# Stock Returns Under Threat


## Abstract

This paper examines how the *Threat Index,* a measure of collective threats in the U.S., influences aggregate market and cross-sectional stock returns across more than 200 anomalies. We find that higher threat levels are associated with lower contemporaneous market returns and higher subsequent market returns, driven by increased risk aversion and investor inattention to threat-related information. Using long-short strategies, we find that the profitability of approximately 15% of the anomalies is affected, with 9% becoming more profitable following elevated threat periods, primarily due to the stronger influence of *Threat Index* on the long leg of these strategies. Our findings suggest that collective threats are a novel factor influencing market return dynamics and anomaly profitability.



**Keywords:** Threat, Anomalies, Risk Aversion, Investor Attention

**JEL classification:** G12; G14

# Stock Returns Under Threat

## 1. Introduction

The negative impact of macro threats on investment decisions and capital market dynamics cannot be overlooked. Ordinary individuals may react drastically to news suggesting a doomsday scenario such as nuclear holocaust or an alien invasion by getting into survival mode. Similarly, the government and Congress tend to enact swift responses to national security threats and make efforts to reassure the public about safety as part of long-term national development goals (Financial Times, 2024). These examples illustrate that threatening information significantly influences market behavior and corporate strategies, warranting in-depth research.

For the public, the corporate sector and the government, threatening information disseminated through advertisements, political rhetoric, social media and news channels can capture attention, activate the brain's fear circuitry, and emphasize the importance of safety and survival awareness in the social environment (Choi et al., 2022). Consequently, behavior driven by strong instincts for self-preservation, coupled with other behavioral biases manifest in financial trading for example, can disrupt capital markets.

Our study innovatively explores how trading biases induced by threatening information signals can result in mispricing in equity markets. Specifically, we utilize the *Threat Linguistic Dictionary* of Choi et al. (2022), which analyzes and quantifies over 9.2 million pages from more than 24,600 newspapers and other information sources. This results in a monthly *Threat Index* that represents the perceived threats by the American public and detects changes in the overall threat environment. Using the *Threat Index* as a focal point, we explored the specific impact of threatening information on the aggregate stock market. Additionally, we examine whether changes in the survival environment - perceived as becoming more hostile or more friendly by the public -

could lead to cognitive biases among investors, including both retail and institutional investors, thereby affecting trading behavior and exacerbating asset mispricing phenomena.

Our paper draws upon two well-documented theoretical constructs in behavioral finance. The first one is *representativeness* and *salience*, where the heightened salience of extreme outcomes causes investors to overestimate the probability of rare catastrophic events (Fischhoff et al., 1977; Snowberg and Wolfers, 2010; Hirshleifer et al., 2023; Huynh and Xia, 2023). The second is thinking vs intuition, where quick assessments provided by human intuitive system (System 1 in the language of Daniel Kahneman) may overshadow rational analysis (System 2). Different types of emotions trigger distinct transient emotional errors. Specifically, positive emotions could increase optimism and risk-taking behavior (Anderson and Galinsky, 2006; Kuhnen and Knutson, 2011), while individuals tend to be more pessimistic and risk-averse when fearful, and more optimistic and risk-seeking when angry (Lerner and Keltner, 2001). Also, previous empirical evidence from financial markets shows that aggregate risk aversion increases following significant economic, political, and health-related crises, much like the immediate reaction of individuals when watching horror movies (Kinreich et al., 2011). Therefore, such attention driven to threatened information is usually accompanied by an overall increase in risk aversion (Guiso et al., 2018; Shear et al., 2020; Chen et al., 2023).

Fundamentally, we hypothesize that threatening information drives the public to overestimate the probability of disasters in a state of panic, prompting them to excessively protect their assets by exiting the market, which depresses current stock prices, leading to a rebound and higher future returns in the following month. When threatening information stimulates public fear, attention in the stock market is drawn toward how to protect their survival conditions, leading to a neglect of rational asset judgment and increased risk aversion. Such fluctuations in stock returns are not driven by market liquidity.

To test this hypothesis, we utilize the Dow Jones Industrial Average, Nasdaq, and S&P 500 indices incorporating the *Threat Index* and building upon related research (Vozlyublennaia, 2014) to examine the predictive power of threatening information on market fluctuations. The results showed that a one-standard-deviation increase in the contemporaneous Threat Index leads to decreases in stock returns of 1.3%, 1.4%, and 1.9% for the S&P 500, Nasdaq, and Dow Jones Industrial Average indices, respectively. Conversely, a one-standard-deviation increase in the lagged Threat Index results in stock return increases of 1.3%, 1.4%, and 2.2% for the same indices. Additionally, by using the Chicago Board Options Exchange Volatility Index (VIX) and the variance risk premium (VRP) as proxies for risk aversion, we further verified that threatening information indeed affects public risk aversion levels, considering it as one of the mediating effects influencing market returns. We also found, through abnormal trading volume analysis, that there is a delayed response from investors to threatening information, which is primarily due to institutional investors' lack of attention.

In addition, we studied 204 significant and well-documented stock market anomalies to investigate whether threatening information plays a corrective or amplifying role in their returns. Different types of investors prioritize portfolio adjustments differently when processing threatening information, leading to varied impacts across anomalies. Unlike previous studies linking market sentiment with short-selling constraints (Stambaugh et al., 2012; Ramachandran and Tayal, 2021), we found that the threat environment significantly influences investor behavior. Among the 28 anomalies predicted by the Threat Index, 18 became more profitable following heightened threat conditions, particularly in long-portfolio performance, further demonstrating the profound impact of the threat environment on investor behavior and market outcomes.

Hence, through the analysis of predictive trends across different types of anomalies—momentum, value versus growth, investment, profitability, intangibles, and market frictions—we found that threatening information affects various investor behaviors and asset pricing in distinct ways. The strengthening of the long-leg portfolio in momentum suggests that investors exhibit underreaction. The negative changes in investment- and profitability-related anomalies, along with the positive predictability of intangibles and trading frictions anomalies, can be attributed to investors displaying a clear preference for risk aversion over speculation, leading to pricing distortions in these assets. These findings provide new insights into the effects of threatening information on financial markets and reveal behavioral differences among various types of investors when responding to market uncertainty.

Our empirical research expands and contributes to the existing literature on risk pricing from multiple perspectives. *First*, while this study is closely related to the literature exploring the impact of disaster risks on markets (e.g., Barro, 2006; Gourio, 2008), it differs in that we incorporate the Threat Index to explain cross-sectional returns, rather than focusing solely on specific tension episodes or crises. We emphasize that any form of threatening information in the information environment—such as wars, natural disasters, pathogens, cultural shifts, political changes, or macroeconomic uncertainty—can trigger public fear and anxiety. This fear affects investors' trading behavior through various channels and is ultimately reflected in asset price fluctuations. Therefore, our study is the first to systematically examine fear as a key factor in asset pricing models.

*Second*, compared to existing uncertainty proxies (such as Baker and Wurgler, 2006, investor sentiment index and Chen et al., 2023, Presidential Economic Approval Rating (PEAR) index), the Threat Index provides a new explanation for the profitability of long positions. Unlike the investor sentiment index, which focuses on short positions, the Threat Index more comprehensively reveals how investors pay different levels of attention to and exhibit varying trading preferences for different types of information during periods of heightened threat. Furthermore, our study distinguishes the psychological responses of individuals when faced with threat information and the behavioral channels of different investors in the stock market. Through these analyses, this paper offers unique empirical evidence, providing a crucial theoretical foundation and practical insights for the development of future asset pricing models.

The rest of the paper is structured as follows: Section 2 outlines the research motivations and hypotheses in detail; Section 3 describes the threat-related data; Section 4 presents robustness tests and key empirical results in the stock market. Section 5 explores the mechanisms of mispricing through two mediation channels. Section 6 demonstrates the Index's predictive power for some anomalies, further confirming that threats can induces mispricing among investors and markets.

# 2. Literature Review and Hypotheses Development

In this section, we explore the motivations driving our research on threatened information and emphasize our contributions relative to previous studies using irrational models for cross-sectional returns. We delve into why a threatening environment affects individual awareness and why a threat attracts our interest in stock market research, elucidate the process of formulating hypotheses, main hypothesis and underscore the significance of our study.

## 2.1 Review of Threats and Fear Effect on Return Predictability

In both humans and animals, the perception of potential threats forms the cornerstone of fear psychology, and limited attentional resources are selectively focused on threatening cues (Hou et al., 2014; Ota, 2018), which has long been harnessed as a persuasive strategy in the public sector, particularly in campaigns aiming to elicit public attention to align attitudes and behaviors with recommended actions (Witte, 1992; Lewis et al., 2007). Such as, road safety and disease prevention campaigns that depict scenarios of injuries, deaths from unsafe practices, and lack of virus protection awareness or illegal behaviors (Dejong and Atkin, 1995). Especially in the digital age, the public fatigue and anxiety are exacerbated due to information overload by the widespread use of social media, making individuals more prone to overreact threatening information and further amplifying public fear (Bright et al., 2015).

For many years, financial researchers have conveyed an underlying belief, supported by empirical evidence, that the beliefs of many stock market investors include a common, time-varying fear component. Regardless of whether this component is shaped by people's subjective perceptions or passively by social norms, it exerts market-wide effects on equity prices. However, the attributes of this component in explaining enduring asset pricing puzzles have yet to be explicitly defined. In the field of finance, fluctuations in fear emotions should be common. Empirical evidence consistently supports the idea that stock market investors' beliefs already incorporate the possibility of rare disaster risk and reflect this in the cross-section of stock returns. Early related research primarily focused on pricing the risk factor inspired by investors' excessive weighting of disaster event probabilities. Major disasters are highly salient, and people tend to overestimate their probabilities due to the psychology of attention. Cumulative prospect theory also implies that investors overweight low probabilities of rare events. Inspired by Rietz (1988), researchers sought to solve the equity risk premium puzzle by introducing low-probability economic disasters. Barro (2006) extended this approach by measuring the frequency and sizes of international economic disasters. Gourio (2008) analyzed returns during events like 9/11 and natural disasters, noting that industries performing well during such events should have low return premia, while those performing poorly should have high return premia, providing nuanced insights into asset pricing dynamics. Gabaix (2012) and Wachter (2013) incorporated time variation in the probability of rare disasters and their severity, arguing that an asset's fundamental value fluctuates during a disaster, leading to time-varying risk premia, volatile asset prices, and return predictability. Investors tend to overvalue assets performing well during disasters, viewing them as good hedges, which subsequently earn low returns.

Besides disaster perceptions, prior literature has also focused on measuring various, including geopolitical, economic and political uncertainty, and its link to financial market performance. Fear of geopolitical instability, arising from wars, terrorist acts, and conflicts, could have worse economic consequences. Rigobon and Sack (2005) and Choi (2022) indicated that increases in war risk caused declines in Treasury yields, equity prices, and stock market volatility. Baker et al. (2016) constructed policy-related economic uncertainty indexes (EPU) based on newspaper coverage frequency, including short-term and long-term public concerns. Their goal is to capture uncertainty about who will make economic policy decisions, what economic policy actions will be undertaken and when, and the uncertainty of policy actions (or inaction) that could have economic impacts of stock and macroenomics, including those related to "non-economic" policy matters such as military actions. Caldara and Iacoviello (2022) found that a shock to geopolitical risk induces persistent declines in investment, employment, and stock prices. Salisu et al. (2022) showed that geopolitical threats have a more considerable adverse effect on stock returns than actual occurrences of adverse events. Hirshleifer et al. (2023) proposed that war-related factors could generate a return premium, arguing that investors tend to overvalue assets increasing in value with disaster probability, leading to lower expected returns for disaster-sensitive stocks. Also, they attempted to capture and regard threat shocks as a proxy for investor sentiment. For instance, Da et al. (2015) constructed the Financial and Economic Attitudes Revealed by Search (FEARS) index by aggregating queries related to economic downturns and unemployment as household potential concerns about future economic conditions.

Summarizing, actual or potential events with threatening attributes can evoke individuals fear attention toward disasters. Therefore, the perception of threat can be integrated into standard macroeconomic models, either by overweighting disaster perception or combining investors' pessimistic sentiments about future returns and uncertainty fears. Our study contributes to several strands of literature by aggregating changes in investors' fear perception to threatened shocks without explicitly identifying the specific source in both predicting aggregate and cross-sectional stock market, providing predictive power for anomalies in asset prices and stock returns.

## 2.2 Empirical Implications, Hypotheses, and Contributions

In this study, we consider that the fluctuation in overall market returns and partial long-term anomalies significantly present in the stock market partially reflect mispricing related to market-wide investor threatened situation. Therefore, we combine the variation in the overall market threat level with investors' attention under fear and their tendency to avoid risk, which are individual-level cognitive biases that are evidently driven by fear, to propose four hypotheses that guide us in empirically exploring whether mispricing could at least partially explain the set of anomalies we are considering.

> H1: Market returns decrease during periods of rising threat, controlling for past returns, macroeconomic variables, and other uncertainty indexes. Then, the Threat Index can predict high returns (reversal) over the next month.
>
> H2: The Threat Index's effective mechanism for the overall stock market is driving up overall risk aversion among the public.
>
> H3: The Threat Index distracts attention away from the stock market by drawing public attention to threatening events and discourse, then they will pay their attention back when the public is aware, hence returns come back.
>
> H4: The Threat Index should significantly predict cross-sectional stock return profitability, which measured by long-short anomaly strategies.

Our research differs from previous studies by explaining asset price mis-valuation induced by public fear, contributing to both theoretical and empirical research. We test a large set of aggregate return and cross-sectional anomalies in the stock market, covering a broader range of characteristics compared to most anomaly explanations. Theoretically, our research complements existing frameworks related to rare disaster assets, avoiding focusing on specific threatening events. Instead, it emphasizes the overall overreaction to the stock market and broader changes in the human survival environment. Any seemingly unrelated threatening events can create a contagious fear among people. For example, threats not proven to have economic consequences can spread fear to a desire for protection and fear of asset devaluation, thus influencing asset price mispricing.

Our study also differs from traditional approaches that measure investor concerns about uncertainty as a manifestation of sentiment. When the Threat Index reflects fear, it cannot measure speculative intentions. Therefore, unlike the conclusion that high investor sentiment increases short position profitability due to constraints (Stambaugh et al., 2012), the Threat Index captures the tendency of investors risk aversion and underreact to threat information.

