Not All Disasters are Alike: Extreme Weather Events and Stock Performance*

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Abstract

We apply an event-study approach to assess the effects of extreme weather and climate disasters on affected stock performance. Between 1980 and 2023, the average cumulative abnormal returns (CARs) following 376 major climate disasters exhibit a prolonged positive post-disaster drift. The impact varies considerably across disaster types: a pronounced negative drift for landfall hurricanes, a significantly positive drift for winter storms, and no clear drift for other climate disasters. The prolonged negative post-hurricane drift is prominent before Hurricane Sandy but largely fades afterward. Our findings suggest that the stock market misprice certain climate disasters and has made progress in efficiently pricing disaster risks post-Sandy.

JEL Codes: G10, G14, Q51, Q54

Keywords: Extreme weather, event study, cumulative abnormal return, post-disaster drift

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1. Introduction

Extreme weather and climate disasters result in immense damage and significant loss of life. According to the National Oceanic and Atmospheric Administration (NOAA), the total inflation-adjusted cost of billion-dollar weather and climate disaster events in the U.S. is estimated to exceed $1.1 trillion in 2024 dollars from 2017 to 2023, and nearly $2.72 trillion in 2024 dollars for 1980-2023.[1] Given the widespread disruptions these disasters cause to human activity in affected areas and their potentially far-reaching societal impacts, it is of natural interest to understand how financial markets react to and price the novel risks stemming from these events. However, evidence on this issue remains scarce.

Our study seeks to address this gap. In this paper, using the NOAA's billion-dollar weather and climate disaster events data we apply an event-study approach to examine the effects of extreme weather and climate disasters on both short-run and long-run stock returns of affected firms. Our findings reveal that, between 1980 and 2023, the average cumulative abnormal returns (CARs) following 376 major climate disasters exhibit a positive post-disaster drift. This drift persists on an upward trajectory for nearly 40 days after the disaster occurrence before reversing course toward zero. This result is robust across different risk models and definitions of event day 0.

The dynamics of CARs vary considerably across different types of weather and climate disasters, both in the short-run and long-run event windows. Tropical cyclones are affiliated with significantly negative and steadily declining CARs, while winter storms are accompanied by significantly positive and monotonically increasing CARs. The other five types of weather and climate disasters appear to have minimal effects on the stock performance of affected firms. The dynamics of CARs also evolve over time. The pre-Hurricane-Sandy period witnesses a

[1] See https://www.ncei.noaa.gov/access/billions/time-series.

more pronounced post-disaster drift compared to the post-Sandy eriod, where CARs tend to revert toward zero more quickly.

Landfall hurricanes are among the most closely monitored and economically destructive weather events. As such, we take a closer look at the impacts of tropical cyclones on stock performance. Our analysis reveals a persistent and prolonged negative post-cyclone drift in the stock market. This drift is particularly pronounced in the pre-Hurricane-Sandy period but largely disappears afterward. However, this drift remains evident in both the pre- and post-Hurricane-Katrina periods.

The existence of this prolonged post-disaster drift suggests that the stock market underreacts to climate disaster risks, including cyclones. The fact that the drift is evident before Sandy but absent afterward indicates that the market has made significant progress in efficiently pricing these risks post-Sandy. Hurricane Sandy's direct impact on Wall Street likely prompted a reassessment of hurricane and broader climate disaster risks by financial markets (also see, e.g., Kruttli, Tran, and Watugala, 2023; Addoum, Eichholtz, Steiner, and Yönder, 2024).

Our study contributes to the climate finance literature. A significant part of the literature examines the impacts of climate change on asset prices and investor activities (see, e.g., Giglio, Kelly, and Stroebel (2021) for a survey of the literature). To our knowledge, we are the first to provide a comprehensive assessment of how different types of extreme weather and climate disasters affect stock returns. We find remarkable heterogeneity across disaster types: stock returns affected by hurricanes experience a prolonged and persistent negative post-disaster drift, while those affected by winter storms exhibit a prolonged positive drift.

Our study also adds to the disaster risk literature that assesses the roles of disasters in influencing financial market outcomes. Recent works in this literature expand the scope of the literature from macroeconomic disasters to natural disasters with a focus on hurricane strikes (e.g., Dessaint and Matray, 2017; Lanfear, Lioui, Siebert, 2019; Kruttli, Tran, and Watugala, 2023). We expand this focus by examining the impacts of a wider range of climate disasters on both short-run and long-run stock performance.

Our findings suggest that the stock market may misprice some, if not all, extreme weather and climate events. This reinforces concerns among academics and policymakers that asset mispricing of climate risks could lead to sudden price corrections, potentially threatening financial stability. As such, a careful assessment of financial market reactions to extreme weather and climate events is crucial, alongside the development of appropriate policy responses to address the risks posed by these disasters.

The remainder of the paper proceeds as follows. Section 2 describes the data and sample construction. Section 3 explains the empirical method. Section 4 presents the empirical results. Section 5 concludes.

2. Data

Our data come from several sources. We gather the data on US. billion-dollar weather and climate disaster events from the U.S. NOAA's National Centers for Environmental Information (NCEI). We obtain daily stock returns from the Center of Research in Security Prices (CRSP) and firm financial information from Standard & Poors' Compustat.

The billion-dollar weather and climate disaster dataset covers 376 disaster events over the 1980-2023 period and classifies disasters into seven types: drought, flooding, freeze, severe storm, tropical cyclone, wildfire, and winter storm. The dataset includes details such as event begin and end dates, cost (both unadjusted and inflation-adjusted), casualties, and affected areas (for more on data analysis, see Smith and Katz (2013)).

We merge the disaster events data with the firm-level data using the firm location information. Specifically, if a firm's headquarter state, if unavailable then supplemented by the firm's incorporation state, lies in an area affected by a weather and climate disaster, we consider the firm to be impacted by that event.

Table 1 reports descriptive information about the weather and climate disasters. Panels A, B, and C present the costs in 2024 dollars, casualties and durations of the disasters, respectively. Across all 376 disasters, the average cost is 7.24 billion dollars with a median of 2.47 billion dollars, casualties average at 43.4 deaths with a median of 5 deaths, and on average the disasters last 33.96 days with a median of 4 days. Among the 376 disasters, there are 31 droughts, 44 floodings, 9 freezes, 186 severe storms, 62 tropical cyclones, 22 wildfires, and 22 winter storms over 1980-2023. Of the seven types of disasters, tropical cyclones (hurricanes mainly) cause the highest average costs, followed by droughts. Indeed, tropical cyclones and droughts are also ranked top 2 when we look at the median costs or the maximum costs. Regarding casualties inflicted, tropical cyclones and droughts again lead the pack of seven types of climate disasters when we refer to the mean or maximum values, and they fall behind winter storms when we compare the median casualties. In terms of durations, droughts stand out with the largest mean and median values, followed by wildfires; their mean and median durations are all longer than 150. Despite the huge losses they bring about, tropical cyclones last for a short period, with a mean value of 4.31 days and a median value of 3 days, respectively.

Panel D of Table 1 lists the number of weather and climate disasters across years. Although the number varies year-by-year, there is a clear uptick trend in the number of disasters per year as time goes by. This trend is particularly prominent since 2008 and on, with the year of 2023 alone witnessing 27 disasters, the largest value in the entire 44-year period.

In summary, the detailed breakdown highlights the economic and human toll of different types of climate disasters, with tropical cyclones standing out as particularly costly and deadly, but relatively short in duration. The rising frequency of disasters underscores the increasing relevance of this issue over time.

3. Empirical Method

We use the event-study approach to assess the impacts of the disaster events on the affected firms' stock returns. As in a typical event study, for each affected stock we first estimate the parameters (intercept, factor loadings, and residual variance) of a risk mode in the pre-event estimation window and apply the estimated intercept and factor loadings to the event window to calculate the expected or "normal" returns. We calculate the abnormal returns in the event window as the difference between the actual returns and the normal returns. We then calculate the cumulative abnormal returns (CARs) for each affected stock along the event time. Finally, we aggregate the stock-level CARs across affected stocks and calculate the corresponding test statistics along the event time.[2]

In implementation, we define event day 0 as the disaster begin date and recenter the other calendar dates relative to event day 0. Therefore, a negative (positive) event day refers to a trading day before (after) the event occurrence. For robustness we also define the disaster end date as event day 0. We use four risk models to obtain CARs: market-adjusted model, Capital Asset Pricing Model (CAPM), Fama-French three-factor model, and Fama-French three-factor plus momentum factor model. We set the length of the estimation window to 100 (in trading days) and require a minimum of 70 non-missing return observations within the estimation window to ensure decent parameter estimations. We choose the event window to start 10 days prior to day 0, and we end the event window at 60 days after day 0 so that we can assess both the short-run and the relatively long-run impacts of the disasters on affected stock returns. To reduce the chances that the disaster-induced return variation affects the risk model estimation in the estimation window, we impose a 50-day gap between the end of the estimation window and the start of the event window. For robustness, we also impose other gaps such as a 5-day

[2] See the detailed explanation of the event-study approach at https://wrds-www.wharton.upenn.edu/pages/wrds-research/applications/event-studies/.

gap, 10-day gap, 15-day gap, etc., between the estimation window and the event window. The results are available on request.

4. Results

4.1 Short-run Impacts

We first examine the short-run impacts of weather and climate disasters on stock performance. For this purpose, we focus on the shorter event window from event day -10 to event day +10.

4.1.1 Impacts of All Disasters

Figure 1 plots the dynamics of average CARs, along with their upper and lower bounds of the 95% confidence intervals, during this short event window when we pool all the weather and climate disasters and use the disaster begin date as event day 0. Panels A, B, C, and D correspond to the following risk models, market-adjusted model, market model (i.e., CAPM), Fama-French three-factor (FF3) model, and Fama-French three-factor-plus-momentum-factor model, respectively.

