor model. Columns (4) – (6) shows the results for the Fama-French five-factor model. The sample period is between 2017Q4 and 2022Q1. Heteroskedasticity-robust standard errors in parentheses. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Panel B: Factor Exposures of Complete Portfolios

| VARIABLES | (1)<br>P10% | (2)<br>P20% | (3)<br>P30% | (4)<br>P10% | (5)<br>P20% | (6)<br>P30% |
|---|---|---|---|---|---|---|
| Mkt-RF | -0.081** | -0.065** | -0.042 | -0.077 | -0.059 | -0.052 |
| | (0.04) | (0.03) | (0.03) | (0.05) | (0.04) | (0.04) |
| SMB | 0.037 | 0.039 | 0.026 | 0.001 | 0.004 | 0.023 |
| | (0.06) | (0.06) | (0.05) | (0.08) | (0.07) | (0.06) |
| HML | 0.022 | 0.021 | 0.026 | 0.052 | 0.044 | 0.047 |
| | (0.04) | (0.04) | (0.04) | (0.07) | (0.06) | (0.06) |
| RMW | | | | -0.086 | -0.089 | -0.017 |
| | | | | (0.10) | (0.09) | (0.07) |
| CMA | | | | -0.065 | -0.044 | -0.075 |
| | | | | (0.13) | (0.11) | (0.11) |
| Constant | 0.246 | 0.267 | 0.241 | 0.298 | 0.311 | 0.284 |
| | (0.19) | (0.16) | (0.15) | (0.22) | (0.19) | (0.18) |
| Observations | 54 | 54 | 54 | 54 | 54 | 54 |
| R-squared | 0.078 | 0.068 | 0.045 | 0.097 | 0.092 | 0.065 |

Note: This table presents the regression results of monthly returns of the climate hedge portfolios on Fama-French factors. Columns (1) – (3) shows the results for the Fama-French three-factor model. Columns (4) – (6) shows the results for the Fama-French five-factor model. The sample period is between 2017Q4 and 2022Q1. Heteroskedasticity-robust standard errors in parentheses. Significance levels: *** p < 0.01; ** p < 0.05; * p < 0.1.

## Online Appendix

Appendix1: Summary Statistics of Political Risk Hedge Portfolios

| Quarter | Political exposure | Refined political exposure | Positive political exposure | Negative political exposure | Hedge portfolios |
|---|---|---|---|---|---|
| 2017Q1 | 668 | 518 | 250 | 268 | - |
| 2017Q2 | 2502 | 1723 | 871 | 852 | - |
| 2017Q3 | 2189 | 1496 | 734 | 761 | - |
| 2017Q4 | 1553 | 692 | 353 | 339 | 404 |
| 2018Q1 | 1725 | 1224 | 600 | 623 | 402 |
| 2018Q2 | 1808 | 1214 | 588 | 626 | 423 |
| 2018Q3 | 2277 | 1607 | 832 | 775 | 370 |
| 2018Q4 | 2654 | 1795 | 906 | 889 | 392 |
| 2019Q1 | 2608 | 1943 | 975 | 968 | 451 |
| 2019Q2 | 2676 | 1819 | 945 | 874 | 473 |
| 2019Q3 | 2598 | 1839 | 930 | 909 | 480 |
| 2019Q4 | 2641 | 1906 | 972 | 933 | 480 |
| 2020Q1 | 2533 | 1850 | 928 | 922 | 485 |
| 2020Q2 | 1176 | 906 | 461 | 445 | 485 |
| 2020Q3 | 2641 | 2133 | 1058 | 1075 | 481 |
| 2020Q4 | 2675 | 2095 | 1043 | 1052 | 502 |
| 2021Q1 | 2755 | 2232 | 1094 | 1138 | 518 |
| 2021Q2 | 2780 | 1485 | 744 | 740 | 533 |
| 2021Q3 | 2766 | 2145 | 1071 | 1074 | 528 |
| 2021Q4 | 2493 | 1998 | 1021 | 977 | 553 |
| 2022Q1 | - | - | - | - | 557 |