# 3. Data and Sample Selection

This section details the construction and acquisition of the critical variables utilized in this study. These include the Threat Index, market-level returns, investor attention, risk aversion proxies, the criteria for selecting anomalies, and the distinctions between the Threat Index and other extensively researched indices of uncertainty and sentiment.

## 3.1 The Threat Index

To measure the public perception of threats, we utilize the Threat Index, which encompasses information from various sources, to understand collective changes related to mass-communicated threats. Choi et al. (2022) developed a 240-word Threat Dictionary using natural language processing (NLP) tools to identify threatening vocabulary from texts with high temporal resolution across media platforms and different levels of analysis. The public resource link for the dictionary is available here: https://bit.ly/3zp2cYi. The 240 words could categorized into eight threat themes for interpretation, that the themes generally including Natural Disasters, Conflict, Crime, and Violence; Health, Safety, and Terrorism; Economic and Social Issues; Psychological Stress, Ethical and Moral Issues; Uncertainty and Unpredictability; and

Others. **Table 1** lists some example words, and the complete list of words is provided in **Appendix A**.

| **Threat Category** | **Sample words** |
|---|---|
| **Natural Disasters** | accidents, calamity, catastrophe, catastrophes |
| **Conflict , Crime and Violence** | accusations, arrests, attack, bloodshed, bombings |
| **Health , Safety and Terrorism** | illness, injuries, lethal, scary, toxic, unsafe |
| **Economic and Social Issues** | debt, demise, destroy, destruction, destructive, dispute |
| **Psychological stressed** | anguish, anxieties, anxiety, despair, doubts, dreadful, fear |
| **Ethical and Moral Issues** | inhumane, insults, irony, irresponsible, senseless, unethical |
| **Uncertainty and Unpredictabilit** | chaos, circumstances, crashes, discord, disruption |
| **Other** | amid, aftermath, approaching, blamed, caused, causing |

**Table 1 Sample words by Themes in Threat Dictionary**

Then, Choi et al. (2022) applied the threat dictionary to https://www.Newspapers.com, the largest online repository of historical and contemporary newspapers in the United States, to analyze time-stamped news articles over the past 100 years. The complete time series can be seen in **Fig. B1** in **Appendix B**, while this study focuses on the threat variations starting from when the overall stock market came into effect in January 1967. This publicly available data source contains over 920 million pages of digitized news content, and the Threat Index was constructed by calculating the frequency of threat dictionary terms in news articles on both monthly and annual basis, state and national levels and adjusted these totals based on the approximate number of article pages published within the corresponding periods. Consequently, the Threat Index serves as our primary time series dataset, tracking the fluctuations in threat levels that coincide with changes in U.S. cultural norms, political attitudes, pathogen outbreaks, and macroeconomic activity over the past 100 years.

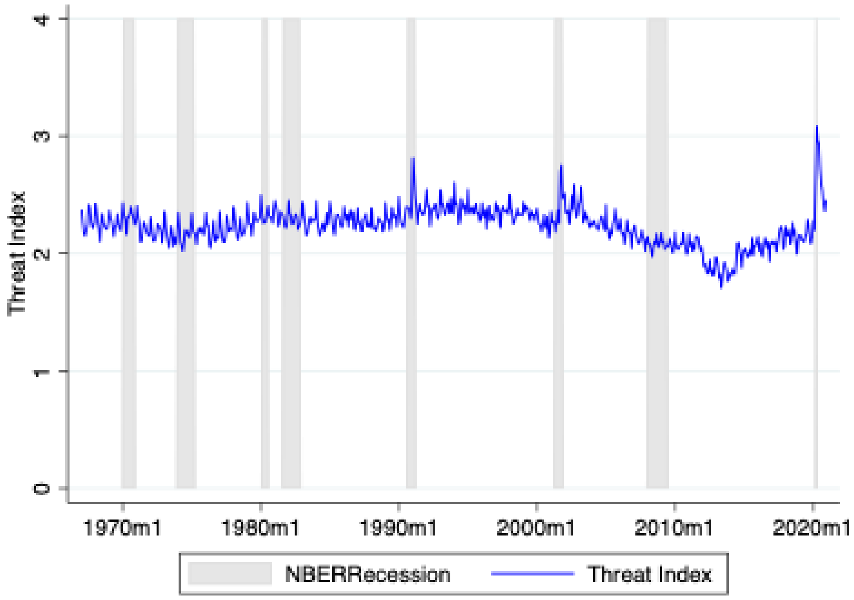


**Fig. 1. Time-Varying Threat Index**

This figure depicts the Threat Index (y-axis) from January 1967 to December 2020, based on the relative use of threat words found in US newspapers and adjusted by an approximate number of article pages published within the corresponding periods.

**Fig. 1** plots the time-series dynamics of the Threat Index with shaded NBER recessions, with values fluctuating between 2.6207 (2020:M1) and 1.710 (2013:M5) and exhibiting a pronounced stable trend, ranging from January 1967 to December 2020. As NBER-dated recessions indicate, the Threat Index often peaks around nearby periods during bad times. Overall, the Threat Index values peaked in January 1991, reaching 2.812, which aligns with the combat phase of the Gulf War, known as Operation Desert Storm, which occurred from January 17, 1991, to February 28, 1991. Subsequently, the Threat Index peaked in September and October 2001, with values of 2.726 and 2.753, respectively. It is well-known that the 9/11 terrorist attacks occurred during this period. Another peak occurred when the Nasdaq Composite Index reached its lowest point, marking one of the troughs in the U.S. stock market following the dot-com bubble burst on October 9, 2001. The Nasdaq Composite Index touched 1,546.42 points, signaling a low point in the aftermath of the dot-com bubble in the United States. The periods with the lowest values of the Threat Index occurred from May (1.710) to November (1.765) of 2013. During this time, the U.S. stock market was stable, with major indices showing an upward trend, and the unemployment rate decreased from 7.6% to 6.7% as the job market gradually improved. Meanwhile, the Consumer Price Index (CPI) only increased by 1.5%, indicating that inflation remained low. Therefore, public perception of threats was at its lowest during economic prosperity, consistent with the strongest public optimism.

To closely observe the characteristics of changes in the Threat Index before and after significant threat events, we further extracted four prominent peaks in threat levels from **Fig. 1**, each representing major threatening events, including an high disapproval rate presidential election, financial crises, terrorist attacks, and pandemic events. As shown in **Fig. 2**, the spread of threatening information tends to increase gradually before major conflicts in the U.S., peaking during the month of the event and then declining afterward. That suggests that the asset mispricing captured by the Threat Index is not merely an exploration of public concerns about asset values, but rather a reflection of the contagion effects on financial markets through other threat channels such as political shifts, wars, and pandemics.

To further illustrate, the Threat Index indeed captures threatening information in society. In **Appendix B**, **Fig. B2**, we compare the standardized Threat Index with the Economic Policy Uncertainty Index (Baker et al., 2016) and find that the Threat Index and EPU exhibit similar trends. However, the fluctuations in the Threat Index are more pronounced, reflecting and responding to threatening information more distinctly.

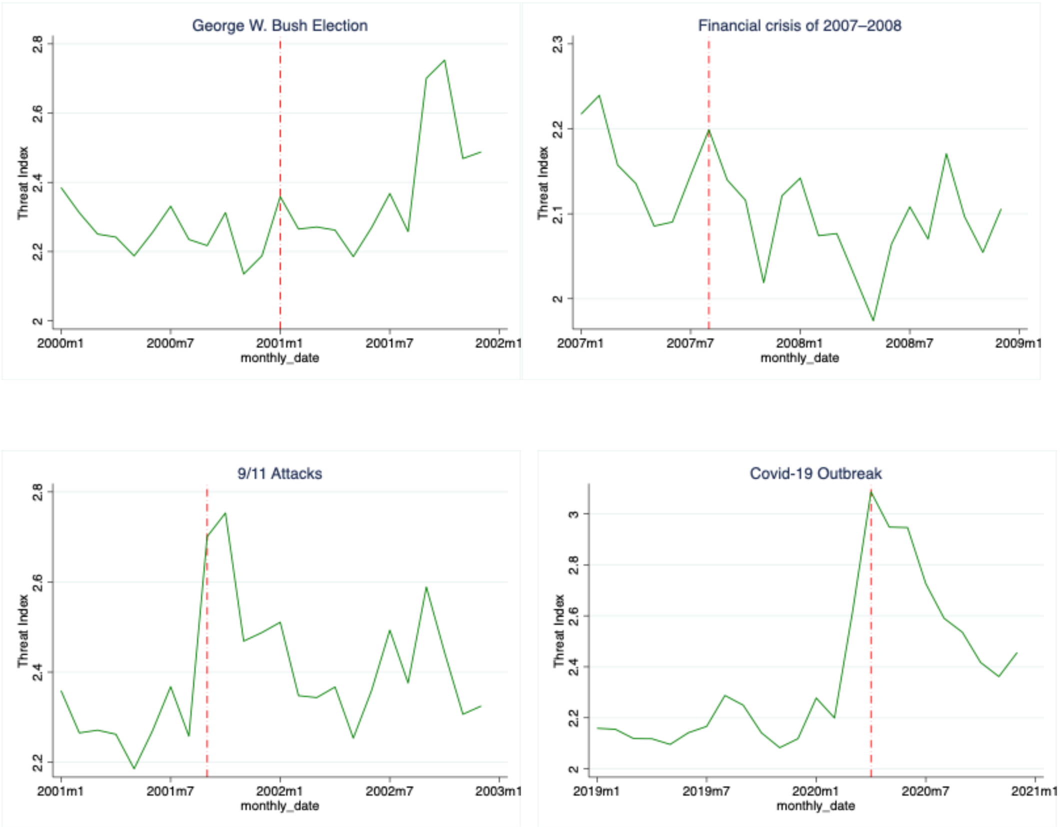


**Fig. 2. Threat Dynamics in Major US Conflicts**

The above four figures depict the trend of changes in the Threat Index before and after major threatening events.

## 3.2 Overall and Cross-Sectional Stock Market Data

We have selected three indices at monthly level from Center for Research in Security Prices (CRSP) database as representatives of the US stock market: the Dow Jones Industrial Average (DJIA) Index as a representative of large companies, the Nasdaq Index for small companies (Nasdaq), and the Standard & Poor's 500 Index (S&P500) for medium-sized companies (Vozlyublennaia, 2014). In this study, except for the Nasdaq Index, which starts in January 1986, the starting dates of the other two indices are set to January 1967 to match the period of our main independent and control variables. To align with the data of the Threat Index, the final date of our study's data collection is December 2020.

In cross-sectional tests, we employed a total of 204 long-short investment portfolios within the framework of the Hou, Xue, and Zhang (2015) q-factor and expected growth model. Specifically, 195 long-short portfolios are derived from Hou, Xue, and Zhang (2020) (hereafter referred to as HXZ), as portfolios are significant presence since January 1967 or, although not significant in empirical asset pricing literature, their notable contribution to research. The sample of HXZ includes all NYSE, Amex, and Nasdaq common stocks (share codes 10 and 11), excluding financial firms (SIC between 6000 and 6999) and firms with negative book equity, and stock returns are adjusted for delisting. Due to data limitations, most of the sample period is from January 1967 and some start after that. They sort stocks with NYSE breakpoints for portfolio construction and provide value-weighted returns. Hence, we directly obtain the returns by decile sorted for each anomaly from the HXZ[1] available public data source of presented in percent format, and we treat each anomaly as its highest minus lowest decile strategy. **Appendix G** provides anomalies definitions and construction procedures under six categories: momentum (42), value-growth (32), investment (32), profitability (48), intangibles (31), and frictions (10). Additionally, we included 9 well-known anomalies from Stambaugh and Yuan (2017)[2], spanning from January 1967 to December 2016, which have accruals, asset growth, composite equity issues, distress, gross profitability premium, investment to assets, momentum, O-score, and net stock issues. Stambaugh and Yuan (2017) employed a calculation similar to HXZ's but without delisting adjustments for each anomaly. However, we only utilized data from 9 anomalies from Stambaugh and Yuan (2017), which are not covered in HXZ’s sample, to avoid duplication. At the same time, the selection of our anomalies' portfolio returns also covers various holding period frequencies, including monthly, semi-annual, and annual. We then employ a regression approach that allows for control of co-movement in market factors, size factors, investment factors, profitability factors, and expected growth.

[1] HXZ anomalies data is available here: http://global-q.org/testingportfolios.html

[2] 11 well-known anomalies data is available here: https://finance.wharton.upenn.edu/~stambaug/

## 3.3 Investor Attention and Risk Aversion Proxies

We follow the methodology of Barber and Odean (2008) and Jiang et al. (2002) by employing abnormal trading volume ($A^{Vol}$) as a proxy for investor attention in the stock market. Specifically, we compute the ratio of trading volume at the end of each month to the average trading volume over the previous year for each stock listed on the NYSE, AMEX, and NASDAQ. Subsequently, we calculate the equal-weighted abnormal trading volume across all stocks to derive a market-level measure of investor attention. The cross-sectional equity trading volumes used in this analysis are sourced from the CRSP database, covering January 1967 to December 2020.

In measuring public aggregate risk aversion, we utilize the variance risk premium (VRP) obtained from Zhou (2018)[3], spanning the period from January 1990 to December 2020. The VRP is the difference between the risk-neutral expected variance and the actual realized variance. This differential typically reflects the premium that investors are willing to pay to mitigate uncertainty, thereby providing a direct measure of risk aversion in the market. In contrast, although the Chicago Board Options Exchange (CBOE) VIX is frequently used to gauge market panic or uncertainty, it essentially captures expectations of future volatility and, unlike the VRP, does not accurately reflect the additional premium demanded by investors due to risk aversion. Consequently, the VRP offers a more comprehensive and superior measure of risk aversion by comparing expected market volatility with realized volatility. Nonetheless, given its widespread adoption in prior studies, we include the VIX as an additional risk aversion proxy in our robustness tests. **Table 2** provides summary statistics for our main research variables: the Threat Index, market index returns, investor attention, and risk aversion measurements.

[3] Variance risk premium index is available at: https://sites.google.com/site/haozhouspersonalhomepage/

# 4. Empirical Analysis

In this section, we first differentiate the Threat Index from other uncertainty and sentiment indices. Next, we examine the impact of rising threat risk on the overall U.S. stock market. Specifically, we investigate whether the threat influences the stock market through two primary channels: by dispersing investor attention and by increasing public risk aversion. Finally, we perform portfolio analyses to evaluate the role of the Threat Index across a broad set of anomalies in cross-sectional stock returns and to determine whether the aforementioned channels are indeed the mechanisms through which threat amplifies mispricing. In other words, we aim to identify which types of mispricing phenomena are most susceptible to amplification by threat-induced emotions. We perform a number of tests to show that our results are robust.