Two important distinctions emerge from comparing the four graphs of Figure 1. First, pre-event CAR dynamics. When using the market-adjusted model or the CAPM, the average CARs are significantly positive starting from event day -7. This suggests that stock prices tend to rise before the event occurrence date when these simpler models are used. In contrast, when using the FF3 model or the FF3 plus momentum model, the average CARs are not significantly different from zero in most of the pre-event days, only becoming significantly positive on event day -1. Second, magnitude of CARs. The CARs obtained using the market-adjusted model and the CAPM are of similar magnitude across event days, suggesting that these two models produce comparable estimates of the abnormal returns. However, the magnitudes of the CARs substantially decrease when additional factors are included in the risk model (i.e., FF3 and FF3 plus momentum models), indicating that the more complex models attribute some of the variation in stock returns to these additional factors, reducing the abnormal returns. These distinctions highlight how the choice of risk model significantly influences the calculation of CARs and, consequently, the interpretation of stock market reactions to climate disasters.

Despite the different CAR estimates from different risk models, there is a striking common pattern in the dynamics of CARs across the four graphs of Figure 1. That is, regardless of the risk models used for estimations, the average CARs are significantly positive starting from event day -1 and continue to remain significantly positive afterwards and throughout the estimation window; moreover, the average CARs display a generally increasing pattern since event day -1.

Despite the differences in CAR estimates produced by various risk models, a striking commonality in the dynamics of CARs is evident across the four graphs in Figure 1. Specifically, regardless of the risk model used (market-adjusted, CAPM, Fama-French three-factor, or Fama-French three-factor-plus-momentum model), the following pattern emerges. The average CARs become significantly positive starting from event day -1 and this significant positivity persists throughout the estimation window. Additionally, the CARs exhibit a generally increasing trend from event day -1 onwards, indicating that stock prices continue to rise after the disaster event has occurred.

Replicating the structure of Figure 1, Figure 2 plots the average CARs during the event window from event day -10 to event day +10, with the disaster end date as event day 0, for all the climate disasters combined. The graphs in Figure 2 largely resemble the corresponding graphs in Figure 1, and our above discussions of Figure 1 carry over to Figure 2. In particular, the average CARs are significantly positive since the disasters hit and still show an increasing pattern initially. Compared to Figure 1, one change in Figure 2 is that the increasing pattern lasts only up to event day +4 then gradually tapes off afterwards; but the average CARs remain significantly positive after day +4.

As shown in both Figure 1 and Figure 2, using different risk models materially affects the calculations of CARs. The CARs obtained using the FF3 and momentum factors are insignificantly different from zero in all the pre-event days except event day -1, which is a desirable feature of an event study. Additionally, among the four sets of CARs based on the four different risk models, the CARs obtained from the four-factor model almost always have the smallest magnitude across the event period. As a result, the ensuing analysis focuses on using the FF3 and momentum factors to calculate the CARs as they provide the most conservative estimates of the impacts of the disasters on stock returns.

4.1.2 Impacts of Individual Types of Disasters

There are seven types of weather and climate disasters: drought, flooding, freeze, severe storm, tropical cyclone, wildfire, and winter storm. We proceed to investigate the short-run impacts of each type of weather and climate disasters on the stock performance. Figure 3, Panels A to G, respectively plot the average CARs, together with their upper and lower 95% confidence limits, for each corresponding type of disasters during the [-10,+10] event window.

We first look at droughts. The figure in Panel A appears to show that droughts do not have a significant effect on stock performance, especially in the event day 0 and after. The average CARs are largely negative but not statistically significant from zero in most days of the entire window. The few exceptions are for event days -5 through -1, during which the average CARs are significantly negative with a trough of -0.34% in event day -2.

We then examine floodings. Similar to droughts, floodings do not appear to significantly affect the stock performance after the event occurs. In Panel B, the average CARs for those days are negative but not statistically significant from zero. However, the average CARs turn significantly negative before the event occurs, starting from -0.16% in event day -8, continuing a decline trend to as low as -0.44% in event day -2, and rebounding in event day -1 then rising to -0.24% in event day 0.

The graph in Panel C show that freezes do not have significant effects on stock performance in the entire event window. None of the average CARs are significantly different from zero.

We move on to Panel D, which graphs the dynamics of the CARs for firms affected by severe storms in the event window. Unlike drought, flooding and freeze, severe storms have a positive impact on these firms' stock performance. The average CARs are all positive throughout the event window; they are significantly positive starting from event day -6 and continue to be significantly positive until event day +1.

Panel E plots the dynamics of the CARs for firms affected by tropical cyclones in the event window. One pronounced phenomenon is that the average CARs are all negative throughout the event window and the negative average CARs are statistically significant starting from event day -8. More strikingly, the average CARs display an almost monotonically decreasing pattern. Specifically, the average CARs equal -0.12% in event day -8, keep declining to -0.26% on event day 0, and continue the decline trajectory after the disasters hit. The average CARs drop to -0.36% by event day +5 and further a sharp drop to -0.79% in event day +10. Clearly, tropical cyclones severely hurt the short-run stock performance of impacted firms. The result is consistent with the anecdotal evidence that this type of extreme weather, although relatively short-lived compared to most of other types of extreme weather conditions, brings substantia damages to the fundamentals of affected firms. In turn, the stock market reacts negatively both before and after the tropical cyclones hit.

The figure in Panel F illustrates the dynamics of the CARs associated with wildfires in the event window. Although the average CARs are positive in most of the event days, they are not significantly different from zero.

We zero in on the last type of climate disaster. Panel G highlights the dynamics of the average CARs for firms affected by winter storms. One prominent pattern is that the average

CARs are all positive and become statistically different from zero starting from event day -4 and onward. Moreover, opposite to those affiliated with tropical cyclones, the average CARs affiliated with winter storms show an almost monotonically increasing pattern throughout the event window. Specifically, the average CARs are insignificant at 0.02% in event day -9, become statistically significant at 0.13% in event day -4, and rise to 0.56% in event day 0. The average CARs continue to increase after the event occurs, equal to 0.76% in event day +1, jumping to 1.13% by event day +6, and furthering their accension to 1.44% in event day +10.

For robustness, we also use the disaster end date as event day 0. Figure 4 illustrates the dynamics of the CARs in the event window for each type of weather and climate disasters. In general, the results are largely similar to the ones using the disaster begin date as event day 0. One notable exception is the case of droughts. Unlike Panel A of Figure 3 which features insignificantly negative CARs in the post-event days, Panel A of Figure 4 shows that the post-event average CARs affiliated with droughts are positive since event day +1 and the positive average CARs are statistically significant since event day +2 and on. This difference could be due to that droughts last a long time, with a mean of 227.5 days and a median of 184 days. Interestingly, in Panel A of Figure 4, the positive average CARs for firms affected by droughts in the post-event days display an inverse U-shape.

In closing this subsection, we emphasize one result prominent in both Figure 3 and Figure 4. That is, the dynamics of CARs vary considerably across different types of weather and climate disasters in the short event window. Tropical cyclones are affiliated with significantly negative and monotonically decreasing CARs, but winter storms are accompanied by significantly positive and monotonically increasing CARs; the other five types of weather and climate disasters appear to have little impacts on the stock performance of affected firms. Additionally, it is also worth point out that, regardless of the definition of event day 0, the magnitude of the CARs associated with winter storms are much larger than the magnitude of the CARs affiliated with the other types of weather and climate disasters. As a result, the dynamics of the overall CARs if we combine all the seven types of disasters, as shown in either Figure 1 or Figure 2, are likely dominated by and thus resemble the dynamics of the CARs affiliated with winter storms, as shown in Panel G of either Figure 3 or Figure 4.

4.2 Longer-run Impacts

To gain some insights into whether the stock market misprices the impacts of the weather and climate disasters, we proceed to assess the longer-run impacts of weather and climate disasters on stock performance. Toward this end, we use a longer event window, specifically, from event day -10 to event day +60.[3]

4.2.1 Full Sample

Figure 5 illustrates the dynamics of average CARs, together with their upper and lower 95% confidence limits, for all climate disasters over the longer event window. Focusing first on the dynamics in Panel A1, where event day 0 is the disaster begin date, two key patterns emerge. First, the average CARs remain positive from event day 0 though day +60 and are significantly positive from event day 0 through day +48. Second, like the dynamics in the shorter event window described earlier, the CARs follow a generally upward trend after event day +10, despite some fluctuations in the interim, reaching a peak of 0.37% on event day +37. After this peak, the average CARs begin a decline on event day +38 and continue this downward trend. By event day +49, the average CARs are no longer significantly different from zero and remain so through day +60.

If event day 0 is the disaster end date, the two patterns — significantly positive average CARs and a general upward trend over time — become even more pronounced. As depicted in

[3] Studies of the post earnings announcement drift (PEAD) usually end the event window at event day +60, with the earnings announcement date as event day 0. Following this practice, we choose to end the longer-run event window of our analysis at event day +60 too.

Panel A2 of Figure 5, the average CARs move along the inverse-U shape, as described above for the short [0.+10] event window, until event day +15, after which the average CARs largely stay put until day +19. Following this brief pause, they resume an upward trajectory, reaching 0.60% on event day +37. Thereafter, the average CARs begin a gradual decline, ending at 0.51% by day +60.

4.2.2 Pre- and Post-Sandy Subperiods

Hurricane Sandy struck the tri-state area around New York City at the end of October 2012, causing severe flooding in New York City, including Wall Street, and unprecedented damage to the region. Researchers argue that, thanks to this experience, financial markets have shown a marked shift in their attention to and pricing of the weather and climate disasters post Hurricane Sandy (e.g., Kruttli, Tran, and Watugala, 2023; Addoum, Eichholtz, Steiner, and Yönder, 2024). Consequently, we divide the full sample period into two subperiods: pre-Sandy (inclusive) and post-Sandy.

We first assess the impact of weather and climate disasters on the stock market during the pre-Sandy subperiod. Panels A2 and B2 of Figure 5 plot the dynamics of average CARs, along with their upper and lower 95% confidence limits, over the longer window, with the disaster begin and end dates as event day 0, respectively. Notably, the CAR dynamics for pre-Sandy climate disasters closely mirror the CAR dynamics for the full sample period. In particular, much like Panels A1 and B1, both Panels A2 and B2 reveal a persistent post-disaster drift in stock market responses to weather and climate disasters during the full subperiod from 1980 through October 2012.