Note: This table presents summary statistics of political risk hedge portfolios by quarter. The sample period of conferences with political risk exposure is from 2017 Q1 to 2021 Q4. The sample period of hedge portfolios is from 2017 Q4 to 2022 Q1. Political exposure represents the number of conferences with at least one conversation related to political risk. Refined political exposure shows the number of conferences after filtering out extreme and no-response conversations. Extreme conversations are identified as those with a duration of less than/equal to one minute or greater than/equal to ten minutes. No-response conversations are identified as those with zero or missing market response. Positive (Negative) political exposure indicates the number of conferences with a positive (negative) average market reaction to the political risk conversations. Hedge portfolios indicates the number of stocks in the hedge portfolios.

Appendix 2: Industrial Distribution of Political Risk Hedge Portfolios.

| | | Number of firms | | | |
|---|---|---|---|---|---|
| GICS | Industry | Avg. | Min | Median | Max |
| 1010 | Energy | 20.1 | 11 | 20 | 28 |
| 1510 | Materials | 16.7 | 13 | 16 | 21 |
| 2010 | Capital Goods | 38.4 | 29 | 37 | 48 |
| 2020 | Commercial & Professional Services | 22.8 | 18 | 22.5 | 29 |
| 2030 | Transportation | 8.3 | 1 | 8.5 | 12 |
| 2510 | Automobiles & Components | 5.7 | 3 | 5 | 9 |
| 2520 | Consumer Durables & Apparel | 15.9 | 9 | 17 | 23 |
| 2530 | Consumer Services | 20.1 | 13 | 18.5 | 27 |
| 2550 | Retailing | 15.6 | 10 | 16 | 20 |
| 3010 | Food & Staples Retailing | 2.6 | 1 | 2 | 6 |
| 3020 | Food, Beverage & Tobacco | 6.8 | 4 | 6.5 | 12 |
| 3030 | Household & Personal Products | 2.9 | 1 | 3 | 5 |
| 3510 | Health Care Equipment & Services | 46.2 | 33 | 43.5 | 59 |
| 3520 | Pharmaceuticals, Biotechnology & Life Sciences | 68.1 | 45 | 70 | 91 |
| 4010 | Banks | 10.0 | 5 | 10.5 | 15 |
| 4020 | Diversified Financials | 29.1 | 22 | 27 | 47 |
| 4030 | Insurance | 8.1 | 6 | 7 | 18 |
| 4510 | Software & Services | 42.5 | 30 | 42.5 | 53 |
| 4520 | Technology Hardware & Equipment | 33.0 | 24 | 33.5 | 40 |
| 4530 | Semiconductors & Semiconductor Equipment | 18.1 | 10 | 18 | 23 |
| 5010 | Telecommunication Services | 8.1 | 3 | 8 | 12 |
| 5020 | Media & Entertainment | 16.1 | 7 | 18 | 24 |
| 5510 | Utilities | 5.9 | 1 | 6 | 8 |
| 6010 | Real Estate | 9.8 | 7 | 9 | 15 |

Note: This table shows the industrial distribution of political risk hedge portfolios. The average, minimum, median, and maximum value of stocks for each industry are at quarterly level. The sample period is between 2017Q3 to 2022Q1.