## 4.1 Pairwise Correlation Between Key Uncertainty Indices

In this section, we will list other well-known and extensively researched sentiment indices and risk factors documented in the literature, which have been shown to exhibit more substantial predictive power in overall and cross-sectional asset pricing than macroeconomic variables. **Appendix C** provides a detailed definitions of 12 stock price uncertainty predictors, including the Baker and Wurgler Sentiment Index ($S^{BW}$), CBOE Volatility Index (VIX), Variance Risk Premium (VRP), PLS Sentiment Index ($S^{PLS}$), Michigan Consumer Sentiment Index ($S^{MC}$), Aruoba-Diebold-Scotti Business Conditions Index (ADS), Geopolitical Risk Index (GPR), Financial and Economic Attitudes Revealed by Search Index (FEARS), Economic Policy Uncertainty (EPU), Presidential Economic Approval Rating Index (PEAR), War Discourse Index (WAR), News Implied Volatility (NVIX).

**Panel A** of **Table 3** presents the mean, median, minimum, maximum, volatility, and time period for each predictor, while **Panel B** reports their level and change correlations.

Since FEARS is only available on a daily basis, we used its average as the monthly value. The correlation between the Threat Index and most of the predictive indices ranges only between 0.1 and 0.2, suggesting that the Threat Index captures different aspects of investor behavior compared to the other indices, particularly in relation to political and economic risks as well as stock market volatility. Notably, the Threat Index shows the highest positive correlations with the Geopolitical Risk (GPR) Index, with correlations of 0.375, at 1% significance level. This indicates that the Threat Index effectively captures information particularly in the context of territorial control and competition.

Further analysis shows that the Threat Index (TI) is also significantly positively correlated with the News Implied Volatility (NVIX) and the Presidential Economic Approval Rating (PEAR) indices, although the correlations are relatively low, at 0.271 and 0.237, respectively. Among these indices, NVIX is primarily driven by changes in warfare, followed by shifts in government policy (Manela and Moreira, 2017), which is similar to the pattern observed with PEAR. This further supports the notion that the Threat Index effectively captures concerns related to geopolitical risk, national security, and international relations. Additionally, the relatively high correlation between changes in the Threat Index and the Financial and Economic Attitudes Revealed by Search (FEARS) index, at 0.322 with 1% significance level, suggests that the Threat Index also captures some public sentiment related to economic recessions. However, since FEARS data only covers the period from July 2004 to December 2011, this conclusion should be interpreted with caution.

Overall, while the Threat Index does reflect public concerns about economic conditions to some extent, it is more effective in capturing threats related to warfare and politics, particularly those affecting national security and diplomatic relations. However, the Threat Index cannot completely replace other uncertainty predictors. It conveys different information in the stock market compared to other indices, and its impact on asset prices is not only driven by concerns about future economic trends but also by the broader transmission of threats intertwined with economic issues. This perspective will be further validated in the subsequent section.

## 4.2 Forecasting Aggregate Stock Market Returns

In this section, we examine the forecasting power of the Threat Index for stock market returns. Following the methodology of previous studies that assess the predictive ability of uncertainty indices (Edmans et al., 2022; Da et al., 2015), we employ the following regression model:

$$RET_{i,t} = \alpha + \beta \cdot ThreatIndex_{t-1} + \Sigma\,\gamma \cdot Controls_{i,t-1} + \mathcal{E}i,t \tag{1}$$

where $RET_{i,t}$ is the monthly return of the S&P 500 Index (SP500), Nasdaq Composite Index (NASDAQ), and Dow Jones Averages Index (DIJA) respectively; and $Controls_{i,t}$ are control variables, including a one-month-lagged market return to address autocorrelation, a set of economic variables commonly used by the forecasting literature to address forecasting information comes from business-cycle-related fundamentals, and a representative investor sentiment index, namely the Baker and Wurgler Sentiment Index ($S^{BW}$) to distinguish that the Threat Index does not serve as a proxy for investor sentiment. The economic variables from Goyal and Welch (2008), who suggest 14 economic variables, and the data are available from Amit Goyal's website (http://www.hec.unil.ch/agoyal/). The **Appendix D** shows a description of these 14 variables. Using all variables together in one regression may result in the multicollinearity problem. Thus, in our model specification, we use 6 of them: CAY, EP, TBL, LTR, DY, and TMS.

From **Table 4**, it is evident that the Threat Index exhibits a significant positive predictive ability for the overall stock market. Specifically, after controlling for macroeconomic predictors and the effects of investor sentiment, a one-standard-deviation increase in the lagged Threat Index leads to increases in stock returns of 1.32%, 1.37%, and 2.25% for the S&P 500 Index, Nasdaq Index, and Dow Jones Industrial Average Index, respectively. In addition, the regression adjusted $R^2$ provides another metric to evaluate the economic significance of the Threat Index's forecasting ability. At the monthly horizon, the adjusted $R^2$ equals 2.91%, 2.50%, and 3.80%, respectively, which is economically significant.

We find our results robust under contemporaneous regression validation, which can explain that when the Threat Index increases during the same period, stock market returns decrease under fear. In the robustness test shown in **Table A1** of **Appendix E**, we find that a one-standard-deviation increase in the contemporaneous Threat Index results in contemporaneous stock return decreases of 1.32%, 1.37%, and 1.93% for the S&P 500 Index, Nasdaq Index, and Dow Jones Industrial Average Index, respectively. This finding aligns with our initial hypothesis that when the threat level in the public's living environment intensifies, investors tend to exit the stock market due to direct concerns about asset devaluation or the spread of fear into financial transactions, leading to a significant average decline in stock market returns of 1.54%. Subsequently, the Threat Index effectively predicts future return reversals, with an average increase of 3.27%, indicating that in the subsequent period after the transmission of threat information, the public's excessive reaction to the threat gradually diminishes, or the peak intensity of the threat has passed. Furthermore, when regressing the Threat Index alongside SBW, EPU, and GPR, the residuals still exhibit a significant positive predictive power for stock market returns, further confirming that the Threat Index provides distinct threat-related information compared to past economic, political, and war risk predictive indices in the stock market. Threatening information includes news, rumors, predictions, or market speculation about potential threats. Such information may not be based on facts, or even if it is factual, its severity and impact may be exaggerated, which is typically disseminated through media and social networks, and can easily trigger more emotional fluctuations in the market. Real-life events typically lead to a direct market response, with the scale and direction of the reaction depending on the severity of the event and the extent of its impact. Market reactions tend to be more rational, as investors are able to assess the impact of the event based on actual facts. Hence, given the uncertainty surrounding the accuracy and severity of the information, market participants may react based on their emotions, cognitive biases, and past experiences. That also indicates that it has a complementary effect on stock market returns, offering additional information that enhances the understanding and prediction of market trends, as shown in **Table A2** of **Appendix E**.

## 4.3 The Role of Risk Aversion and Investor Attention

This section provides details on whether risk aversion and investor attention are widely recognized variables that may drive stock market returns when elevated and if they serve as mediators in the effect of the Threat Index. Following Azevedo et al. (2024), we will illustrate the proposed mediation relationship through the diagram below by performing the mediation analysis (or pathway analysis).

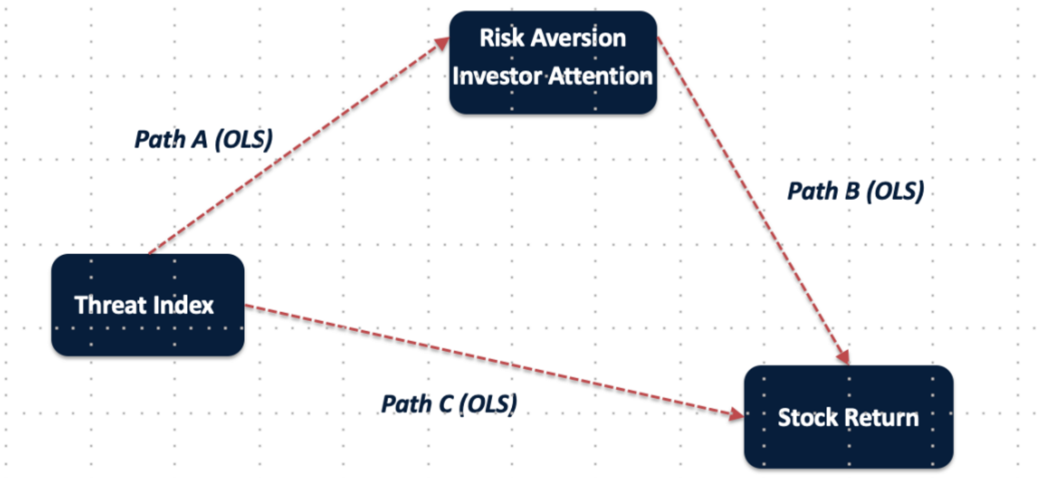


**Fig. 3. Mediation Effect of Risk Aversion or Investor Attention**

This figure illustrates how the mediation relationship works by risk aversion and investor attention separately. The first step relates to Path A using an Ordinary Least Square model (OLS). It shows how stock returns related to risk aversion and investor attention respectively is affected by the Threat Index.

The second step relates to Path B using another Ordinary Least Square model (OLS). In this step, we show how the stock returns is driven by risk aversion and investor attention respectively.

Path A indicates the association between the causal variable (Threat Index) and the mediating variable (risk aversion or investor attention), which in our case is established through an OLS regression. Path B shows the link between the mediating variable and the outcome variable (stock market return of S&P 500, Nasdaq Index, and Dow Jones Industrial Average Index), which is established through OLS that includes both the causal and the mediating variables. When the mediation effect to exist, three conditions have to be met. First, the causal variable should significantly relate to the outcome variable that is indicated as Path C in the figure. In **Table 4** in the main paper, we have already established that our causal variables (Threat Index) predict significantly the stock return increase outcome. Second, in Path A, the causal variable has to be significantly related to the mediating variables (risk aversion or investor attention). Finally, in Path B the outcome variable is regressed on both the causal variable and the mediator. For a mediation to take place between the Threat Index and stock return, the coefficient of the mediator should be statistically significant. We also compute the Sobel (1982) test to examine whether the mediation effect of the economic performance variables is statistically significant. Specifically, the Sobel test is computed in **Appendix F**.

Combining the results from **Panel A** and **Panel B** in **Table 5**, we find that the outbreak of threatening events significantly increases investors' risk aversion, affecting stock market returns by raising the current and subsequent levels of risk aversion. This finding is consistent with the conclusions of Smales (2016), who also discovered a significant negative correlation between VIX changes and stock returns. Specifically, the coefficient of the independent variable in Path A is significantly larger than in Path B, indicating that public risk aversion is an essential channel through which threatening events impact market returns. Moreover, we observe that the risk aversion coefficient for the current period is positive, while the coefficient for the next period is negative. That aligns with intuition: when the threat environment intensifies, investors tend to adopt more defensive strategies, such as selling high-risk assets and shifting to safe-haven assets, thereby amplifying short-term market volatility. However, as the threat subsides, investors' excessive caution suppresses the recovery of stock market returns.

Further analysis of **Panel C** and **Panel D** in **Table 5** reveals that an increase in threatening information significantly enhances investors' attention to the stock market in both the current and subsequent periods, particularly in the latter, where it has an amplifying effect on stock market return rebounds. According to Bajo (2010), investor attention is typically measured by abnormal trading volume, which is widely considered to be related to the inflow of new or private information. However, this attention only plays an amplifying role in stock market return rebounds during the period following the outbreak of threatening information. Typically, when most investors perceive the information as positive, stock prices may rise, leading to a positive correlation between abnormal trading volume and concurrent stock returns.

Thus, based on the results from **Panel C** and **Panel D**, we can conclude that although investors become aware of the threatening information as it arrives, they do not rush to incorporate it into stock prices—possibly due to a conservative strategy or a delayed reaction, which can be considered an "underreaction." Subsequently, investor attention amplifies the impact of the threatening information on stock returns, possibly because attention helps investors correct their overly risk-averse behavior or because they recognize the market opportunities brought by the threatening information. As a result, they may actively participate in the market, which, under the combined effect of the spreading threatening information and heightened attention, pushes stock market returns higher.

Combining the above results, we can delve deeper into investors' behavioral patterns during and after the outbreak of threatening events. Investors' behavior in these periods can be better understood. When a threatening event occurs, market uncertainty increases, and investors typically adopt more defensive strategies, often engaging in frequent trading to swiftly adjust their portfolios. This behavior reflects the defensive and sometimes irrational characteristics of investors when faced with uncertainty. Despite becoming more risk-averse, investors tend to underreact when incorporating fear-driven emotions caused by the threat into prices. Speculators are more inclined to view the market's return to stability, as the threat gradually dissipates, as a new investment opportunity.

This hypothesis aligns with Barber and Odean's (2008) view, which suggests that institutional investors, equipped with more resources and tools to monitor and analyze a wider range of stocks, are less influenced by attention-grabbing events in their trading decisions. However, this does not contradict the conclusion that the rise in contemporaneous attention has no significant effect on returns. The equilibrium market price reflects the weighted average of beliefs formed by different investors based on their attention signals, with these weights determined by the relative size and risk tolerance of each investor group.

When retail investors dominate the response to threatening events, their limited attention tends to focus on the most immediate and salient threats. Relying on a few key signals to make investment decisions, they attempt to quickly respond to potential risks. However, for the overall market, the attention of retail investors may not be sufficient in the short term to drive a full market reaction to these threatening events.