We then analyze the impact of weather and climate disasters on stock performance during the post-Sandy subperiod. When event day 0 is the disaster start date, the average CARs exhibit a gradual overall decline in Panel A3. Starting with a significantly positive value of 0.27% on event day 0, the average CARs rise to a peak of 0.32% by day +4, then gradually decline to a still significantly positive value of 0.19% by day +14, and further the downward movement, reaching -0.03% by day +60. It is important to note that from event day +15 onwards, the average CARs are no longer statistically different from zero, a pattern that persists until event day +60. When event day 0 is the disaster end date, the average CARs are significantly positive from event day -1 through event day +56 and exhibit a somewhat inverse-U shape throughout the longer event window in Panel B3. Beginning with 0.14% in event day -1, the average CARs rise to 0.34% in day +3, fall back to 0.21% in day +7, then resume a choppy upward ride to 0.47% by day +33, followed by a gradual decline to 0.23% by day +60.

The CAR dynamics in the post-Sandy subperiod vary with different choices of event day 0. This is partly due to that average duration of disasters is almost 34 days. More importantly, the CAR dynamics in the post-Sandy subperiod differ notably from the CAR dynamics in the pre-Sandy subperiod, suggesting that the stock market has experienced some significant shift in evaluating and pricing the impacts of weather and climate disasters over time.

4.2.3 Discussions

In summary, Panels A1 and B1 clearly show a prolonged post-climate-disaster drift in stock market responses to weather and climate disasters throughout the full sample period from 1980 to 2023. When the sample is divided into pre-Sandy and post-Sandy subperiods, this prolonged drift is evident in the pre-Sandy subperiod but absent in the post-Sandy period. This finding suggests that the overall pattern is primarily driven by the pre-Sandy dynamics. Furthermore, in the post-Sandy subperiod, the CARs do not display a clear pattern, let alone a prolonged drift; this is particularly apparent when event day 0 is the disaster start date, whereas the average CARs are not significantly different from zero on most post-disaster days.

Drawing an analogy to the post-earnings-announcement drift, our evidence of a prolonged post-climate-disaster drift suggests that the stock market underreact to weather and climate disasters. Previous research has reported similar mispricing of extreme weather events in the financial market. For instance, Hong, Li, and Xu (2019) find evidence of market underreactions when using drought indices to predict food company stock returns. Conversely, Alok, Kumar, and Wermers (2020) document evidence of market overreactions when examining mutual fund performance following natural disasters.

Notably, the post-climate-disaster drift is evident in the pre-Sandy subperiod but disappears in the post-Sandy period, implying that the stock market underreactions to climate disasters were prominent before Sandy and became significantly weaker afterwards. Other studies have drawn similar conclusions in different contexts. For example, in assessing the impacts of landfall hurricanes on affected firm return volatility, Kruttli, Tran, and Watugala (2023) find that the stock market underreacts to hurricane risk, but this underreaction diminishes after Hurricane Sandy. Similarly, Addoum, Eichholtz, Steiner, and Yönder (2024) show that commercial real estate markets experienced a large and persistent price decline after Hurricane Sandy, indicating that professional investors underestimated flood risks prior to Sandy and adjusted this underreaction post-Sandy.

4.3 Dive into Impacts of Tropical Cyclones

Landfall hurricanes are among the most watched and economically destructive weather and climate disasters, impacting a wide range of major economic centers. Researchers often focus on hurricane strikes when studying the impacts of natural disasters on economic and financial outcomes (e.g., Dessaint and Matray, 2017; Lanfear, Lioui, Siebert, 2019; Kruttli, Tran, and Watugala, 2024). In this subsection, we dive into the effects of tropical cyclones on the stock performance of affected firms.

4.3.1 Long-term Impacts

Figure 6 plots the dynamics of average CARs, along with their upper and lower 95% confidence bounds, in the longer event window from day -60 to day +60, where event day 0 is the disaster begin date. Panel A illustrates the market reactions to all tropical cyclones during the full sample period. Extending the shorter-run dynamics shown in Panel E of Figure 3, the average CARs continue their almost-monotonic decline trend and remain significantly negative throughout the longer event window. In the shorter event window, the average CARs drop sharply from -0.51% on event day 0 to -1.14% by day +10. Beyond this period, the downward trend continues, with the average CARs falling to -1.87% by event day +20, -2.37% by day +30, -2.54% by day +40, and -2.99% by day +50. By event day +60, the average CARs recover only slightly to -2.93%.

Hurricane Sandy directly impacted Wall Street and disrupted financial market operations in late October 2012. There is evidence suggesting that financial markets have shifted in how they price hurricane risk since then (e.g., Kruttli, Tran, and Watugala, 2023; Addoum, Eichholtz, Steiner, and Yönder, 2024). As a result, we divide the full sample period into pre-Sandy (including Sandy) and post-Sandy subperiods. Panels B and C of Figure 6 illustrate the CAR dynamics associated with tropical cyclones during these two subperiods, revealing a striking contrast.

In the pre-Sandy subperiod (Panel B), the average CARs are all significantly negative and exhibit a persistent decline until event day +32, followed by a gradual and largely upward movement. Specifically, the average CARs start at -0.24% on event day -3, reach -0.28% on event day 0, decline to -0.85% by event day +10, -1.51% by day +20, and bottom out at -1.96% by day +32. Afterward, the average CARs recover slightly to -1.85% by day +40, dip again to -1.96% by day +50, and finally rebound to -1.57% by event day +60. In contrast, during the post-Sandy subperiod (Panel C), the average CARs largely fluctuate around zero between event day -10 and event day +24, before turning negative. However, most of these values are not statistically significant, except for the period from event day +37 to event day +56, during which the average CARs are significantly negative.

To gain further insights into the evolution of financial market reactions to tropical cyclones, we also divide the full sample period into pre- and post-Katrina subperiods. Hurricane Katrina first struck South Florida, regained strength in the Gulf of Mexico, and made landfall on coastal Louisiana in late August 2005, inundating New Orleans. It caused the largest dollar loss to date and the second-highest number of deaths, surpassed only by Hurricane Maria in September 2017.

Panels D and E of Figure 6 depict the CAR dynamics associated with tropical cyclones in the pre- and post-Katrina subperiods, respectively. The two panels display a prominent common pattern: in both subperiods, the average CARs exhibit a persistent and prolonged decline starting from event day 0, followed by a V-shaped bounce after a considerable period. Additionally, the average CARs on and after event day 0 are all significantly negative. One notable difference is that the impact of tropical cyclones is both longer-lasting and significantly stronger in the post-Katrina subperiod. In the pre-Katrina subperiod, the average CARs begin at -0.23% on event day 0, decline steadily to a low of -1.53% on event day +29, and then take a V-shaped turn, inching up to -0.80% by day +60. In the post-Katrina subperiod, the average CARs start at -0.33% on event day 0, continue to fall to a low of -4.27% by day +50, and then recover slightly to -3.30% by day +60.

We further investigate whether the impact of tropical cyclones on stock performance varies based on the severity of the cyclones. We classify tropical cyclones into two groups according to their estimated damage costs. Severe cyclones include eight hurricanes—Katrina, Harvey, Ian, Maria, Sandy, Ida, Irma, and Andrew—each of which caused losses exceeding 60 billion 2024 dollars. The remaining tropical cyclones are classified as mild. Panels F and G of Figure 6 display the CAR dynamics for mild and severe cyclones, respectively, over the longer event window.

The two panels reveal a clear distinction in the CAR dynamics between the two types of cyclones. For mild cyclones, the average CARs are significantly negative, showing a persistent and prolonged decline until event day +50, followed by a mild recovery. In contrast, the average CARs for severe cyclones remain relatively flat, hovering around -0.50% until event day +37, after which they drop to -0.86% by day +40 and then rise to 0.80% by day +60. However, throughout the entire event window, the average CARs for severe cyclones are not statistically significantly different from zero.

4.3.2 Discussions

In summary, Figure 6 reveals a persistent and prolonged post-cyclone drift in the stock market. This drift is particularly pronounced in the pre-Sandy subperiod but largely disappears in the post-Sandy subperiod. However, the drift remains evident in both the pre- and post-Katrina subperiods. Additionally, the drift is clear for mild cyclones but absent for severe ones. As a robustness check, we replicate the analysis of CAR dynamics using the cyclone end date as event day 0, with the corresponding results shown in Figure 7, Panels A to G. The findings in Figure 7 closely mirror those in Figure 6 and, for brevity, we do not restate them.

The existence of a persistent and prolonged post-cyclone drift suggests that the stock market underreacts to cyclone risks. Moreover, the fact that this drift is evident in the pre-Sandy subperiod but absent in the post-Sandy subperiod indicates that the stock market underreacted to cyclone risks before Sandy but became more efficient at pricing these risks afterward. This shift likely reflects the direct impact of Hurricane Sandy on Wall Street, leading to a reassessment of hurricane risk by financial markets (see, e.g., Kruttli, Tran, and Watugala, 2023; Addoum, Eichholtz, Steiner, and Yönder, 2024).

In contrast, despite Hurricane Katrina being the most costly hurricane recorded to date, it did not prompt a similar shift in stock market pricing efficiency. Our finding that the post-cyclone drift persists in both the pre- and post-Katrina subperiods supports this conclusion. In a different context, Kruttli, Tran, and Watugala (2023) also concluded that Hurricane Katrina did not significantly alter the stock market's approach to pricing hurricane risks. Furthermore, because six of the eight severe hurricanes occurred after Sandy, our finding that the post-cyclone drift is nonexistent for severe cyclones but prominent for mild ones aligns with the stock market becoming more efficient at pricing hurricane risks after Hurricane Sandy.

5. Conclusions

In this paper, we use an event-study approach to evaluate the effects of extreme weather and climate disasters on stock performance of affected firms. We find that, between 1980 and 2023, the average cumulative abnormal returns (CARs) associated with 376 major climate disasters in the U.S. exhibit a prolonged positive post-disaster drift. The positive drift is more pronounced in the pre-Hurricane-Sandy period than in the post-Sandy period. The impact varies considerably across different types of climate disasters: a pronounced negative drift for landfall hurricanes, a significantly positive drift for winter storms, and no clear drift for other climate disasters. The prolonged negative post-hurricane drift is particularly evident in the pre-Sandy period but largely disappears afterward. In contrast, this negative post-hurricane drift persists in both the pre- and post-Hurricane-Katrina periods. Taken together, our results suggest that the stock market misprice some, if not all, extreme climate disasters, but has made significant progress in efficiently pricing hurricane and broader climate disaster risks post-Sandy.