Appendix 3: Decomposition of Political Risk Hedge Portfolios

| Quarter | Incumbent | New entrant | Exit | Positive | Negative | Position change |
|---|---|---|---|---|---|---|
| 2017Q4 | 0 | 404 | 0 | 203 | 201 | 0 |
| 2018Q1 | 368 | 34 | 36 | 202 | 200 | 0 |
| 2018Q2 | 308 | 115 | 94 | 210 | 213 | 3 |
| 2018Q3 | 237 | 133 | 186 | 185 | 185 | 4 |
| 2018Q4 | 231 | 161 | 139 | 194 | 198 | 10 |
| 2019Q1 | 270 | 181 | 122 | 225 | 226 | 14 |
| 2019Q2 | 309 | 164 | 142 | 236 | 237 | 15 |
| 2019Q3 | 346 | 134 | 127 | 239 | 241 | 22 |
| 2019Q4 | 340 | 140 | 140 | 241 | 239 | 26 |
| 2020Q1 | 327 | 158 | 153 | 244 | 241 | 36 |
| 2020Q2 | 322 | 163 | 163 | 244 | 241 | 39 |
| 2020Q3 | 359 | 122 | 126 | 240 | 241 | 36 |
| 2020Q4 | 308 | 194 | 173 | 253 | 249 | 38 |
| 2021Q1 | 344 | 174 | 158 | 262 | 256 | 40 |
| 2021Q2 | 338 | 195 | 180 | 265 | 268 | 51 |
| 2021Q3 | 422 | 106 | 111 | 261 | 267 | 59 |
| 2021Q4 | 346 | 207 | 182 | 276 | 277 | 54 |
| 2022Q1 | 369 | 188 | 184 | 280 | 277 | 54 |

Note: This table displays a decomposition of political risk hedge portfolios by quarter. Incumbent (New entrant) represents the number of stocks that were (were not) held in the last quarter. Exit represents number of stocks were held in the last quarter but are absent in this quarter. Positive (Negative) shows the number of stocks in portfolios with a positive (negative) average market reaction to climate change. Position change indicates the number of stocks in given quarter changed their position in the portfolios. Past four quarters are used to construct quarterly portfolios except for 2017Q4. Three historical quarters are used to construct the portfolios in 2017Q4

Appendix 4: Factor Exposures of Political Risk Hedge Portfolios

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | P10% | P20% | P30% | P10% | P20% | P30% |
| Mkt-RF | -0.001 | -0.010 | -0.024 | 0.018 | -0.001 | -0.022 |
| | (0.04) | (0.03) | (0.02) | (0.05) | (0.04) | (0.03) |
| SMB | -0.290*** | -0.125** | -0.125** | -0.376*** | -0.154** | -0.147*** |
| | (0.07) | (0.06) | (0.05) | (0.08) | (0.07) | (0.05) |
| HML | 0.009 | -0.041 | -0.025 | 0.147** | 0.011 | 0.029 |
| | (0.04) | (0.03) | (0.02) | (0.06) | (0.05) | (0.04) |
| RMW | | | | -0.157 | -0.061 | -0.040 |
| | | | | (0.10) | (0.08) | (0.06) |
| CMA | | | | -0.150 | -0.048 | -0.068 |
| | | | | (0.12) | (0.09) | (0.07) |
| Constant | -0.280 | -0.041 | -0.064 | -0.195 | -0.012 | -0.031 |
| | (0.24) | (0.15) | (0.11) | (0.23) | (0.16) | (0.11) |
| Observations | 54 | 54 | 54 | 54 | 54 | 54 |
| R-squared | 0.199 | 0.126 | 0.233 | 0.246 | 0.137 | 0.255 |

Note: This table presents the regression results of monthly returns of the political risk hedge portfolios on Fama-French factors. Columns (1) – (3) shows the results for the Fama-French three-factor model. Columns (4) – (6) shows the results for the Fama-French five-factor model. The sample period is between 2017Q4 and 2022Q1. Heteroskedasticity-robust standard errors in parentheses. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.
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Appendix 5: Summary Statistics of Pandemic Risk Hedge Portfolios

| Quarter | Pandemic exposure | Refined pandemic exposure | Positive pandemic exposure | Negative pandemic exposure | Hedging portfolios |
|---|---|---|---|---|---|
| 2020Q1 | 1052 | 648 | 328 | 320 | - |
| 2020Q2 | 965 | 666 | 347 | 319 | - |
| 2020Q3 | 2193 | 1594 | 820 | 774 | 219 |
| 2020Q4 | 2149 | 1499 | 725 | 774 | 383 |
| 2021Q1 | 1967 | 1428 | 715 | 713 | 431 |
| 2021Q2 | 1750 | 799 | 414 | 385 | 453 |
| 2021Q3 | 1645 | 1101 | 562 | 539 | 450 |
| 2021Q4 | 1235 | 648 | 404 | 435 | 451 |
| 2022Q1 | - | - | - | - | 421 |