## 4.4 Threatening Effect on Cross-sectional Return Prediction

This section will examine the impact of the threatening effect on cross-sectional stock returns, using the Threat Index to forecast 204 value-weighted portfolios. For each anomaly, we analyze a strategy that goes long on the top-performing decile stocks and short on the bottom-performing decile stocks. We employ a regression approach based on the following formula to conduct formal significance tests. Additionally, we distinguish novel predictability effects from well-known co-movement using multivariate regression.

$$R_{X\,i,t} = \alpha + b \cdot (ThreatIndex_{t-1}) + \ c \cdot MKT_t \ + \ d \cdot r_t^{ME} \ + \ e \cdot r_t^{I/A} + m \cdot r_t^{ROE} + h \cdot r_t^{EG} + \varepsilon_{i,t} \qquad \textbf{(5)}$$

where $R_{X\,i,t}$ is the strategy's excess return in month t. $MKT$ is the market excess return; $r^{ME}$ is the difference between the return on a portfolio of small size stocks and the return on a portfolio of big size stocks; $r^{I/A}$ is the difference between the return on a portfolio of low investment stocks and the return on a portfolio of high investment stocks; $r^{ROE}$ is the difference between the return on a portfolio of high profitability stocks and the return on a portfolio of low profitability stocks; $r^{EG}$ is the difference between high expected investment growth should earn higher expected returns than firms with low expected investment growth.

**Table 6** reports the 28 anomalies, out of 204 anomalies returned, that can be significantly predicted by the Threat Index, accounting for approximately one-seventh of the total anomalies. These anomalies explore threat-related mispricing as at least a partial explanation for anomalies that persist after adjusting for exposure to q-factors and expected growth factors. This finding partially supports our Hypothesis 4. However, the direction of the prediction in 28 anomalies is not uniformly consistent, which may reflect different types of investors or varying reactions to information and risk sensitivity, and how these investors dominate in responding to different types of information, which warrants further discussion.

In detail, among the 28 anomalies, 18 exhibit a noticeable deterioration in the subsequent period following an increase in the Threat Index, meaning that when the Threat Index is high, subsequent long-short portfolio returns are elevated. This suggests that mispricing behavior intensifies after the release of high-threat information. Notably, this contrasts with the exaggerated role of investor sentiment and short-sale impediments in anomalies, as discussed by Stambaugh et al. (2012). In these 18 anomalies, the increase in long-short portfolio profitability is driven by significantly higher returns in the long-leg portfolios compared to the short-leg portfolios. Meanwhile, 10 anomalies exhibit a significant deceleration in their mispricing behavior due to the profitability of their short-leg returns. The implications of these results for investor trading behavior and risk preferences need to be analyzed further based on different anomaly categories. This outcome aligns with our previous hypothesis that investors are indeed influenced by threat information when the Threat Index rises. However, since different types of investors prioritize different trading signals, the response varies across anomalies.

Overall, as shown in **Table 6**, the anomalies we focus on can be categorized into six types: momentum, value-versus-growth, investment, profitability, intangibles, and frictions. Generally, the Threat Index demonstrates stronger predictive power, both in terms of quantity and ability, for anomalies related to profitability, with most predictions showing a negative direction, which contrasts with the predictions for other anomalies. This indicates that, after the intensification of threatening information, anomalies related to company profitability are more likely to weaken. Similarly, anomalies in the value-versus-growth category also exhibit negative predictive effects. In other words, under the influence of threatening information, the market's response to these profitability, value, and growth indicators is not particularly strong. In fact, these anomalies tend to correct themselves in the presence of threat information.

For anomalies related to profitability, including Ohlson’s O (distress) anomaly, the Threat Index has explanatory power for both long-leg and short-leg portfolios. We believe this highlights institutional investors' attention to profitability-related information. Typically, institutional investors, such as pension funds and mutual funds, have more resources and expertise to thoroughly analyze a company's financial condition, profitability, and long-term prospects. As style-driven investors, they tend to focus more on a company's fundamental factors (Froot and Teo, 2008). This suggests that institutional investors are more likely to react to threat information by paying closer attention to a company's profitability, opting to reduce their positions or exit risky assets in the stock market. Even though these companies may have stable cash flow and profitability, institutional investors, seeking to preserve capital in an uncertain market environment, may prefer to hold safer assets such as cash or bonds. This conclusion is consistent with our earlier hypothesis explaining the overall decline in stock market returns during the same period. This behavior further depresses the valuations of highly profitable companies. Similarly, due to short-selling constraints during periods of heightened threat, the valuations of companies with strong profitability or growth potential are inflated. This leads to different performance outcomes for profitable portfolios in the subsequent phase of threat dissemination, depending on whether capital preservation or short-selling constraints dominate. Hence, most negatively predicted returns suggest that short-selling constraints play a significant role when public attention to profitability-related information is triggered by threat information.

Similarly, the negative predicted returns of dividend yield investment strategies indicate that, during periods of heightened threat information, growth companies tend to be undervalued. This typically suggests that the market may harbor doubts about these companies' future growth potential or profitability. For investment-type anomalies, an increase in the Threat Index suggests a strengthening of these anomalies, meaning that high-risk companies with higher investment ratios tend to be undervalued during periods of heightened threat. Although past research has not directly compared institutional and retail investors' focus on investment information, high investment ratios often represent high-risk companies. Intuitively, the public tends to avoid risk when threats are heightened, leading to an undervaluation of such companies' stocks. Similarly, the trading frictions anomaly also exhibits this pattern.

As for information related to intangible assets, these assets, unlike tangible ones, are harder to quantify and evaluate. Their value largely depends on market expectations and investor confidence in the future. When the Threat Index rises, uncertainty about the future increases, causing investors to focus more on the potential risks associated with companies that hold intangible assets. These companies are more susceptible to market sentiment in high-threat environments, leading investors to reduce their exposure, resulting in an undervaluation and a subsequent reversal in returns.

In momentum-related anomalies, their intensification following heightened threat situations aligns with the implications we derive from investor attention, reflecting an underreaction by investors to threat information. Momentum strategies typically succeed due to low reaction, as they rely on the continued price movements of stocks. This further supports previous findings that investors tend to respond to new information more slowly than expected, leading to gradual rather than immediate price adjustments. Institutional investors, in particular, are more prone to underreact to bad news compared to retail investors (Nagel, 2005). This is consistent with our previous research on investor attention, suggesting that investors do not instantly recognize the threat posed by new information to the stock market and do not immediately incorporate it into price adjustments. Especially for institutional investors, limited attention is often associated with slow information diffusion and underreaction to news (Ben-Rephael et al., 2017).

In sum, the explanatory power and direction of the Threat Index's impact on different types of anomalies suggest that investors of different types—due to their varying focus on information, levels of risk aversion, and investment styles—exhibit different risk-avoidance behaviors and asset-holding patterns under the influence of threatening information, with no single defined behavioral model.

# 5. Conclusions

This paper provides novel insights into how threatening information, as captured by the Threat Index, affects both aggregate market returns and cross-sectional stock returns across various anomalies. Our analysis shows that higher levels of perceived threats are associated with lower contemporaneous market returns and higher subsequent market returns, supporting the hypothesis that investor behavior, particularly risk aversion and inattention, plays a key role in market mispricing during periods of heightened threats.

We identify that among the 204 anomalies studied, approximately one-seventh exhibit significant sensitivity to the Threat Index, with 18 anomalies becoming more profitable in the post-threat period, primarily driven by long-leg portfolio performance. This finding suggests that mispricing phenomena intensify following the release of threatening information, indicating that investors underreact to such information in the short term, which later leads to price corrections and increased returns.

Our results also highlight the differing reactions of various types of investors to threatening information. Institutional investors, equipped with more resources and analytical tools, tend to exhibit less emotional reaction to short-term threats compared to retail investors, whose limited attention and higher risk aversion drive more pronounced mispricing. The divergence in anomaly performance—particularly in profitability-related and momentum anomalies—further supports the notion that different investor groups respond to market threats in distinct ways, leading to varying asset pricing outcomes.

Overall, the Threat Index proves to be a valuable predictor of market dynamics and cross-sectional returns, offering a fresh perspective on the role of external threats in driving market inefficiencies. Our findings suggest that investor behavior under threat conditions is a critical factor in shaping asset mispricing, providing important implications for both market participants and policymakers seeking to understand the impact of uncertainty on financial markets. Future research can further explore why the prediction directions of different anomalies are inconsistent or why different investors react differently, and conduct in-depth analysis of the specific reasons or economic mechanisms behind these differences. Additionally, the underreaction mechanism in the market's response to threat information could be examined in conjunction with a broader body of literature to provide further explanation and enhance the depth of discussion.

# Tables

**Table 2 Summary Statistics of Main Variables**

This table reports summary statistics (full sample average) on our main variables. The sample period is mostly from January, 1967, to December 31, 2020. The Threat Index measures the monthly threat level by calculating the frequency of threat-related words in news articles, adjusted for the total number of article pages published during the corresponding periods. $RET^{SP500}$, $RET^{Nasdaq}$ and $RET^{DIJA}$ are monthly returns of the Dow Jones Industrial Average Index (DJIA), the Nasdaq Index (Nasdaq), and the Standard & Poor's 500 Index (SP500) separately. VRP and VIX represent variance risk premium and CBOE Volatility respectively. $A^{Vol}$ is abnormal trading volume and $A^{sPCA}$ is aggregate investor attention. SD is the standard deviation.

| Variable | Observations | Mean | SD | Sample Period |
|---|---|---|---|---|
| $Threat$ | 648 | 2.236 | 0.161 | 1967:01-2020:12 |
| $RET^{SP500}$ | 648 | 0.007 | 0.044 | 1967:01-2020:12 |
| $RET^{NASDAQ}$ | 420 | 0.011 | 0.062 | 1986:01-2020:12 |
| $RET^{DIJA}$ | 648 | 0.007 | 0.044 | 1967:01-2020:12 |
| $A^{VOL}$ | 648 | 1.072 | 0.179 | 1967:01-2020:12 |
| $VRP$ | 372 | 14.774 | 29.856 | 1990:01-2020:12 |
| $VIX$ | 372 | 19.518 | 7.695 | 1990:01-2020:12 |

**Table 3 The Comparison Between Threat Index and Oher Uncertainty Indices.**

Panel A in Table 3 presents summary statistics (full sample average) on the 10 predictive uncertainty indices, including observations, the mean, standard deviation (SD), and sample period for 10 predictive uncertainty indices besides VIX and VRP. Panel B displays the level correlations among 13 indices, while Panel C shows the change correlations among them. The *p-value* is presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: Descriptive Statistics of 10 Indices**

| Variable | Observations | Mean | SD | Sample Period |
|---|---|---|---|---|
| $S^{BW}$ | 648 | 0.265 | 2.216 | 1967:01-2020:12 |
| $S^{PLS}$ | 648 | 0.019 | 1.007 | 1967:01-2020:12 |
| $S^{MC}$ | 516 | 86.2 | 12.597 | 1978:01-2020:12 |
| ADS | 648 | -0.086 | 1.391 | 1967:01-2020:12 |
| GPR | 432 | 99.362 | 47.238 | 1985:01-2020:12 |
| FEARS | 90 | 0.002 | 0.037 | 2004:07-2011:12 |
| EPU | 432 | 112.902 | 39.475 | 1985:01-2020:12 |
| PEAR | 477 | 46.997 | 11.481 | 1981:04-2019:12 |
| WAR | 590 | 0.116 | 0.209 | 1967:01-2019:10 |
| NVIX | 590 | 23.257 | 5.157 | 1967:01-2016:03 |

**Panel B: Correlation Between 13 Indices Level**

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Threat | 1.000 | | | | | | | | | | | | |
| (2) $S^{BW}$ | -0.015 | 1.000 | | | | | | | | | | | |
| | (0.706) | | | | | | | | | | | | |
| (3) $S^{PLS}$ | 0.144*** | 0.119*** | 1.000 | | | | | | | | | | |
| | (0.000) | (0.002) | | | | | | | | | | | |
| (4) $S^{MC}$ | 0.110 | -0.022 | -0.119*** | 1.000 | | | | | | | | | |
| | (0.012) | (0.611) | (0.007) | | | | | | | | | | |
| (5) ADS | -0.079 | -0.019 | -0.037 | 0.218*** | 1.000 | | | | | | | | |
| | (0.045) | (0.628) | (0.345) | (0.000) | | | | | | | | | |
| (6) GPR | 0.279*** | -0.029 | -0.007 | -0.133*** | -0.072 | 1.000 | | | | | | | |
| | (0.000) | (0.550) | (0.880) | (0.006) | (0.133) | | | | | | | | |
| (7) FEARS | 0.137 | -0.003 | -0.081 | 0.098 | -0.099 | 0.042 | 1.000 | | | | | | |
| | (0.198) | (0.981) | (0.447) | (0.356) | (0.353) | (0.696) | | | | | | | |
| (8) EPU | 0.054 | 0.023 | 0.035 | -0.507*** | -0.199*** | 0.108 | 0.028 | 1.000 | | | | | |
| | (0.262) | (0.628) | (0.463) | (0.000) | (0.000) | (0.025) | (0.793) | | | | | | |
| (9) PEAR | 0.237*** | -0.041 | 0.254* | 0.625*** | 0.087 | -0.050 | -0.051 | -0.147*** | 1.000 | | | | |
| | (0.000) | (0.377) | (0.000) | (0.000) | (0.057) | (0.302) | (0.633) | (0.002) | | | | | |
| (10) WAR | 0.315*** | -0.015 | 0.007 | -0.057 | -0.052 | 0.446*** | -0.040 | 0.104 | -0.010 | 1.000 | | | |
| | (0.000) | (0.716) | (0.862) | (0.222) | (0.208) | (0.000) | (0.710) | (0.045) | (0.843) | | | | |
| (11) NVIX | -0.217*** | 0.108*** | -0.002 | -0.264*** | -0.311*** | 0.073 | -0.081 | 0.614*** | 0.051 | 0.038 | 1.000 | | |
| | (0.000) | (0.008) | (0.953) | (0.000) | (0.000) | (0.159) | (0.450) | (0.000) | (0.296) | (0.359) | | | |
| (12) VIX | 0.181*** | 0.124 | 0.282*** | -0.257*** | -0.291*** | 0.051 | -0.088 | 0.439*** | 0.220*** | 0.111 | 0.794*** | 1.000 | |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (0.000) | (0.017) | (0.000) | (0.000) | (0.000) | (0.326) | (0.410) | (0.000) | (0.000) | (0.049) | (0.000) | | |
| (13) VRP | 0.058 | 0.016 | 0.090 | 0.032 | 0.392*** | 0.091 | 0.184 | -0.129 | 0.220*** | 0.107 | 0.102 | 0.027 | 1.000 |
| | (0.268) | (0.758) | (0.083) | (0.537) | (0.000) | (0.080) | (0.082) | (0.013) | (0.000) | (0.058) | (0.070) | (0.610) | |