Our study adds to the understanding of whether financial markets efficiently price emerging risks related to climate change. Our findings align with the views of finance professionals and academics, who argue that financial markets tend to underestimate and/or underreact to climate risks (Stroebel and Wurgler, 2021). Moreover, our analysis has implications for policy making aimed at addressing the challenges posed by climate change.

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Table 1. Descriptive statistics

This table reports summary information about the billion-dollar weather and climate disasters in U.S. over the 1980-2023 period. Panels A, B and C present the costs (in 2024 dollars), deaths, and durations (in number of days) of the disasters, respectively. Panel D lists the number of disasters across years. The data source is National Oceanic and Atmospheric Administration's (NOAA) National Centers for Environmental Information (NCEI): https://www.ncei.noaa.gov/access/billions/.

Panel A. Inflation-adjusted dollar cost

	Nobs	Mean	Median	Minimum	Maximum	Stdev
Drought	31	11.647	7.010	2.018	54.411	12.434
Flooding	44	4.571	2.542	1.133	46.114	7.177
Freeze	9	4.126	3.576	1.290	8.398	2.307
Severe Storm	186	2.501	1.856	1.064	14.311	1.932
Tropical Cyclone	62	22.768	6.491	1.071	200.047	39.205
Wildfire	22	6.633	3.205	1.477	30.000	7.772
Winter Storm	22	4.557	2.530	1.185	26.997	5.731
All	376	7.240	2.466	1.064	200.047	18.155

Panel B. Deaths caused by the disasters

	Nobs	Mean	Median	Minimum	Maximum	Stdev
Drought	31	145.9	16	0	1260	281.6
Flooding	44	16.77	10.5	0	62	15.26
Freeze	9	18	0	0	151	49.98
Severe Storm	186	11.26	1	0	321	31.73
Tropical Cyclone	62	111.2	21	0	2981	436.8
Wildfire	22	24.32	16.5	0	106	28.81
Winter Storm	22	63.73	23.5	0	270	82.73
All	376	43.48	5	0	2981	201.7

Panel C. Duration of the disasters

	Nobs	Mean	Median	Minimum	Maximum	Stdev
Drought	31	227.5	184	92	366	102.2
Flooding	44	24.75	6.5	2	139	35.87
Freeze	9	6	7	3	11	3.082
Severe Storm	186	3.747	3	1	90	6.6
Tropical Cyclone	62	4.306	3	1	15	2.695
Wildfire	22	158.1	183	1	365	80.09
Winter Storm	22	5.909	4	2	31	5.935
All	376	33.96	4	1	366	77.72

Panel D. Number of disasters across years

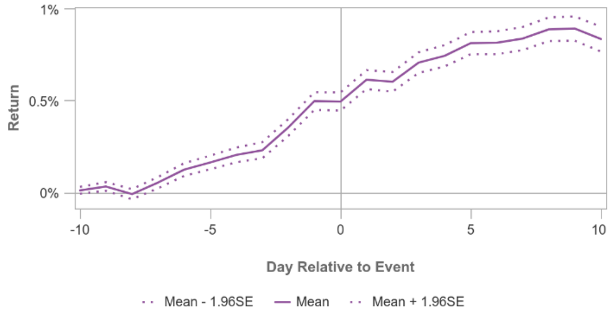
Year	Drought	Flooding	Freeze	Severe Storm	Tropical Cyclone	Wildfire	Winter Storm	Total
1980	1	1	0	0	1	0	0	3
1981	0	0	1	1	0	0	0	2
1982	0	2	0	2	0	0	1	5
1983	1	1	1	0	1	0	0	4
1984	0	0	0	2	0	0	0	2
1985	0	1	1	1	3	0	1	7
1986	1	1	0	1	0	0	0	3

1988	1	0	0	0	0	0	0	1
1989	1	0	1	1	2	0	1	6
1990	0	1	1	1	0	1	0	4
1991	1	0	0	1	1	1	0	4
1992	0	0	0	4	2	0	1	7
1993	1	1	0	1	0	1	1	5
1994	0	1	0	1	1	1	2	6
1995	1	1	0	2	3	0	0	7
1996	1	2	0	0	1	0	1	5
1997	0	2	0	2	0	0	0	4
1998	1	1	1	3	3	0	1	10
1999	1	0	0	1	1	0	2	5
2000	1	1	0	1	0	1	1	5
2001	0	0	0	2	1	0	0	3
2002	1	0	0	2	2	1	0	6
2003	1	0	0	4	1	1	0	7
2004	0	0	0	2	4	0	0	6
2005	1	0	0	1	4	0	0	6
2006	1	1	0	5	0	1	0	8
2007	1	0	2	1	0	1	0	5
2008	1	1	0	6	3	1	0	12
2009	1	1	0	6	0	1	0	9
2010	0	2	0	4	0	0	1	7
2011	1	2	0	10	2	1	2	18
2012	1	0	0	7	2	1	0	11
2013	1	2	0	7	0	0	0	10
2014	1	1	0	7	0	0	1	10
2015	1	2	0	6	0	1	1	11
2016	1	4	0	8	1	1	0	15
2017	1	2	1	11	3	1	0	19
2018	1	0	0	10	2	1	2	16
2019	0	3	0	8	2	1	0	14
2020	1	0	0	13	7	1	0	22
2021	1	2	0	11	4	1	1	20
2022	1	2	0	11	3	1	1	19
2023	1	3	0	19	2	1	1	27
1980-2023	31	44	9	186	62	22	22	376

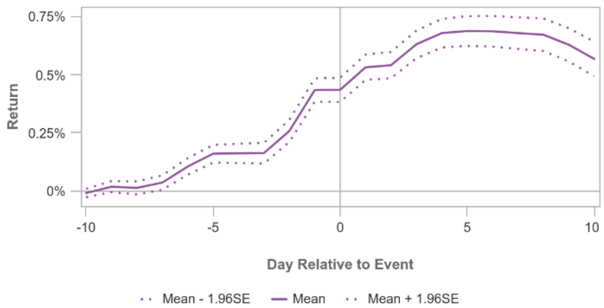
Figure 1. CARs: All Climate Disaster Events Combined

This figure plots the cumulative abnormal returns (CARs) from day -10 to day +10, where day 0 is the disaster begin date, for all weather and climate disaster events over the 1980-2023 period. The solid line graphs the mean CARs, and the top and bottom dotted lines represent the upper and lower 95% confidence limits, respectively. In Panels A, B, C, and D, we use the market adjustment model, market model (i.e., CAPM), and Fama-French three-factor (FF3) model, and Fama-French three factors plus momentum to calculate the abnormal returns, respectively. A total of 230,815 firm-events with non-missing returns are used in the calculations.

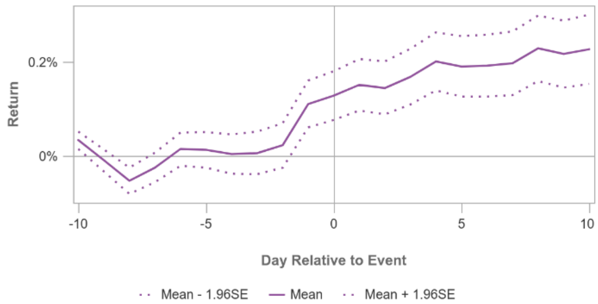
Panel A. Market-adjusted model



Panel B. Market model



Panel C. Fama-French three-factor (FF3) model



Panel D. FF3 plus momentum model

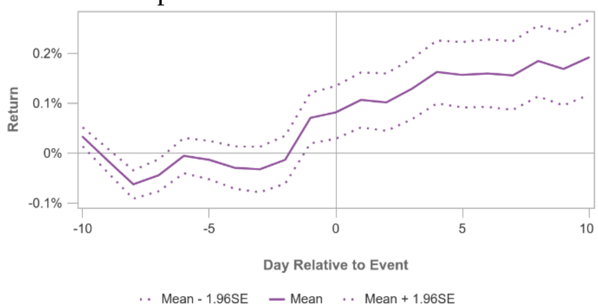
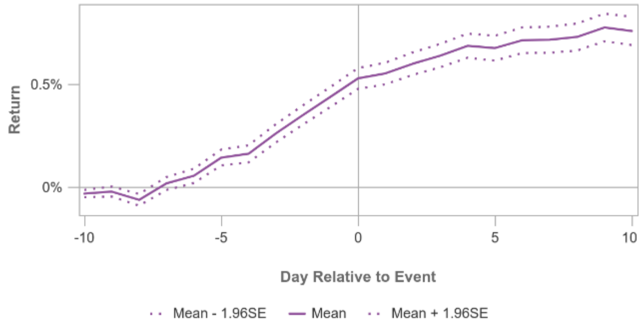


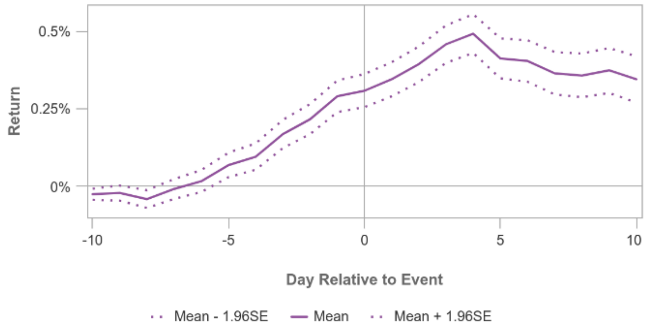
Figure 2. CARs: All Climate Disaster Events Combined – Alternative Day 0

This figure plots the cumulative abnormal returns (CARs) from day -10 to day +10, where day 0 is the disaster end date, for all weather and climate disaster events over the 1980-2023 period. The solid line graphs the mean CARs, and the top and bottom dotted lines represent the upper and lower 95% confidence limits, respectively. In Panels A, B, C, and D, we use the market adjustment model, market model (i.e., CAPM), and Fama-French three-factor (FF3) model, and Fama-French three factors plus momentum to calculate the abnormal returns, respectively. A total of 233,223 firm-events with non-missing returns are used in the calculations.