Note: This table presents summary statistics of pandemic risk hedge portfolios by quarter. The sample period of conferences with pandemic risk exposure is from 2020 Q1 to 2021 Q4. The sample period of pandemic risk hedge portfolios is from 2020 Q3 to 2022 Q1. Pandemic exposure represents the number of conferences with at least one conversation related to pandemic risk. Refined pandemic exposure shows the number of conferences after filtering out extreme and no-response conversations. Extreme conversations are identified as those with a duration of less than/equal to one minute or greater than/equal to ten minutes. No-response conversations are identified as those with zero or missing market response. Positive (Negative) political exposure indicates the number of conferences with a positive (negative) average market reaction to the pandemic risk conversations. Hedge portfolios indicates the number of stocks in the hedge portfolios.

Appendix 6: Industrial Distribution of Pandemic Risk Hedge Portfolios.

| GICS | Industry | Number of firms Avg. | Min | Median | Max |
|---|---|---|---|---|---|
| 1010 | Energy | 12.6 | 6 | 13 | 18 |
| 1510 | Materials | 13.3 | 10 | 13 | 17 |
| 2010 | Capital Goods | 30.6 | 16 | 32 | 36 |
| 2020 | Commercial & Professional Services | 19.7 | 8 | 21 | 25 |
| 2030 | Transportation | 8.0 | 6 | 7 | 11 |
| 2510 | Automobiles & Components | 4.7 | 3 | 5 | 7 |
| 2520 | Consumer Durables & Apparel | 16.1 | 8 | 17 | 21 |
| 2530 | Consumer Services | 20.1 | 16 | 20 | 24 |
| 2550 | Retailing | 14.0 | 10 | 15 | 18 |
| 3010 | Food & Staples Retailing | 2.2 | 1 | 2 | 3 |
| 3020 | Food, Beverage & Tobacco | 9.3 | 7 | 9 | 11 |
| 3030 | Household & Personal Products | 3.0 | 1 | 3 | 4 |
| 3510 | Health Care Equipment & Services | 45.7 | 19 | 49 | 56 |
| 3520 | Pharmaceuticals, Biotechnology & Life Sciences | 61.7 | 31 | 67 | 73 |
| 4010 | Banks | 7.7 | 1 | 8 | 12 |
| 4020 | Diversified Financials | 21.4 | 9 | 23 | 32 |
| 4030 | Insurance | 6.7 | 2 | 7 | 9 |
| 4510 | Software & Services | 38.4 | 16 | 41 | 49 |
| 4520 | Technology Hardware & Equipment | 22.3 | 7 | 25 | 27 |
| 4530 | Semiconductors & Semiconductor Equipment | 12.6 | 5 | 14 | 19 |
| 5010 | Telecommunication Services | 3.4 | 2 | 3 | 5 |
| 5020 | Media & Entertainment | 15.0 | 12 | 15 | 18 |
| 5510 | Utilities | 4.4 | 1 | 4 | 7 |
| 6010 | Real Estate | 6.9 | 5 | 6 | 11 |

Note: This table shows the industrial distribution of stocks with pandemic risk hedge portfolios. The average, minimum, median, and maximum value of stocks for each industry are at quarterly level. The sample period is between 2020Q3 to 2022Q1.