**** p<0.01, ** p<0.05, * p<0.1*

**Panel C: Correlation Between Changes**

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) ΔThreat | 1.000 | | | | | | | | | | | | |
| (2) $\Delta S^{BW}$ | -0.051 | 1.000 | | | | | | | | | | | |
| | (0.193) | | | | | | | | | | | | |
| (3) $\Delta S^{PLS}$ | -0.023 | 0.076 | 1.000 | | | | | | | | | | |
| | (0.559) | (0.055) | | | | | | | | | | | |
| (4) $\Delta S^{MC}$ | -0.084 | -0.056 | 0.001 | 1.000 | | | | | | | | | |
| | (0.056) | (0.206) | (0.982) | | | | | | | | | | |
| (5) ΔADS | -0.210*** | -0.019 | 0.009 | 0.126*** | 1.000 | | | | | | | | |
| | (0.000) | (0.633) | (0.813) | (0.004) | | | | | | | | | |
| (6) ΔGPR | 0.381*** | -0.003 | 0.027 | -0.146*** | -0.016 | 1.000 | | | | | | | |
| | (0.000) | (0.952) | (0.579) | (0.002) | (0.736) | | | | | | | | |
| (7) ΔFEARS | 0.322* | 0.040 | -0.044 | 0.236 | -0.303*** | 0.115 | 1.000 | | | | | | |
| | (0.002) | (0.712) | (0.681) | (0.026) | (0.004) | (0.284) | | | | | | | |
| (8) ΔEPU | 0.204*** | 0.055 | 0.049 | -0.210* | -0.033 | 0.218*** | 0.093 | 1.000 | | | | | |
| | (0.000) | (0.255) | (0.312) | (0.000) | (0.497) | (0.000) | (0.387) | | | | | | |
| (9) ΔPEAR | 0.057 | -0.071 | -0.026 | 0.146*** | -0.008 | 0.054 | -0.005 | 0.011 | 1.000 | | | | |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (0.217) | (0.124) | (0.576) | (0.001) | (0.868) | (0.264) | (0.964) | (0.820) | | | | | |
| (10) ΔWAR | 0.172*** | -0.012 | 0.003 | -0.045 | -0.009 | 0.399*** | 0.014 | 0.205* | 0.024 | 1.000 | | | |
| | (0.000) | (0.762) | (0.937) | (0.334) | (0.836) | (0.000) | (0.900) | (0.000) | (0.620) | | | | |
| (11) ΔNVIX | 0.103 | 0.130*** | 0.047 | -0.118 | 0.047 | 0.145*** | -0.125 | 0.325* | 0.028 | 0.107*** | 1.000 | | |
| | (0.013) | (0.002) | (0.253) | (0.012) | (0.252) | (0.005) | (0.242) | (0.000) | (0.564) | (0.010) | | | |
| (12) ΔVIX | 0.105 | 0.188*** | 0.122 | -0.074 | -0.042 | 0.103 | -0.105 | 0.218*** | 0.036 | -0.009 | 0.727*** | 1.000 | |
| | (0.044) | (0.000) | (0.019) | (0.158) | (0.415) | (0.047) | (0.329) | (0.000) | (0.491) | (0.876) | (0.000) | | |
| (13) ΔVRP | -0.022 | 0.097 | 0.006 | 0.046 | 0.157*** | 0.026 | 0.155 | -0.224*** | 0.050 | 0.000 | 0.046 | -0.064 | 1.000 |
| | (0.676) | (0.063) | (0.914) | (0.378) | (0.002) | (0.612) | (0.147) | (0.000) | (0.342) | (0.996) | (0.418) | (0.218) | |

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Table 4 Threat Index Predict Stock Market Returns Results.**

This table reports results from prediction regression estimates from Eq. (1). The dependent variable is the monthly stock market return (RET) in S&P 500 Index (SP500), Nasdaq Index (NASDAQ), and Dow Jones Industrial Average Index (DJIA) separately. The independent variable, is the lagged month in Threat Index. The control variables are the one-month-lagged dependent variable ($RET_{t-1}$), which is not reported with constants. And contemporaneous or lagged $DY$, $DFY$, $TBL$, $CAY$, and $S\hat{}BW$. Newey and West (1987) adjusted t-statistics are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively. We standardize all predictors to have 0 mean and unit variance. Each panel reports estimates of regression slopes and adjusted $R^2$ in percentage form. Intercepts are included in all the regressions but unreported for brevity. The sample period is 1967:01–2020:12 for S&P 500 Index (SP500) and Dow Jones Industrial Average Index (DJIA), and 1986:01–2020:12 for Nasdaq Index.

| | $RET_t^{SP500}$ | $RET_t^{DIJA}$ | $RET_t^{NASDAQ}$ |
|---|---|---|---|
| $Threat_{t-1}$ | 0.024*** | 0.025*** | .041*** |
| | (3.25) | (3.50) | (2.94) |
| $RET_{t-1}$ | -0.012 | -0.018 | 0.006 |
| | (-0.23) | (-0.41) | (0.09) |
| $CAY_{t-1}$ | 0.004* | 0.005** | 0.004 |
| | (1.94) | (2.42) | (0.87) |

| | | | |
|---|---|---|---|
| $EP_{t-1}$ | 0.005 | 0.004 | .004 |
| | (0.98) | (0.91) | (0.68) |
| $TBL_{t-1}$ | -0.005 | -0.004 | -.002 |
| | (-1.54) | (-1.30) | (-0.32) |
| $LTR_{t-1}$ | 0.003* | 0.003** | .002 |
| | (1.91) | (1.98) | (0.85) |
| $DY_{t-1}$ | 0.010* | 0.009* | .016 |
| | (1.78) | (1.73) | (1.71) |
| $TMS_{t-1}$ | -0.008 | -0.008* | -.019 |
| | (-1.62) | (1.71) | (-1.73) |
| $S_{t-1}^{BW}$ | -0.002 | -0.002 | -.007 |
| | (-1.41) | (-1.16) | (-2.33) |
| #(obs.) | 648 | 648 | 420 |
| Adj. $R^2$ | 2.91 | 2.50 | 3.80 |

**Table 5 Risk Aversion and Investor Attention: Separate Mediation Effects in Predicting Stock Returns.** This table presents the results of our mediation tests examining whether threat shocks, represented by the Threat Index, affect public risk aversion (natural logarithm of the Variance Risk Premium) and investor attention (natural logarithm of stock abnormal trading volume), which in turn, influence stock market returns. Panel A (B) reports the results from the mediation tests where risk aversion serves as one of the channels through which threat information impacts the stock market. Panel C (D) reports the results where investor attention is the other channel through which threat information affects the stock market. In Path A, we regress risk aversion and investor attention (mediators) on the Threat Index separately. In Path B, we regress the returns of different stock indices on the independent variable (Threat Index) as well as on the mediators (public risk aversion or investor attention) and control variables (CAY, EP, TBL, LTR, DY, TMS, SBW) simultaneously. Panel E presents the computed values of the Sobel tests as per Equation (5) and the proportion of the mediated effect. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All model variables are defined in Appendix C.

| | $RET_t^{SP500}$ | | $RET_t^{DIJA}$ | | $RET_t^{NASDAQ}$ | |
|---|---|---|---|---|---|---|
| | Path A | Path B | Path A | Path B | Path A | Path B |
| | (1) | (2) | (1) | (2) | (1) | (2) |
| **Panel A: Contemptuous Risk Aversion** | | | | | | |
| $Threat_{t-1}$ | 0.709*** | 0.020** | 0.709*** | 0.024** | 0.709*** | 0.036** |
| | (5.60) | (2.17) | (5.60) | (2.51) | (5.60) | (2.53) |
| $\ln(VRP)_{t-1}$ | | 0.006** | | 0.004 | | 0.011*** |
| | | (2.13) | | (1.34) | | (2.79) |
| #(obs.) | 348 | 348 | 348 | 348 | 348 | 348 |
| Adj. $R^2$ | 8.04 | 3.65 | 8.04 | 2.18 | 8.04 | 4.26 |
| **Panel B: Forward Risk Aversion** | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| $Threat_{t-1}$ | 0.697*** | 0.013 | 0.697*** | 0.016* | 0.697*** | 0.028** |
| | (5.62) | (1.48) | (5.62) | (1.75) | (5.62) | (2.53) |
| $\ln(VRP)_t$ | | -0.008** | | -0.009*** | | -0.007* |
| | | (-3.21) | | (-3.64) | | (-1.74) |
| #(obs.) | 348 | 348 | 348 | 348 | 348 | 348 |
| Adj. $R^2$ | 8.01 | 4.20 | 8.01 | 3.89 | 8.01 | 2.06 |

| | $RET_t^{SP500}$ | | $RET_t^{DIJA}$ | | $RET_t^{NASDAQ}$ | |
|---|---|---|---|---|---|---|
| | Path A | Path B | Path A | Path B | Path A | Path B |
| | (1) | (2) | (1) | (2) | (1) | (2) |
| **Panel C: Contemptuous Investor Attention** | | | | | | |
| $Threat_{t-1}$ | 0.096*** | 0.024*** | 0.096*** | 0.024*** | 0.096*** | 0.041*** |
| | (3.77) | (3.35) | (3.77) | (3.42) | (3.77) | (3.22) |
| $\ln(A^{AOL})_{t-1}$ | | 0.004 | | 0.004 | | -0.001 |
| | | (0.36) | | (0.39) | | (-0.06) |
| #(obs.) | 647 | 647 | 647 | 647 | 647 | 647 |
| Adj. $R^2$ | 7.55 | 4.49 | 7.55 | 3.95 | 6.80 | 4.25 |
| **Panel D: Forward Investor Attention** | | | | | | |
| $Threat_{t-1}$ | 0.067** | 0.022** | 0.067** | 0.022*** | 0.067** | 0.040*** |
| | (2.59) | (3.11) | (2.59) | (3.20) | (2.59) | (3.20) |
| $\ln(A^{AOL})_t$ | | 0.038*** | | 0.036*** | | 0.042* |
| | | (3.54) | | (3.30) | | (1.70) |
| #(obs.) | 647 | 647 | 647 | 647 | 647 | 647 |
| Adj. $R^2$ | 7.55 | 4.49 | 7.55 | 3.95 | 6.80 | 4.25 |

**Panel E: Sobel Test**

| | $\underline{RET_t^{SP500}}$ | $\underline{RET_t^{DIJA}}$ | $\underline{RET_t^{NASDAQ}}$ |
|---|---|---|---|
| **Outcome 1: Contemptuous Risk Aversion** | | | |
| Sobel Test | 1.978* | 1.290 | 2.485*** |
| p-value | 0.048 | 0.197 | 0.003 |
| % Proportion Mediated | 17.45% | 10.55% | 19.11% |
| **Outcome 2: Forward Risk Aversion** | | | |
| Sobel Test | -2.881*** | -3.124*** | -1.769* |
| p-value | 0.001 | 0.002 | 0.077 |
| %Proportion Mediated | -47.47% | -49.46% | -20.23% |
| **Outcome 3: Contemptuous Investor Attention** | | | |
| Sobel Test | 0.360 | 0.384 | -0.060 |

| | | | |
|---|---|---|---|
| p-value | 0.719 | 0.701 | 0.952 |
| %Proportion Mediated | 1.03% | 1.97% | 0% |
| **Outcome 4: Forward Investor Attention** | | | |
| Sobel Test | 2.137** | 2.080** | 1.43 |
| p-value | 0.033 | 0.038 | 0.151 |
| %Proportion Mediated | 5.12% | 10.43% | 2.81% |

**Table 6 Threat Index Effectively Predicted 28 out of 204 Anomalies.** The table reports estimates of b in the time series regression of portfolio returns from 1967 to 2020 which Threat Index could significant predict.

$$R_{X\,i,t} = \alpha + b \cdot (ThreatIndex_{t-1}) + \ c \cdot MKT_t \ + \ d \cdot r_t^{ME} \ + \ e \cdot r_t^{I/A} + m \cdot r_t^{ROE} + h \cdot r_t^{EG} + \varepsilon_{i,t} \qquad \textbf{(6)}$$

Regressions of excess return in month t on either the long leg, the short leg, or the long-short portfolio returns on lagged Threat Index, the market risk premium factor ($MKT_t$), size factor ($r_t^{ME}$), investment factor ($r_t^{I/A}$), return on equity factor ($\cdot\ r_t^{ROE}$), and the expected growth factor ($\cdot\ r_t^{EG}$). The sample period is mostly from 1967:01 to 2020:12. But Revisions in analyst earnings forecasts, whose data begin 1976:7, Net External Equity Financing, whose data begin 1972:7, quarterly return on net operating assets, quarterly operating profits-to-lagged assets, 1-month, 6-month and 12-month, quarterly asset liquidity, 1-month holding period holding period whose data begin 1976:1, quarterly capital turnover, 1-month and 12-month, quarterly operating profits-to-lagged book equity, 1-month holding period, whose data begin 1972:1, Ohlson's O (distress) , whose data begin 1973:10 . Newey and West (1987) adjusted t-statistics are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively.