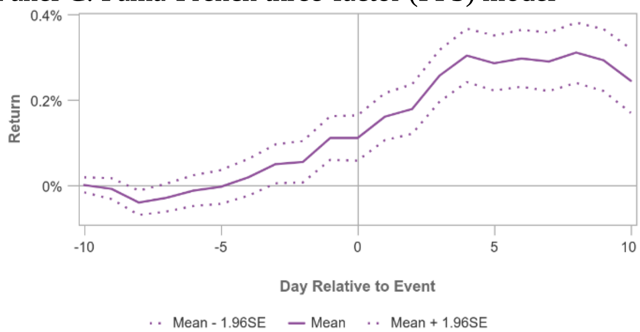
Panel A. Market-adjusted model



Panel B. Market model



Panel C. Fama-French three-factor (FF3) model



Panel D. FF3 plus momentum model

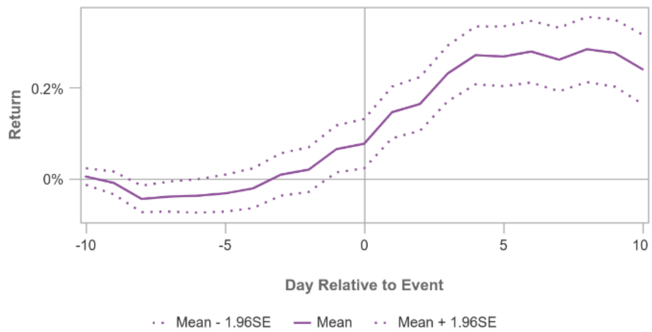
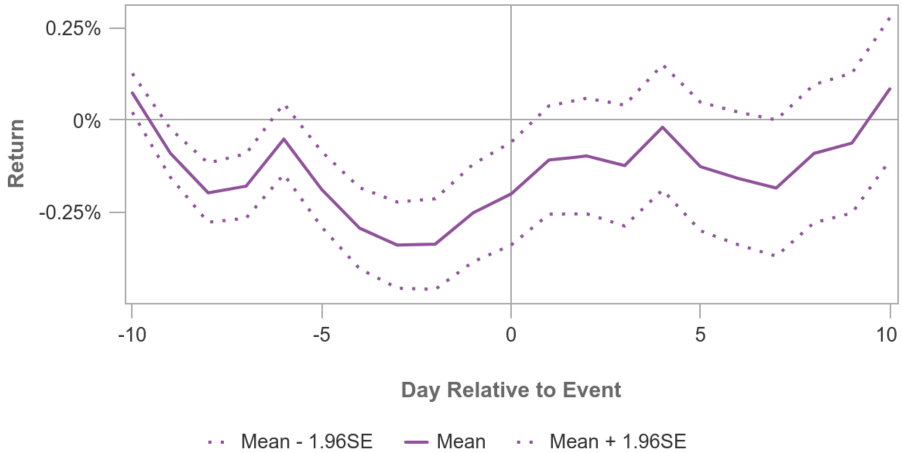


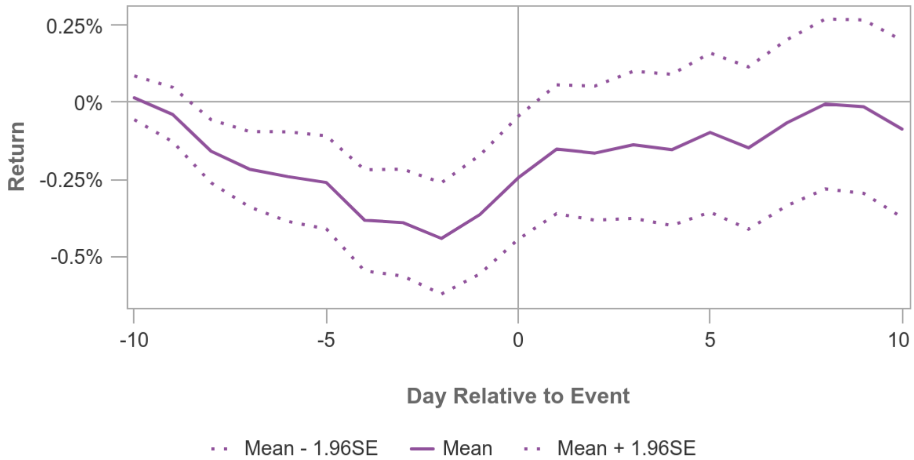
Figure 3. CARs: Different Types of Climate Disasters

This figure plots the cumulative abnormal returns (CARs) from day -10 to day +10, where day 0 is the disaster begin date, for seven types of weather and climate disaster events over the 1980-2023 period. We use the Fama-French three factors plus momentum to calculate the abnormal returns. The solid line graphs the mean CARs, and the top and bottom dotted lines plot the upper and lower 95% confidence limits, respectively. The graphs in Panels A to G are respectively for the following climate disasters: drought (36,156), flooding (16,256), freeze (4,640), severe storm (96,806), tropical cyclone (26,588), wildfire (18,185), and winter storm (36,709), with the quantities in parentheses standing for the number of firm-events with non-missing returns used in the CAR calculations for each corresponding type of climate disaster events.