Appendix 7: Decomposition of Pandemic Risk Hedge Portfolios

| Quarter | Incumbent | New entrant | Exit | Positive | Negative | Position change |
|---|---|---|---|---|---|---|
| 2020Q3 | 0 | 219 | 0 | 109 | 110 | 0 |
| 2020Q4 | 158 | 225 | 61 | 191 | 192 | 3 |
| 2021Q1 | 295 | 136 | 88 | 217 | 214 | 4 |
| 2021Q2 | 320 | 133 | 111 | 227 | 226 | 17 |
| 2021Q3 | 369 | 81 | 84 | 225 | 225 | 26 |
| 2021Q4 | 286 | 165 | 164 | 225 | 226 | 46 |
| 2022Q1 | 283 | 138 | 168 | 212 | 209 | 67 |

Note: This table displays a decomposition of pandemic risk hedge portfolios by quarter. Incumbent (New entrant) represents the number of stocks that were (were not) held in the last quarter. Exit represents number of stocks were held in the last quarter but are absent in this quarter. Positive (Negative) shows the number of stocks in portfolios with a positive (negative) average market reaction to pandemic risks. Position change indicates the number of stocks in given quarter that have previously altered their position within the portfolios. Past four quarters are used to construct quarterly portfolios except for 2017Q4. Three historical quarters are used to construct the portfolios in 2017Q4.

Appendix 8: Factor Exposures of Pandemic Risk Hedge Portfolios

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | P10% | P20% | P30% | P10% | P20% | P30% |
| Mkt-RF | -0.011 | -0.052 | -0.036 | 0.110 | -0.012 | -0.001 |
| | (0.18) | (0.09) | (0.05) | (0.13) | (0.08) | (0.04) |
| SMB | 0.397 | 0.012 | 0.030 | 0.108 | -0.058 | -0.035 |
| | (0.31) | (0.12) | (0.07) | (0.28) | (0.12) | (0.07) |
| HML | 0.098 | -0.053 | -0.069* | -0.068 | -0.088 | -0.108** |
| | (0.14) | (0.06) | (0.04) | (0.18) | (0.08) | (0.05) |
| RMW | | | | -0.433 | -0.120 | -0.103 |
| | | | | (0.26) | (0.12) | (0.06) |
| CMA | | | | 0.543 | 0.176 | 0.168** |
| | | | | (0.33) | (0.11) | (0.06) |
| Constant | 0.183 | 0.045 | -0.039 | 0.019 | -0.041 | -0.122 |
| | (0.73) | (0.31) | (0.20) | (0.63) | (0.32) | (0.17) |
| Observations | 21 | 21 | 21 | 21 | 21 | 21 |
| R-squared | 0.145 | 0.0305 | 0.113 | 0.324 | 0.141 | 0.348 |

Note: This table presents the regression results of monthly returns of the pandemic risk hedge portfolios on Fama-French factors. Columns (1) – (3) shows the results for the Fama-French three-factor model. Columns (4) – (6) shows the results for the Fama-French five-factor model. The sample period is between 2017Q4 and 2022Q1. Heteroskedasticity-robust standard errors in parentheses. Significance levels: *** p < 0.01; ** p < 0.05; * p < 0.1.

Appendix 9: Hedge Performance

Panel A: Political Risk performance

| Percentile | Correlation | EPU |
|---|---|---|
| 10% | Pearson | 0.208 |
| 10% | Spearman | 0.200 |
| 20% | Pearson | 0.219 |
| 20% | Spearman | 0.306 |
| 30% | Pearson | 0.168 |
| 30% | Spearman | 0.168 |

Panel B: Pandemic Risk performance

| Percentile | Correlation | Infection |
|---|---|---|
| 10% | Pearson | 0.305 |
| 10% | Spearman | 0.265 |
| 20% | Pearson | 0.300 |
| 20% | Spearman | 0.384 |
| 30% | Pearson | 0.257 |
| 30% | Spearman | 0.173 |

Note: This table displays the monthly correlations between the returns of political risk and pandemic risk hedge portfolios and AR(1) innovations of political or pandemic index series. The portfolios are constructed with sorting thresholds set at 10%, 20%, and 30% respectively. All target index series are coded so that higher numbers indicate negative news. Consequently, positive correlation coefficients indicate successful hedges. Panel A (B) shows the political (pandemic) risk hedge performance. For political risk news series (EPU), the sample period of hedge portfolio is from 2017Q4 to 2022Q1. For pandemic risk news series (Infection), the sample period of hedge portfolio is from 2020Q3 to 2022 Q1.