| **Anomaly** | Long leg | | Shot leg | | Long-short | |
|---|---|---|---|---|---|---|
| | $\hat{b}$ | t-statistic | $\hat{b}$ | t-statistic | $\hat{b}$ | t-statistic |
| **Momentum** | | | | | | |
| Revisions in analyst earnings forecasts (1-month holding period) | -0.377 | -0.61 | 1.600** | 2.19 | -1.977** | -2.18 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 6-month Residual Momentum (6-month holding period) | 1.792*** | 4.17 | 0.209 | 0.58 | 1.583** | 2.37 |
| 6-month Residual Momentum (12-month holding period) | 1.229*** | 3.51 | 0.155 | 0.55 | 1.074** | 2.11 |
| 11-month Residual Momentum (1-month holding period) | 2.014*** | 3.02 | 0.043 | 0.09 | 1.970* | 1.95 |
| 11-month Residual Momentum (6-month holding period) | 2.129*** | 4.06 | 0 .320 | 0.90 | 1.809** | 2.54 |
| **Value-versus-growth** | | | | | | |
| Dividend Yield | -0.704 | -1.00 | 1.796*** | 3.07 | -2.500*** | -2.63 |
| **Investment** | | | | | | |
| Net Operating Assets | 0.759* | 1.85 | -0.324 | -0.66 | 1.083* | 1.71 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Inventory Growth | 1.266* | 1.93 | 0.015 | 0.04 | 1.250* | 1.75 |
| Operating Accruals | 1.665*** | 2.69 | 0 .451 | 0.91 | 1.214* | 1.71 |
| Net External Equity Financing | 0.966*** | 2.59 | -0.041 | -0.09 | 1.006* | 1.69 |
| **Profitability** | | | | | | |
| Quarterly Return on Net Operating Assets (1-month holding period) | 0.411 | 1.04 | 1.628*** | 2.60 | -1.977** | -2.18 |
| Quarterly Capital Turnover (1-month holding period) | 1.605*** | 3.06 | 0.233 | 0.41 | 1.373* | 1.87 |
| Quarterly Capital Turnover (12-month holding period) | 0.979*** | 30.14 | 0 .845*** | 27.71 | 0.134*** | 2.77 |
| Gross Profits-to-Assets | 1.818*** | 3.98 | -0.221 | -0.36 | 2.040*** | 2.66 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Quarterly Operating Profits-to-Lagged Book Equity (1-month holding period) | 0.250 | 0.62 | 1.845*** | 2.59 | -1.596** | -2.04 |
| Operating Profits-to-Assets | 0.938** | 2.53 | 2.333*** | 3.53 | -1.395* | -1.79 |
| Quarterly Operating Profits-to-Lagged Assets (1-month holding period) | 0.738* | 1.79 | 2.253*** | 3.35 | -1.515** | -2.08 |
| Quarterly Operating Profits-to-Lagged Assets (6-month holding period) | 0.824** | 2.00 | 2.226*** | 3.57 | -1.402* | -1.82 |
| Quarterly Operating Profits-to-Lagged Assets (12-month holding period) | 0.794* | 1.76 | 2.326*** | 3.87 | -1.532* | -1.95 |
| **Intangibles** | | | | | | |
| Operating Leverage | 1.817*** | 3.08 | 0.357 | 0.48 | 1.4602* | 1.83 |
| Effective Tax Rate | 0.879* | 1.68 | -0.741 | -1.11 | 1.620** | 2.35 |
| Quarterly Asset Liquidity | 2.302*** | 4.10 | 0.907** | 2.30 | 1.395** | 1.88 |

| | | | | | | |
|---|---|---|---|---|---|---|
| (1-month holding period) | | | | | | |
| Seasonality (average return from month t-11 to t-1) | 0.726 | 0.99 | 3.745*** | 2.94 | -3.019* | -1.72 |
| Seasonality (average return across months t-24, t-36, t-48, and t-60) | 2.210*** | 3.89 | -0.080 | -0.11 | 2.290** | 2.52 |
| Seasonality (average return from month t-120 to t-61 except for months t-72, t-84, t-96, t-108, and t-120) | 0.229 | 0.45 | 1.992*** | 2.65 | -1.762** | -2.06 |
| **Frictions** | | | | | | |
| Market Equity | 3.070*** | 3.48 | 0.333 | 1.62 | 2.737*** | 2.77 |
| Market Beta (1-month holding period) | 2.583*** | 2.95 | -0.047 | -0.10 | 2.630** | 2.32 |
| Idiosyncratic Skewness (1-month holding period) | 0.779** | 2.35 | -0.409 | -1.05 | 1.187** | 2.56 |
| **Well-Documented Anomalies** | | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Ohlson's O (distress) | 0.001 | 0.23 | 0.020** | 2.48 | | -.0190** | -2.20 |

## Appendix A. Threat Dictionary Word List

| | | | | |
|---|---|---|---|---|
| accidents | danger | frightening | outbreak | terrorist |
| accusations | dangerous | grief | outbreaks | terrorists |
| advised | dangers | harassment | outrage | threat |
| afraid | deadly | harm | plagued | threaten |
| aftermath | death | harmed | polluted | threatened |
| alleged | deaths | harmful | potential | threatening |
| amid | debacle | harming | precautions | threatens |
| anger | debt | harms | prevent | threats |
| anguish | deemed | hatred | preventable | toxic |
| anxieties | demands | hazardous | problem | tragedies |
| anxiety | demise | hazards | problematic | tragedy |
| approaching | despair | homicides | problems | tragic |
| arrests | destroy | horrific | prolonged | trouble |
| assaults | destruction | horrifying | prompted | troubles |
| attack | destructive | hurricane | protect | turmoil |
| attacks | detrimental | hurt | ramifications | unacceptable |
| averted | devastating | hurting | rapes | uncertainty |
| avoid | devastation | illegal | recession | undesirable |
| aware | died | illness | repercussions | unethical |
| blamed | difficult | imminent | resolve | unfit |
| bloodshed | disaster | impending | riots | unfortunate |
| bombings | disasters | impossible | risk | unhygienic |
| calamity | discord | inadequate | risks | unimaginable |
| casualties | disease | incident | scary | unpleasant |
| catastrophe | dispute | incidents | scenario | unprecedented |

| | | | | |
|---|---|---|---|---|
| catastrophes | disruption | ineffective | sectarian | unregulated |
| catastrophic | disturbing | inevitable | security | unreliable |
| caused | doubts | inflict | senseless | unrest |
| causing | dreadful | inflicted | severe | unsafe |
| caution | emergencies | inhumane | shootings | unsanitary |
| challenges | enemy | injuries | situation | unstable |
| chaos | epidemic | insults | situations | unsuitable |
| circumstances | escape | irony | sorrow | upheaval |
| clashes | eventual | irresponsible | speculation | victim |
| collapse | explosion | issue | storm | victims |
| complaints | extinction | kill | storms | violence |
| concern | extremely | killed | struggle | violent |
| concerns | facing | killings | struggles | vulnerable |
| conflict | factors | kills | suffer | war |
| conflicts | famine | lethal | suffering | warn |
| confront | fatalities | looming | suicide | warned |
| confrontation | fear | meltdown | suicides | warning |
| consequences | fears | midst | survivors | warns |
| contaminated | fighting | misery | suspected | woes |
| crashes | flood | murder | targets | worries |
| crisis | flooding | murders | tension | worry |
| damage | floods | nearing | tensions | worse |
| damaging | forces | nightmare | terrorism | worst |

## Appendix B Trends in the Threat Index and Comparison with EPU

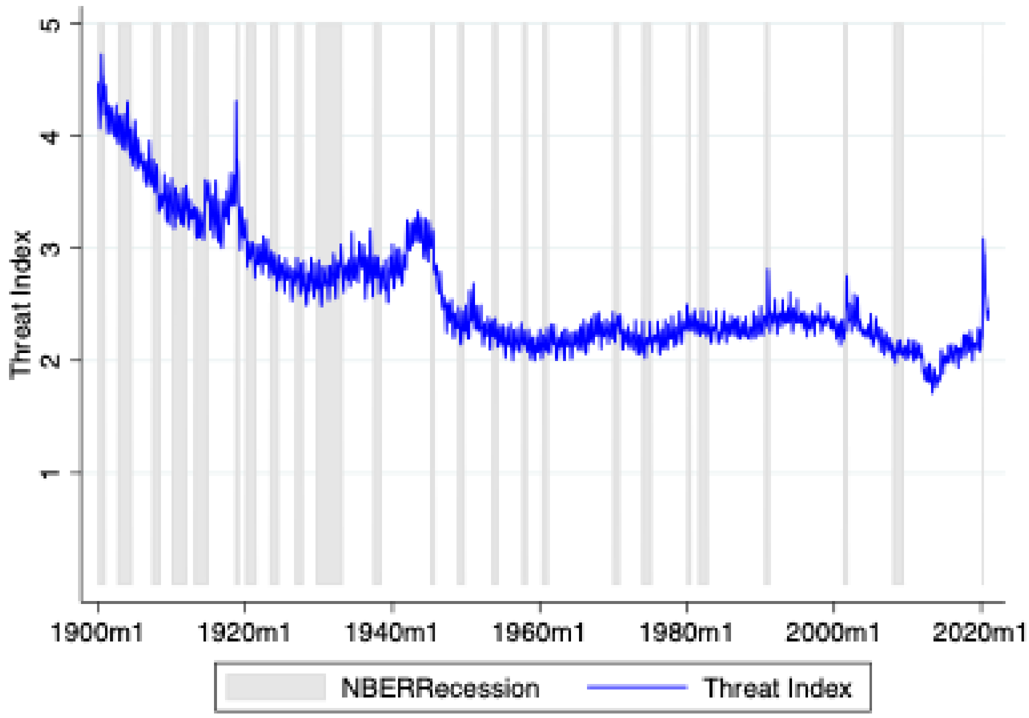


**Fig. B1. Time-Varying Threat Index Over 100 Years**

This figure depicts the Threat Index (y-axis) from January 1900 to December 2020, based on the relative use of threat words found in US newspapers and adjusted by an approximate number of article pages published within the corresponding periods.

**Fig. B1** plots the time-series dynamics of the Threat Index with shaded NBER recessions, which ranges from January 1900 to December 2020, with values fluctuating between 4.722 (1900:M7) and 1.710 (2013:M5). Specifically, the changing trends of the Threat Index data over more than 100 years exhibited a pronounced temporal trend before 1945. And post-1945, they mostly range between 2 and 3 and relatively stable. That finding, consistent with the findings of numerous scholars (Pinker 2011; Goldstein 2012; Gurr 1981), indicates that threat levels are in historical decline. During bad times, as indicated by NBER-dated recessions, the Threat Index will increase accordingly.

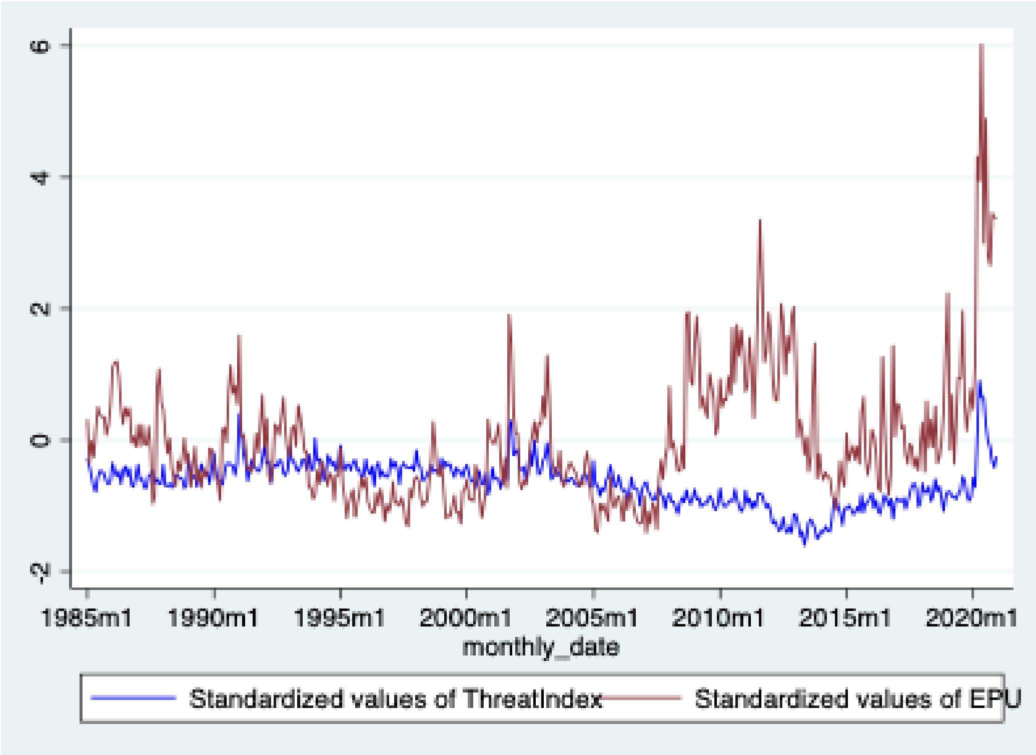


**Fig. B2. Threat vs. EPU**

This figure plots the comparison of the trends in the standardized Threat Index and the standardized EPU from January 1985 to December 2020.

## Appendix C Comparison of Construction Procedures Among 12 Uncertainty Indices

| No. | Index | Time Period and Frequency | Original Study | Construction Procedure |
|---|---|---|---|---|
| 1 | Baker and Wurgler Sentiment Index ($S^{BW}$) | July 1965-June 2022<br><br>Monthly | Baker and Wurgler (2006) | Based on first principal component of FIVE (standardized) sentiment proxies: Value-weighted dividend premium; First-day returns on IPOs; IPO volume; Closed-end fund discount; Equity share in new issues.[4] |
| 2 | CBOE Volatility Index (VIX) | Since January 1990<br><br>Daily, weekly or m onthly | Whaley (2000) | The VIX index is the "risk-neutral" expected stock market variance for the US S&P500 contract and is computed from a panel of options prices. The VIX is widely recognized as a "fear index" for asset markets as it reflects both stock market uncertainty and the "physical" expected volatility. |
| 3 | Variance Risk Premium (VRP) | Since January 1990<br><br>Monthly | Zhou (2018) | The VRP is defined as the difference between the risk-neutral and objective expectations of realized variance. The risk-neutral expectation of variance is measured as the end-of-month VIX-squared de-annualized (VIX^2/12), while the realized variance is calculated as the sum of squared 5-minute log returns of the S&P 500 index over the month. |

[4] Unlike in Baker and Wurgler (2006, 2007), NYSE turnover has been dropped as one of the six sentiment indicators (Wurgler, 2023).