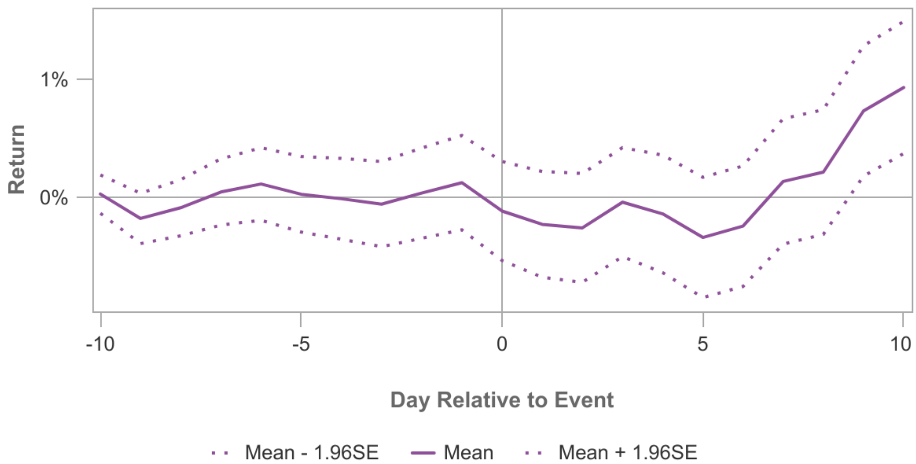
Panel A. Drought



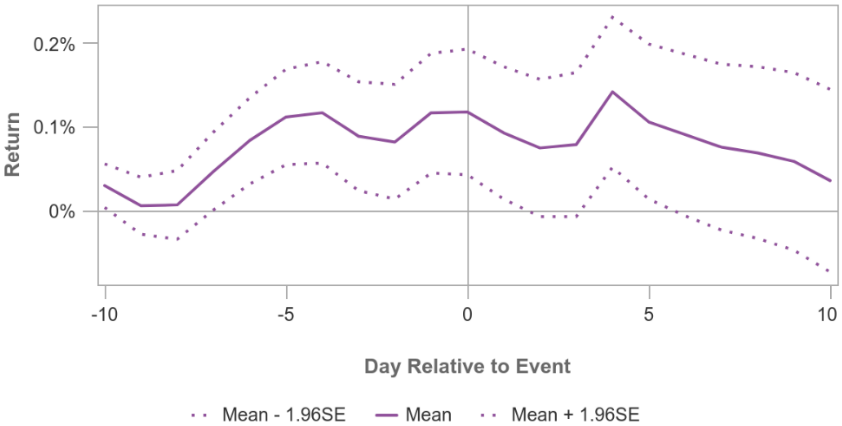
Panel B. Flooding



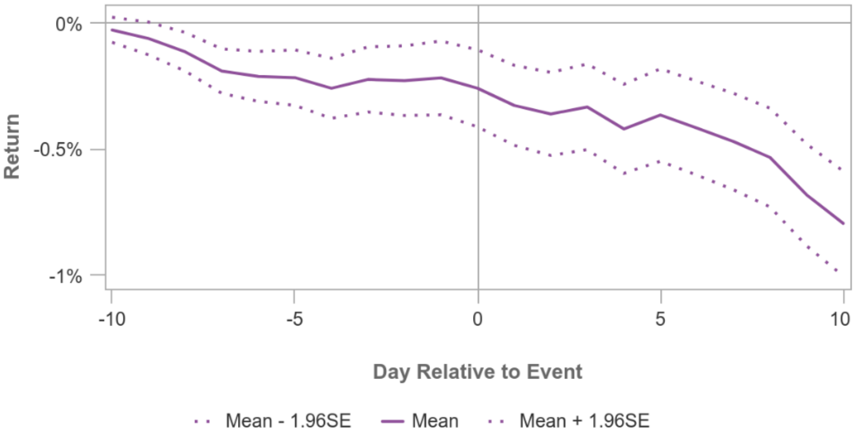
Panel C. Freeze



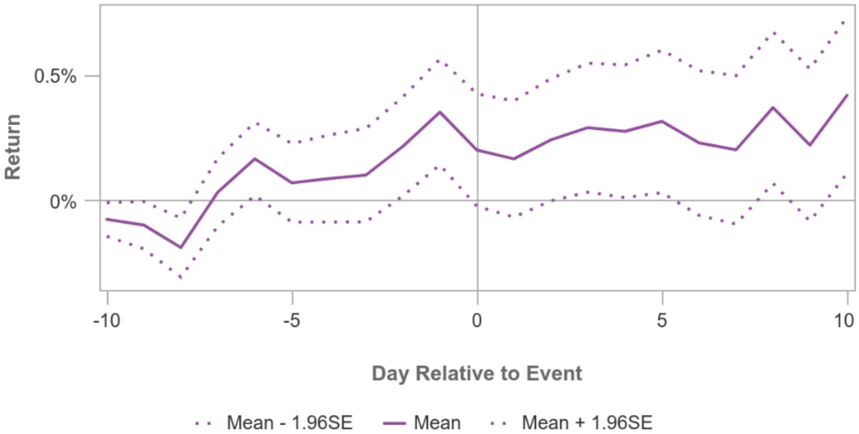
Panel D. Severe Storm



Panel E. Tropical Cyclone



Panel F. Wildfire



Panel G. Winter Storm

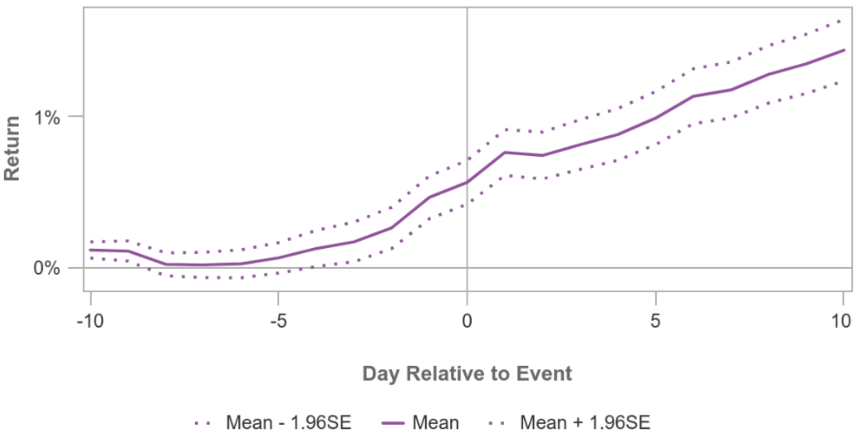
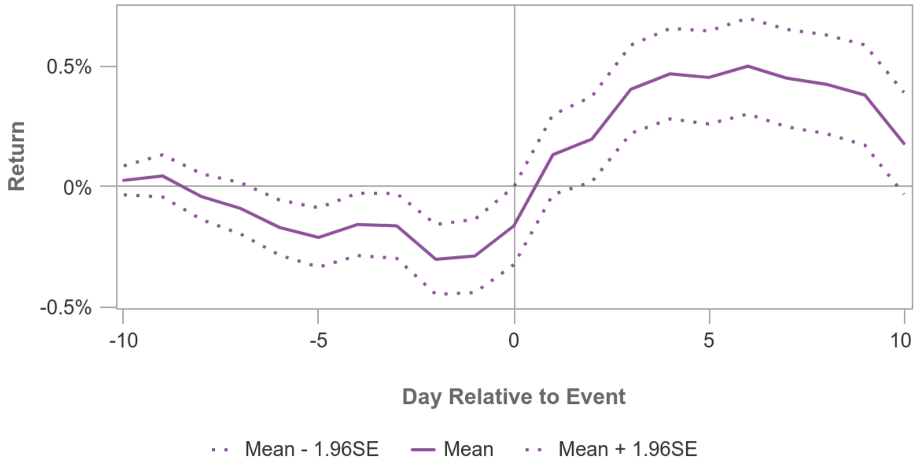


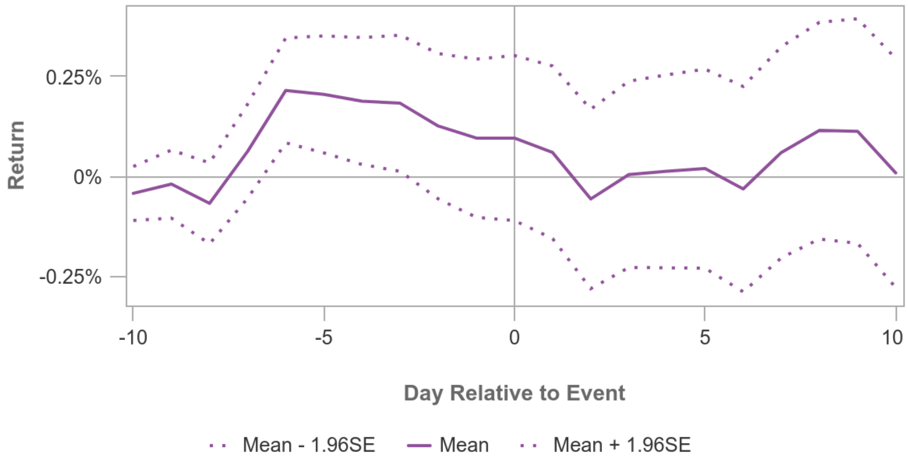
Figure 4. CARs: Different Types of Climate Disasters – Alternative Day 0

This figure plots the cumulative abnormal returns (CARs) from day -10 to day +10, where day 0 is the disaster end date, for seven types of weather and climate disaster events over the 1980-2023 period. We use the Fama-French three factors plus momentum to calculate the abnormal returns. The solid line graphs the mean CARs, and the top and bottom dotted lines plot the upper and lower 95% confidence limits, respectively. The graphs in Panels A to G are respectively for the following climate disasters: drought (37,283), flooding (16,335), freeze (4,646), severe storm (96,887), tropical cyclone (26,591), wildfire (18,681), and winter storm (36,776), with the quantities in parentheses standing for the number of firm-events with non-missing returns used in the CAR calculations for each corresponding type of climate disaster events.

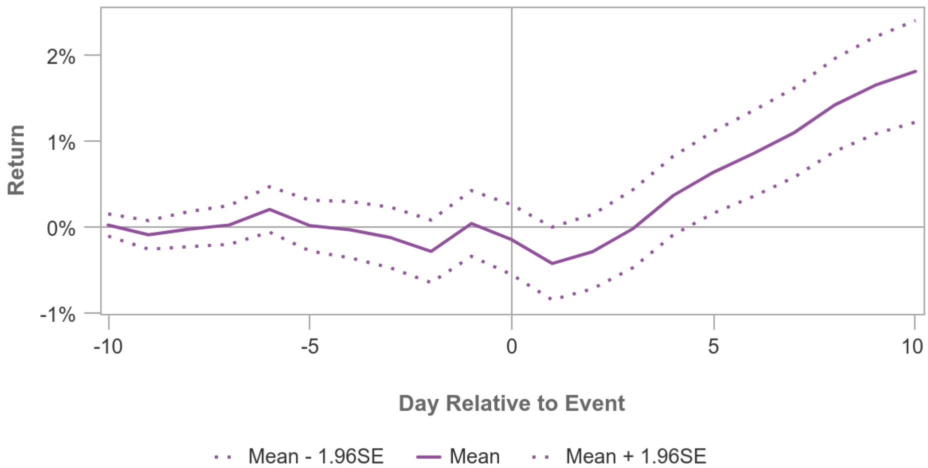
Panel A. Drought



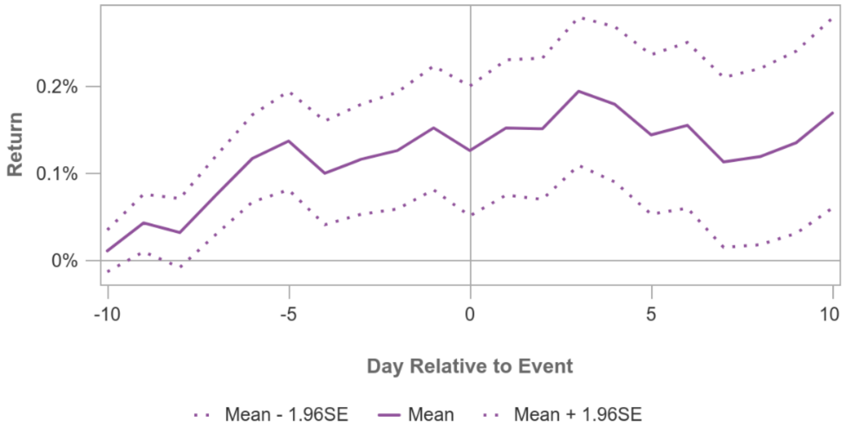
Panel B. Flooding



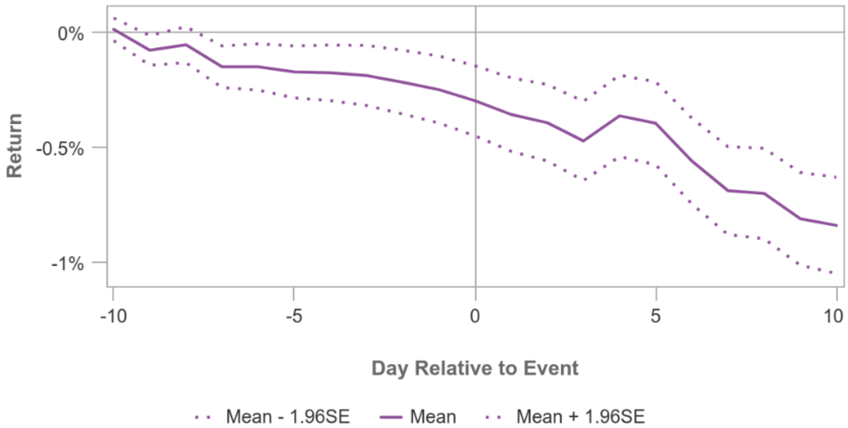
Panel C. Freeze



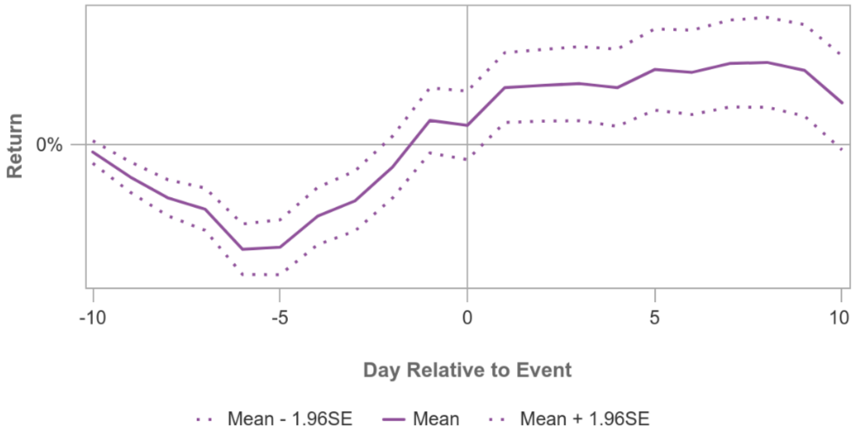
Panel D. Severe Storm



Panel E. Tropical Cyclone



Panel F. Wildfire



Panel G. Winter Storm

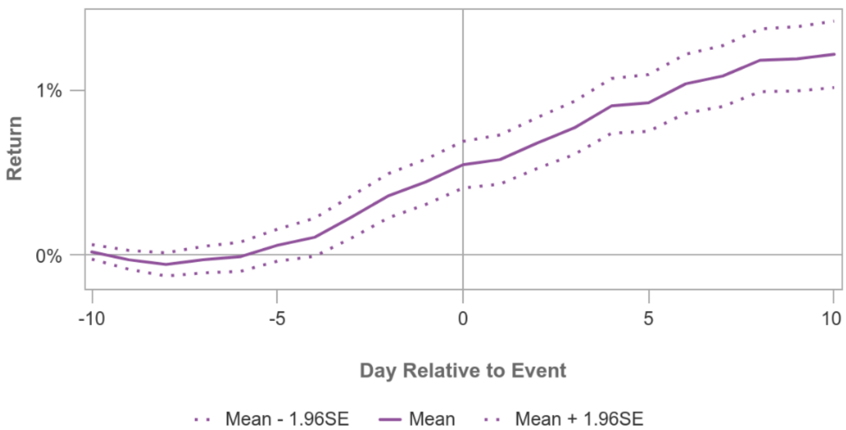
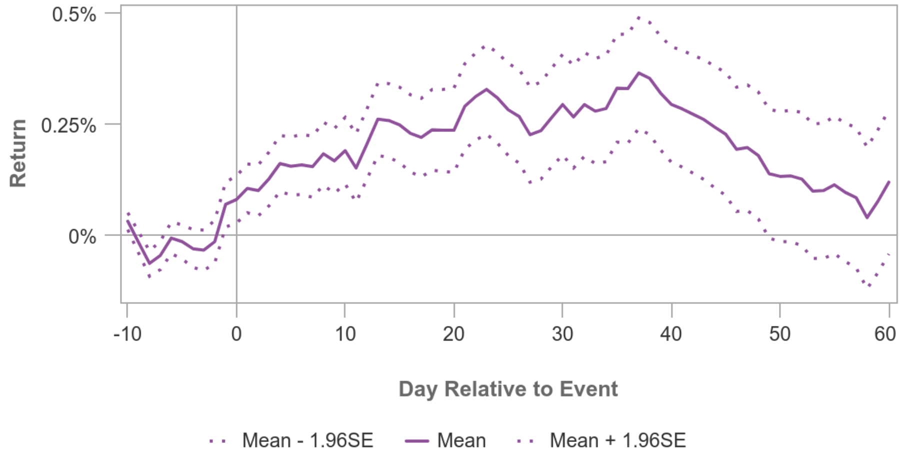


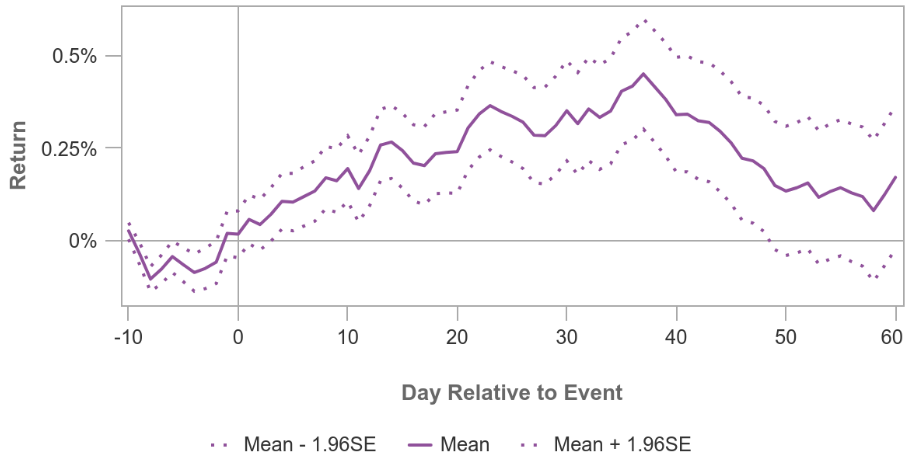
Figure 5. CARs of All Climate Disasters: Longer-Term View

This figure plots the cumulative abnormal returns (CARs) from day -10 to day +60 for all the weather and climate disaster events over 1980-2023. Event day 0 is the disaster begin date in Panels A1, B1, and C1 and is the disaster end date in Panels A2, B2, and C2. We use the Fama-French three factors plus momentum to calculate the abnormal returns. The solid line graphs the mean CARs, and the top and bottom dotted lines plot the upper and lower 95% confidence limits, respectively. Panels A1 and A2 are for all the disasters. Panels B1 and B2 are for all the disasters pre-Hurricane Sandy (Hurricane Sandy included). Panels C1 and C2 are for all the disasters post-Sandy. Quantities in parentheses are the number of firm-events with non-missing returns used in the CAR calculations in each panel.

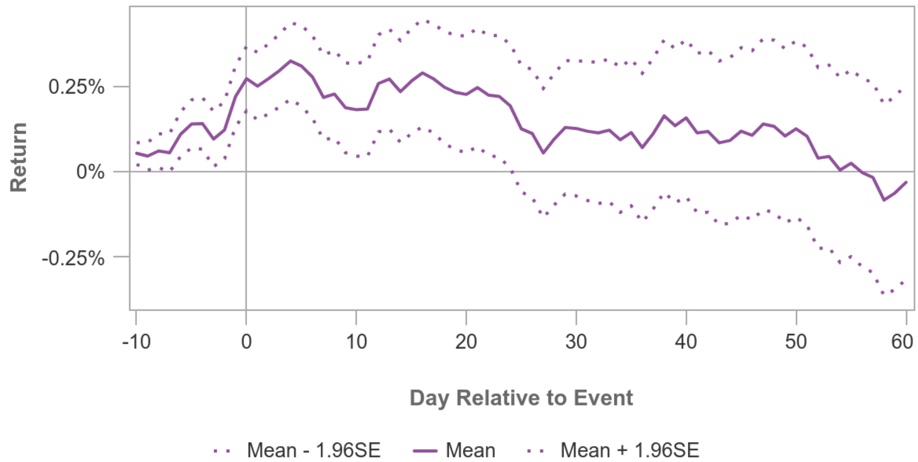
Panel A1. All Disasters (230,835 firm-events)



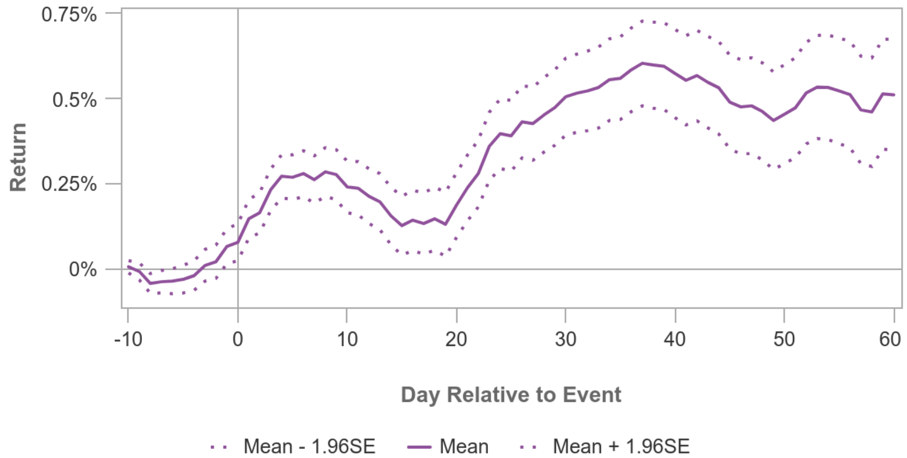
Panel B1. All Disasters Pre-Sanday (including Hurricane Sandy, 171,813 firm-events)



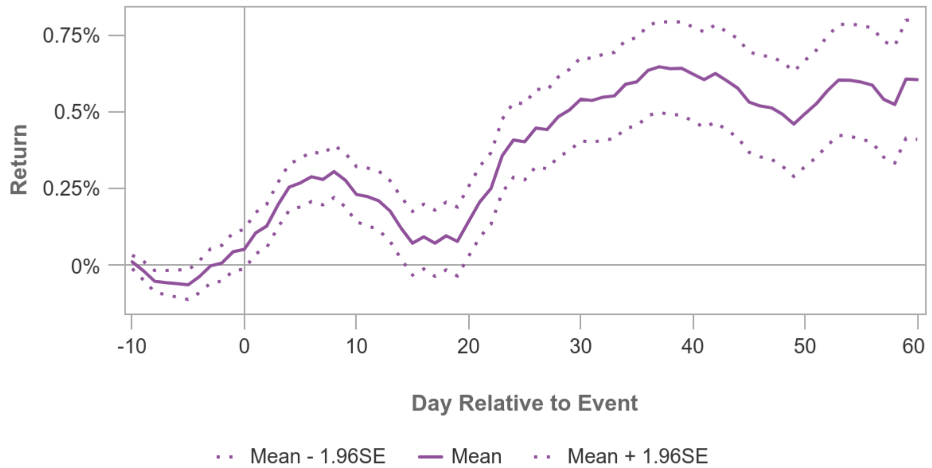
Panel C1. All Disasters Post-Sandy (59,022 firm-events)



Panel A2. All Disasters (233,244 firm-events)



Panel B2. All Disasters Pre-Sanday (including Hurricane Sandy, 174,742 firm-events)



Panel C2. All Disasters Post-Sandy (58,502 firm-events)