| | | | | |
|---|---|---|---|---|
| 4 | PLS Sentiment Index ($S^{PLS}$) | July 1965-June 2022<br><br>Monthly | Huang et al. (2015) | Based on the widely used Baker and Wurgler's (2006) six proxies and by using the partial least squares (PLS) method introduced to the finance literature by Kelly and Pruitt (2013). |
| 5 | Michigan Consumer Sentiment Index<br><br>($S^{MC}$) | Since January 1978<br><br>Monthly | George Katona (1940) | To calculate the Index of Consumer Sentiment, first, compute the relative scores for each of the five index questions in three areas: how consumers view prospects for their own financial situation, how they perceive prospects for the general economy over the near term, and their outlook on prospects for the economy over the long term. Then, the relative scores are obtained by subtracting the percentage of unfavorable replies from the percentage of favorable replies and then adding 100. |
| 6 | Aruoba-Diebold-Scotti Business Conditions (ADS) Index | Since March 1960<br><br>Daily | Aruoba et al. (2009) | The ADS index on this web page is updated in real time and designed to track real business conditions at high observation frequency using a dynamic model. Its underlying (seasonally adjusted) economic indicators are weekly initial jobless claims; monthly payroll employment, monthly industrial production, monthly real personal income less transfer payments, monthly real manufacturing and trade sales; and quarterly real GDP, which are blend high-frequency and low-frequency data. |
| 7 | Geopolitical Risk (GPR) Index | January 1985 - December 2017 | Caldara and Iacoviello (2022) | The geopolitical risk is defined as the risk associated with wars, terrorist acts, and tensions between states, affecting the normal course of international relations. It captures the risk of these events occurring |

| | | | | |
|---|---|---|---|---|
| | | Monthly | | and the threat risks associated with future adverse geopolitical events. The GPR index is constructed by counting occurrences in leading English-language newspapers of articles discussing geopolitical events and risks. It could be decomposed into two subindexes: Geopolitical Threats (GPRT), including categories like War Threats, Peace Threats, Military Buildups, Nuclear Threats, and Terror Threats; and Geopolitical Acts (GPRA), including words like Beginning of War, Escalation of War, Terror Acts. |
| 8 | Financial and Economic Attitudes Revealed by Search (FEARS) Index | July 2004 - December 2011<br><br>Daily | Da et al. (2015) | The FEARS index is generated by aggregating the search volume changes of the 30 most relevant search terms related to economic sentiment and market returns and then averaging them. The "FEARS" terms are reported in Appendix E. |
| 9 | Economic Policy Uncertainty (EPU) | January 1985 - October 2023<br><br>Monthly and Daily | Baker et al. (2016) | The EPU is constructed from three types of underlying components: News Coverage about Policy-related Economic Uncertainty from search results from 10 large newspapers; Data reports by the Congressional Budget Office (CBO) that compile lists of temporary federal tax code provisions; Economic Forecaster Disagreement. |
| 10 | Presidential Economic Approval Rating (PEAR) Index | April 1981 - December 2019<br><br>monthly | Chen et al. (2023) | The PEAR index is constructed by averaging ratings on the president’s handling of the economy across various national polls available in each month. |

| | | | | |
|---|---|---|---|---|
| 11 | War Disclosure Index (WAR) | January 1927 - October 2019<br><br>Monthly | Hirshleifer et al. (2023) | Authors utilized the 'War' seed word and employing the sLDA model (a semi-supervised topic model), extract the war topic from a dataset of 7,000,000 New York Times articles spanning 160 years. They monthly re-estimated an AR(1) process on the War index using data up to the current month (the beginning of the sample is 01/1926) and used the residuals as War Factor. This is to ensure that War Factor is available in the real time. |
| 12 | News Implied Volatility (NVIX) | July 1889 - December 2009<br><br>Monthly | Manela and Moreira (2017) | A news-based measure of uncertainty is estimated derived from the co-movement between the front-page coverage of the Wall Street Journal and options implied volatility (VIX). Specifically, relying on machine learning techniques, the authors break titles and abstracts into one- and two-word n-grams. Subsequently, they aggregate the most influential n-gram counts for VIX prediction to the monthly frequency, creating a substantial body of text for each observation. This news data is then merged with the estimation target, the implied volatility indices VIX and VXO reported by the Chicago Board Options Exchange (CBOE), to obtain NVIX.<br><br>They decompose the text into five categories plausibly related (to a varying degree) to disaster concerns: War, Financial Intermediation, Government, Stock Markets, and Natural Disasters. Then, they find that a large part of the variation in risk premia is related to wars (53%) and government (27%). A substantial part of the time-series variation in risk premia NVIX identifies is driven by concerns tightly |

| | |
|---|---|
| | related to the type of events discussed in the rare disasters literature. |

## Appendix D 14 Economic Variables Description

| | |
|---|---|
| Book-to-market ratio, BM | Ratio of book value to market value for the Dow Jones Industrial Average |
| Default return spread, DFR | Long-term corporate bond return minus the long-term government bond return |
| Default yield spread, DFY | Difference between BAA- and AAA-rated corporate bond yields. |
| Dividend–payout ratio (log), DE | Log of the 12-month moving sum of dividends minus the log of the 12-month moving sum of earnings. |
| Dividend–price ratio (log), DP | Log of the 12-month moving sum of dividends paid on the Standard & Poor’s (S&P) 500 index minus the log of stock prices (S&P 500 index). |
| Dividend yield (log), DY | Log of the 12-month moving sum of dividends minus the log of lagged stock prices. |
| Earnings–price ratio (log), EP | Log of the 12-month moving sum of earnings on the S&P 500 index minus the log of stock prices. |
| Inflation, INFL | Calculated from the Consumer Price Index (CPI) for all urban con- sumers; we use lagged 2-month inflation in the regression to account for the delay in CPI releases. |
| Long-term return, LTR | Return on long-term government bonds. |
| Long-term yield, LTY | Long-term government bond yield. |
| Net equity expansion, NTIS | Ratio of the 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks. |

| | |
|---|---|
| Stock return variance, SVAR | Sum of squared daily returns on the S&P 500 index. Term spread, TMS: Long-term yield minus the Treasury bill rate. |
| Treasury bill rate, TBL | Interest rate on a 3-month Treasury bill (secondary market). |

## Appendix E Robustness Tests on the Explanation of Threat Index for Stock Market Returns and the Predictive Power of Residuals

### Table A1 Threat Index Explain Stock Market Returns Results.

This table reports results from contemporaneous regression estimates from Eq. (2).

$$RET_{i,t} = \alpha + \beta \cdot ThreatIndex_t + \Sigma\, \gamma \cdot Controls_{i,t-1} + \mathcal{E}i,t \quad \textbf{(2)}$$

The dependent variable is the monthly stock market return (RET) in S&P 500 Index (SP500), Nasdaq Index (NASDAQ), and Dow Jones Industrial Average Index (DJIA) separately. The independent variable, is the contemporaneous month in Threat Index. The control variables are the one-month-lagged dependent variable ($RET_{t-1}$), which is not reported with constants. And contemporaneous or lagged $DY$, $DFY$, $TBL$, $CAY$, and $S^BW$. Newey and West (1987) adjusted t-statistics are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively. We standardize all predictors to have 0 mean and unit variance. Each panel reports estimates of regression slopes and adjusted $R^2$ in percentage form. Intercepts are included in all the regressions but unreported for brevity. The sample period is 1967:01–2020:12 for S&P 500 Index (SP500) and Dow Jones Industrial Average Index (DJIA), and 1986:01–2020:12 for Nasdaq Index.

| | $\boldsymbol{RET_t^{SP500}}$ | $\boldsymbol{RET_t^{DIJA}}$ | $\boldsymbol{RET_t^{NASDAQ}}$ |
|---|---|---|---|
| $\boldsymbol{\Delta Threat_t}$ | -0.024** | -0.025** | -0.035* |
| | (-2.18) | (-2.15) | (-1.69) |
| $\boldsymbol{RET_{t-1}}$ | -0.010 | -0.018 | 0.014 |
| | (-0.19) | (-0.39) | (0.20) |
| $\boldsymbol{CAY_{t-1}}$ | 0.002 | 0.003 | -0.004 |
| | (0.74) | (1.05) | (-1.27) |
| $\boldsymbol{EP_{t-1}}$ | 0.002 | 0.001 | 0 |
| | (0.44) | (0.26) | (-0.02) |

| | | | |
|---|---|---|---|
| $\boldsymbol{TBL_{t-1}}$ | -0.003 | -0.002 | 0.001 |
| | (-0.93) | (-0.65) | (0.23) |
| $\boldsymbol{LTR_{t-1}}$ | 0.003** | 0.003** | 0.003 |
| | (2.43) | (2.55) | (1.65) |
| $\boldsymbol{DY_{t-1}}$ | 0.007 | 0.007 | 0.011 |
| | (1.47) | (1.37) | (1.35) |
| $\boldsymbol{TMS_{t-1}}$ | -0.004 | -0.004 | -0.004 |
| | (-0.72) | (-0.78) | (-0.48) |
| $\boldsymbol{S_{t-1}^{BW}}$ | -0.002 | -0.002 | -0.007 |
| | (-1.52) | (-1.28) | (-2.50) |
| #(obs.) | 648 | 648 | 420 |
| Adj. $R^2$ | 1.87 | 1.57 | 2.31 |

**Table A2 Residual Predictive and Explanation Power on Stock Market Returns Results.**

This table reports the results from using residuals from regressing the Baker and Wurgler Sentiment Index ($S^{BW}$), policy-related economic uncertainty indexes (EPU), and the Geopolitical Risk Index (GPR) on the Threat Index to predict or explain the monthly stock market returns (RET) in the S&P 500 Index (SP500), Nasdaq Index (NASDAQ), and Dow Jones Industrial Average Index (DJIA) separately, according to Eq. (3).

$$\boldsymbol{Threat_t = \alpha + \beta 1 \cdot S_t^{BW} + \beta 2 \cdot EPU_t \cdot \beta 3 \cdot GPR_t + \varepsilon_t} \qquad \textbf{(3)}$$

The independent variable, is the lagged or contemporaneous residual. The control variables are the one-month-lagged dependent variable ($RET_{t-1}$), which is not reported with constants. And lagged $DY$, $DFY$, $TBL$, $CAY$, and $S^{BW}$. Newey and West (1987) adjusted t-statistics are reported in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% level, respectively. We standardize all predictors to have 0 mean and unit variance. Each panel reports estimates of regression slopes and adjusted $R^2$ in percentage form. Intercepts are included in all the regressions but unreported for brevity. The sample period is 1985:01–2020:12 for S&P 500 Index (SP500) and Dow Jones Industrial Average Index (DJIA), and 1986:01–2020:12 for Nasdaq Index.

| | $\boldsymbol{RET_t^{SP500}}$ | | $\boldsymbol{RET_t^{DIJA}}$ | | $\boldsymbol{RET_t^{NASDAQ}}$ | |
|---|---|---|---|---|---|---|
| $\Delta\mathcal{E}_t$ | -0.017 | | -0.020 | | -0.005 | |
| | (-1.20) | | (-1.39) | | (-0.23) | |
| $\mathcal{E}_{t-1}$ | | 0.020** | | 0.022** | | 0.034** |
| | | (1.97) | | (2.11) | | (2.57) |
| $\boldsymbol{RET_{t-1}}$ | 0.013 | 0.010 | -0.007 | -0.008 | 0.079 | 0.067 |
| | (0.18) | (0.15) | (-0.11) | (-0.13) | (1.50) | (1.26) |
| $\boldsymbol{CAY_{t-1}}$ | -0.002 | 0.002 | -0.001 | 0.003 | -0.004 | 0.003 |
| | (-0.77) | (0.47) | (-0.35) | (0.84) | (-1.21) | (0.59) |
| $\boldsymbol{EP_{t-1}}$ | 0.002 | 0.004 | 0.001 | 0.003 | 0 | 0.003 |
| | (0.41) | (0.73) | (0.31) | (0.71) | (0.11) | (0.65) |
| $\boldsymbol{TBL_{t-1}}$ | 0.005 | 0.002 | 0.006 | 0.003 | 0.001 | -0.004 |
| | (1.07) | (0.40) | (1.41) | (0.63) | (0.10) | (-0.56) |
| $\boldsymbol{LTR_{t-1}}$ | 0.001 | 0.001 | 0.001 | 0.001 | 0.003 | 0.002 |
| | (0.75) | (0.40) | (0.64) | (0.28) | (1.25) | (0.80) |
| $\boldsymbol{DY_{t-1}}$ | 0.009 | 0.012* | 0.009 | 0.012** | 0.011 | 0.015 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (1.57) | (1.87) | (1.64) | (1.98) | (1.20) | (1.53) |
| $\boldsymbol{TMS_{t-1}}$ | -0.007 | -0.012* | -0.008 | -0.013* | -0.004 | -0.015 |
| | (-1.11) | (-1.72) | (-1.19) | (-1.81) | (-0.46) | (-1.39) |
| #(obs.) | 431 | 431 | 431 | 431 | 420 | 420 |
| Adj. $R^2$ | 0.96 | 1.61 | 0.62 | 1.34 | 0.73 | 2.08 |

**Appendix F Sobel Test**

Following Azevedo et al. (2024), We compute the Sobel (1982) test to examine whether the mediation effect of the economic performance variables are statistically significant. Specifically, the Sobel test is computed as:

$$\text{SobelTest} = \frac{\beta_1 \delta_2}{\sqrt{(\delta_2^2 \epsilon^2) + (\beta_1^2 \eta^2)}} \tag{4}$$

where $\beta_1$ and $\varepsilon$ are the estimated coefficient of A and the standard error from the Path A regression, respectively; $\delta_2$ and $\eta$ are the estimated coefficient of M and the standard error from Path B regression, respectively.

## Appendix G 204 Anomalies and Construction Procedure

HXZ adopt a variety of methods to evaluate the reliability of the predictive power of an anomaly variable. For portfolio sorts (into deciles), they vary breakpoints and return weights, including NYSE breakpoints. For annually sorted deciles, they split stocks at the end of June of each year t into deciles on a variable measured at the fiscal year ending in calendar year t−1 and calculate decile returns from July of year t to June of t+1. Following Beaver, McNichols, and Price (2007), they adjust monthly stock returns for delisting returns by compounding returns in the month before delisting with delisting returns from CRSP. Their sample includes all NYSE, Amex, and Nasdaq common stocks with a CRSP share code of 10 or 11. They exclude financial firms (SIC between 6000 and 6999) and firms with negative book equity. Stock returns are adjusted for delisting. The sample period is from January 1967 to December 2022. Due to data limitations, some testing portfolios start later than January 1967. With microcaps mitigated via NYSE breakpoints and value-weighted returns. Monthly returns are from the Center for Research in Security Prices (CRSP) and accounting information from the Compustat Annual and Quarterly Fundamental Files. The sample period is from January 1967 to December 2016. They exclude financial firms and firms with negative book equity. Some studies exclude stocks with prices per share lower than $1 or $5. They do not impose such a screen. In particular, microcaps are included in our sample.

Stambaugh and Yuan (2017) they compute the spread for each anomaly, between the value-weighted returns in month  on stocks in the first and tenth NYSE deciles of the ranking variable in a sort at the end of month  of all NYSE/AMEX/NASDAQ stocks with share prices greater than $5. Below table lists the definitions and abbreviations for the 195 anomalies from HXZ and 9 prominent anomalies from Stambaugh and Yuan (2017):

| **Momentum (42)** |
| --- |

| | | |
|---|---|---|
| 1 | Standardized unexpected earnings | sue_1 |
| 2 | standard unexpected earnings, 6-month holding period | Sue6 |
| 3 | Cumulative abnormal returns around earnings announcement dates, 1-month holding period | abr_1 |
| 4 | cumulative abnormal returns around earnings announcement dates, 6-month holding period; | abr_6 |
| 5 | cumulative abnormal returns around earnings announcement dates, 12-month holding period; | abr_12 |
| 6 | revisions in analyst earnings forecasts, 1-month holding period | re_1 |
| 7 | revisions in analyst earnings forecasts, 6-month holding period | re_6 |
| 8 | Price momentum, prior 6-month returns | r6_1 |
| 9 | prior 6-month returns, 6-month holding period | r6_6 |
| 10 | prior 6-month returns, 12-month holding period | r6_12 |
| 11 | prior 11-month returns, 1-month holding period; | r11_1 |
| 12 | prior 11-month returns, 6-month holding period; | r11_6 |
| 13 | prior 11-month returns, 12-month holding period; | r11_12 |
| 14 | Industry momentum | im_1 |
| 15 | industry momentum, 6-month holding period | im_6 |
| 16 | industry momentum, 12-month holding period | im_12 |
| 17 | Revenue surprises | rs_1 |
| 18 | Changes in Analyst Earnings Forecasts | def_1 |
| 19 | changes in analyst earnings forecasts, 6-month holding period; | def_6 |
| 20 | changes in analyst earnings forecasts, 12-month holding period; | def_12 |
| 21 | The number of quarters with consecutive earnings increase | nei_1 |
| 22 | 52-week high, 6-month holding period; | p52w_6 |
| 23 | 52-week high, 12-month holding period; | p52w_12 |
| 24 | 6-month residual momentum, 6-month holding period | resid6_6 |

| | | |
|---|---|---|
| 25 | 6-month residual momentum, 12-month holding period | resid6_12 |
| 26 | 11-month residual momentum, 1-month holding period | resid11_1 |
| 27 | 11-month residual momentum, 6-month holding period | resid11_6 |
| 28 | 11-month residual momentum, 12-month holding period | resid11_12 |
| 29 | Segment momentum, 1-month holding period | sm_1 |
| 30 | Segment momentum, 12-month holding period | sm_12 |
| 31 | Industry lead-lag effect in prior returns, 1-month holding period | ilr_1 |
| 32 | Industry lead-lag effect in prior returns, 6-month holding period | ilr_6 |
| 33 | Industry lead-lag effect in prior returns, 12-month holding period | ilr_12 |
| 34 | industry lead-lag effect in earnings surprises, 1-month holding period | ile_1 |
| 35 | customer momentum, 1-month holding period | cm_1 |
| 36 | customer momentum, 6-month holding period | cm_6 |
| 37 | customer momentum, 12-month holding period | cm_12 |
| 38 | customer industries momentum, 1-month holding period | cim_1 |
| 39 | customer industries momentum, 6-month holding period | cim_6 |
| 40 | customer industries momentum, 12-month holding period | cim_12 |
| 41 | supplier industries momentum, 1-month holding period | sim_1 |
| 42 | supplier industries momentum, 12-month holding period | sim_12 |
| | **Value versus growth (32)** | |
| 1 | Book-to-market equity | bm |
| 2 | Book-to-June-end market equity | bmj |
| 3 | Quarterly book-to-market equity | bmq_12 |
| 4 | Long-term reversal, 1-month holding period | rev_1 |

| | | |
|---|---|---|
| 5 | Long -term reversal, 6-month holding period | rev_6 |
| 6 | Long -term reversal, 12-month holding period | rev_12 |
| 7 | Earnings-to-price | ep |
| 8 | Quarterly earnings-to-price, 1-month holding period | epq_1 |
| 9 | Quarterly earnings-to-price, 6-month holding period | epq_6 |
| 10 | Quarterly earnings-to-price, 12-month holding period | epq_12 |
| 11 | Cash flow-to-price | cp |
| 12 | Quarterly cash flow-to-price, 1-month holding period | cpq_1 |
| 13 | Quarterly cash flow-to-price, 6-month holding period | cpq_6 |
| 14 | Quarterly cash flow-to-price, 12-month holding period | cpq_12 |
| 15 | Dividend yield | dp |
| 16 | Payout yield | op |
| 17 | Net payout yield | nop |
| 18 | Enterprise multiple | em |
| 19 | Quarterly enterprise multiple, 1-month holding period | emq_1 |
| 20 | Quarterly enterprise multiple, 6-month holding period | emq_6 |
| 21 | Quarterly enterprise multiple, 12-month holding period | emq_12 |
| 22 | Sales-to-price | sp |
| 23 | Quarterly sales-to-price, 1-month holding period | spq_1 |
| 24 | Quarterly sales-to-price, 6-month holding period | spq_6 |
| 25 | Quarterly sales-to-price, 12-month holding period | spq_12 |
| 26 | Operating Cash Flow-to-price | ocp |
| 27 | Quarterly Operating Cash Flow-to-price | ocpq_1 |
| 28 | Intangible return | ir |

| | | |
|---|---|---|
| 29 | Roe-based intrinsic value-to-market | vhp |
| 30 | Analyst-based Intrinsic Value-to-market | vfp |
| 31 | Enterprise Book-to-price | ebp |
| 32 | Equity duration | dur |
| | **Investment (32)** | |
| 1 | Abnormal corporate investment | aci |
| 2 | Investment-to-assets | ia |
| 3 | quarterly investment-to-assets (asset growth), 1-month holding period | iaq_1 |
| 4 | quarterly investment-to-assets (asset growth), 6-month holding period | iaq_6 |
| 5 | quarterly investment-to-assets (asset growth), 12-month holding period | iaq_12 |
| 6 | Changes in PPE and inventory-to-assets | dpia |
| 7 | net operating assets; | noa |
| 8 | changes in net operating assets; | dnoa |
| 9 | Changes in long-term net operating assets. | dlno |
| 10 | Investment growth | ig |
| 11 | 2-year investment growth | ig2 |
| 12 | Net stock issues | nsi |
| 13 | Percentage change in investment relative to industry | dii |
| 14 | Composite equity issuance | cei |
| 15 | Inventory growth | ivg |
| 16 | Inventory changes | ivc |
| 17 | Operating accruals | oa |
| 18 | Total accruals | ta |

| | | |
|---|---|---|
| 19 | changes in net non-cash working capital; | dwc |
| 20 | changes in current operating assets; | dcoa |
| 21 | Changes in noncurrent operating assets | dnco |
| 22 | Changes in net noncurrent operating assets | dnca |
| 23 | Changes in book equity | dbe |
| 24 | Changes in net financial assets | dfin |
| 25 | Changes in financial liabilities | dfnl |
| 26 | Changes in in long-term investments | dlti |
| 27 | Discretionary accruals computed from Nasdaq Index NYSE and Amex | dac |
| 28 | Percent operating accruals | poa |
| 29 | Percent total accruals | pta |
| 30 | Percent discretionary accruals | pda |
| 31 | Net debt financing | ndf |
| 32 | Net external financing | nxf |
| | **Profitability (48)** | |
| 1 | return on equity, 1-month holding period; | roe_1 |
| 2 | return on equity, 6-month holding period; | roe_6 |
| 3 | 4-quarter changes in return on equity, 1-month holding period | droe_1 |
| 4 | 4-quarter changes in return on equity, 6-month holding period | droe_6 |
| 5 | 4-quarter changes in return on equity, 12-month holding period | droe_12 |
| 6 | return on assets, 1-month holding period | roa_1 |
| 7 | return on assets, 6-month holding period | roa_6 |
| 8 | 4-quarter changes in return on assets, 1-month holding period | droa_1 |

| | | |
|---|---|---|
| 9 | 4-quarter changes in return on assets, 6-month holding period | droa_6 |
| 10 | Assets turnover | ato |
| 11 | Capital turnover | cto |
| 12 | quarterly return on net operating assets, 1-month holding period | rnaq_1 |
| 13 | quarterly return on net operating assets, 6-month holding period | rnaq_6 |
| 14 | quarterly return on net operating assets, 12-month holding period | rnaq_12 |
| 15 | quarterly profit margin, 1-month holding period | pmq_1 |
| 16 | quarterly assets turnover, 1-month holding period | atoq_1 |
| 17 | quarterly assets turnover, 6-month holding period | atoq_6 |
| 18 | quarterly assets turnover, 12-month holding period | atoq_12 |
| 19 | quarterly capital turnover, 1-month holding period | ctoq_1 |
| 20 | quarterly capital turnover, 6-month holding period | ctoq_6 |
| 21 | quarterly capital turnover, 12-month holding period | ctoq_12 |
| 22 | Gross profits-to-assets. | gpa |
| 23 | quarterly gross profits-to-lagged assets, 1-month holding period | glaq_1 |
| 24 | quarterly gross profits-to-lagged assets, 6-month holding period | glaq_6 |
| 25 | quarterly gross profits-to-lagged assets, 12-month holding period | glaq_12 |
| 26 | Operating profits to equity | ope |
| 27 | quarterly operating profits-to-lagged book equity, 1-month holding period | oleq_1 |
| 28 | quarterly operating profits-to-lagged book equity, 6-month holding period | oleq_6 |
| 29 | Operating profits-to-assets | opa |
| 30 | quarterly operating profits-to-lagged assets, 1-month holding period | olaq_1 |
| 31 | quarterly operating profits-to-lagged assets, 6-month holding period | olaq_6 |

| | | |
|---|---|---|
| 32 | quarterly operating profits-to-lagged assets, 12-month holding period | olaq_12 |
| 33 | Cash-based operating profitability | cop |
| 34 | Cash-based operating profits-to-lagged asset | cla |
| 35 | quarterly cash-based operating profits-to-lagged assets, 1-month holding period | claq_1 |
| 36 | quarterly cash-based operating profits-to-lagged assets, 6-month holding period | claq_6 |
| 37 | quarterly cash-based operating profits-to-lagged assets, 12-month holding period | claq_12 |
| 38 | quarterly fundamental score, 1-month holding period | fq_1 |
| 39 | quarterly fundamental score, 6-month holding period | fq_6 |
| 40 | quarterly fundamental score, 12-month holding period | fq_12 |
| 41 | Failure Probability | fp_6 |
| 42 | Quarterly O-score | oq_1 |
| 43 | quarterly tax income-to-book income, 6-month holding period | tbiq_6 |
| 44 | quarterly tax income-to-book income, 12-month holding period | tbiq_12 |
| 45 | quarterly sales growth, 1-month holding period | sgq_1 |
| 46 | expected growth, 1-month holding period | eg_1 |
| 47 | expected growth, 6-month holding period | eg_6 |
| 48 | expected growth, 12-month holding period | eg_12 |
| | **Intangibles (31)** | |
| 1 | Industry adjusted organizational capital-to-assets | oca |
| 2 | (Industry-adjusted) Organizational Capital-to-assets | ioca |
| 3 | Advertising expense-to-market | adm |
| 4 | R&D expense-to-market | Rdm |
| 5 | quarterly R&D expense-to-market, 1-month holding period | rdmq_1 |

| | | |
|---|---|---|
| 6 | quarterly R&D expense-to-market, 6-month holding period | rdmq_6 |
| 7 | quarterly R&D expense-to-market, 12-month holding period | rdmq_12 |
| 8 | quarterly R&D expense-to-sales, 6-month holding period; | rdsq_6 |
| 9 | quarterly R&D expense-to-sales, 12-month holding period; | rdsq_12 |
| 10 | Operating leverage | ol |
| 11 | quarterly operating leverage, 1-month holding period | olq_1 |
| 12 | quarterly operating leverage, 6-month holding period | olq_6 |
| 13 | quarterly operating leverage, 12-month holding period | olq_12 |
| 14 | R&D capital-to-assets | rca |
| 15 | Hs, industry concentration (sales) | Hs |
| 16 | Effective tax rate | etr |
| 17 | Industry-adjusted real estate ratio | rer |
| 18 | Earnings Predictability | eprd |
| 19 | Earnings timeliness | Etl |
| 20 | quarterly asset liquidity, 1-month holding period | almq_1 |
| 21 | quarterly asset liquidity, 6-month holding period | almq_6 |
| 22 | quarterly asset liquidity, 12-month holding period | almq_12 |
| 23 | Disparity between Long- and Short-term Earnings Growth Forecasts | dls_1 |
| 24 | seasonality, return in month *t*-12 | r1a |
| 25 | seasonality, average return from month *t*-11 to *t*-1 | r1n |
| 26 | seasonality, average return across months *t*-24, *t*-36, *t*-48, and *t*-60 | r5a |
| 27 | seasonality, average return from month *t*-60 to *t*-13 except for months *t*-24, *t*-36, *t*-48, and *t*-60 | r5n |
| 28 | seasonality, average return across months *t*-72, *t*-84, *t*-96, *t*-108, and *t*-120 | r10a |
| 29 | seasonality, average return from month *t*-120 to *t*-61 except for months *t*-72, *t*-84, *t*-96, *t*-108, and *t*-120 | r10n |

| | | |
|---|---|---|
| 30 | seasonality, average return across months *t*-132, *t*-144, *t*-156, *t*-168, and *t*-180; | r15a |
| 31 | seasonality, average return across months *t*-192, *t*-204, *t*-216, *t*-228, and *t*-240 | r20a |
| | **Trading frictions (10)** | |
| 1 | Me, market equity | me |
| 2 | Idiosyncratic volatility per the Fama and French (1993) 3-factor model | Ivff1 |
| 3 | Idiosyncratic volatility | Ivq1 |
| 4 | Total volatility | tv_1 |
| 5 | Systematic Volatility Risk | sv_1 |
| 6 | Market beta | beta_1 |
| 7 | Dollar trading volume | dtv_12 |
| 8 | F.6.21 idiosyncratic skewness per the Fama and French | isff_1 |
| 9 | Idiosyncratic Skewness per the q-factor Model | isq_1 |
| 10 | Short-term reversal | srev |
| | **Prominent Anomalies (9)** | |
| 1 | Total accruals | accrual |
| 2 | Asset growth | asset_growth |
| 3 | Composite equity issues | composite_issue |
| 4 | Distress | distress |
| 5 | Gross profitability premium | gp |
| 6 | Investment-to-assets | invasset |
| 7 | Momentum | momentum |
| 8 | O-score | oscore |

| | | |
|---|---|---|
| 9 | Net stock issues | stock_issue |

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