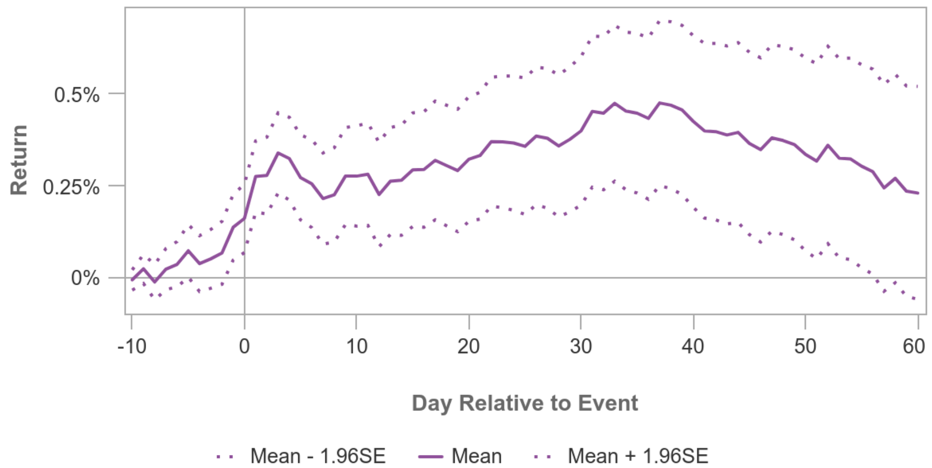
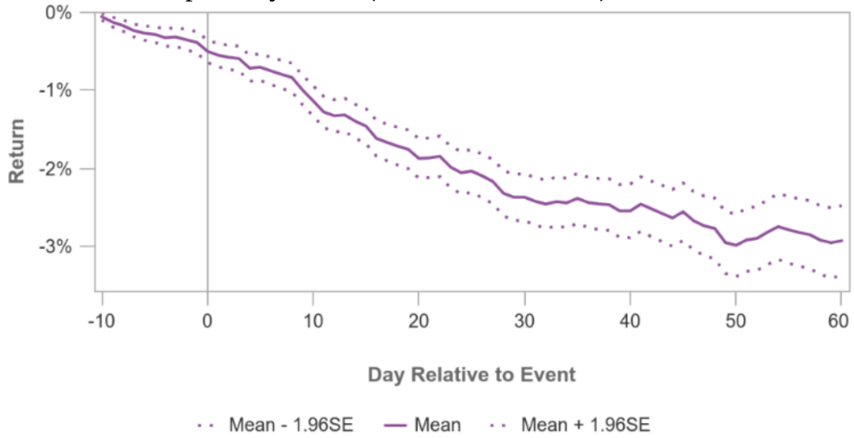


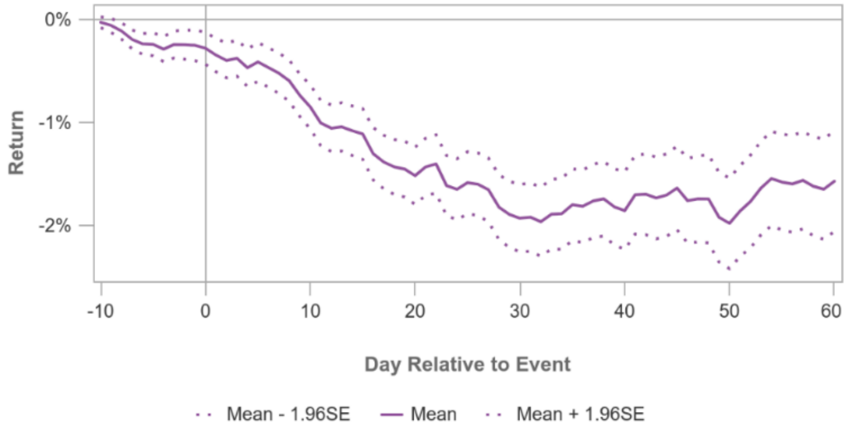
Figure 6. CARs of (Landfall) Tropical Cyclones: Longer-Term View

This figure plots the cumulative abnormal returns (CARs) from day -10 to day +60, where day 0 is the disaster begin date, for the landfall tropical cyclones over 1980-2023. We use the Fama-French three factors plus momentum to calculate the abnormal returns. The solid line graphs the mean CARs, and the top and bottom dotted lines plot the upper and lower 95% confidence limits, respectively. Panel A is for all the tropical cyclone strikes. Panels B and C are for the tropical cyclones that occur pre Hurricane Sandy (included) and post Hurricane Sandy, respectively. Panels D and E are for the tropical cyclones that strike pre Hurricane Katrina (included) and post Hurricane Katrina, respectively. Panels F and G are respectively for the "mild" and "severe" tropical cyclones, whereas a tropical cyclone is severe (mild) if it causes losses over (below) 60 billion 2024 dollars. The severe cyclones are Hurricanes Katrina, Harvey, Ian, Maria, Sandy, Ida, Irma, and Andrew, listed in a decreasing order of loss amount. Quantities in parentheses are the number of firm-events with non-missing returns used in the CAR calculations in each panel.

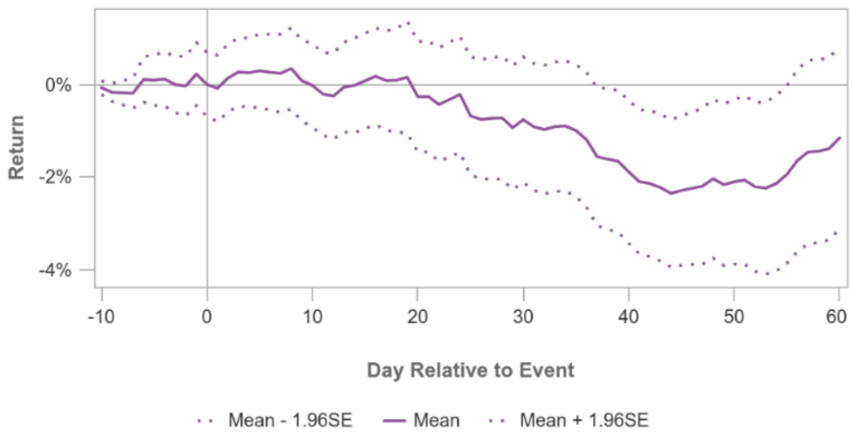
Panel A. All Tropical Cyclones (33,469 firm-events)



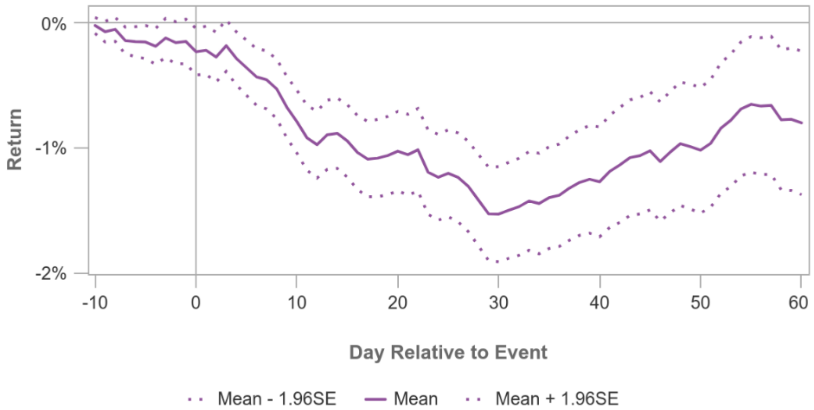
Panel B. All Tropical Cyclones Pre-Sanday (including Hurricane Sandy; 24,925 firm-events)



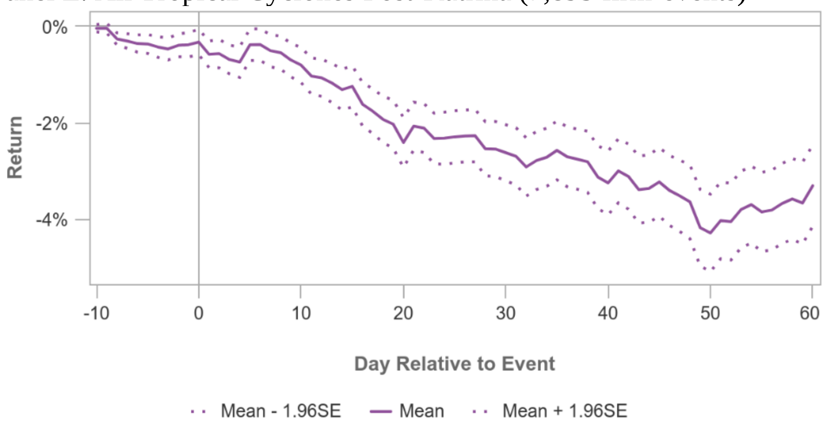
Panel C. All Tropical Cyclones Post-Sandy (1,667 firm-events)



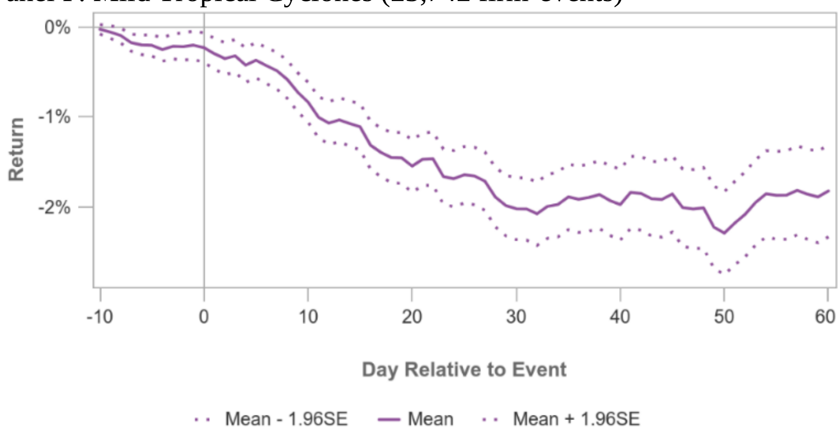
Panel D. All Tropical Cyclones Pre-Katrina (including Hurricane Katrina; 18,697 firm-events)



Panel E. All Tropical Cyclones Post-Katrina (7,895 firm-events)



Panel F. Mild Tropical Cyclones (23,742 firm-events)



Panel G. Severe Tropical Cyclones (2,850 firm-events)

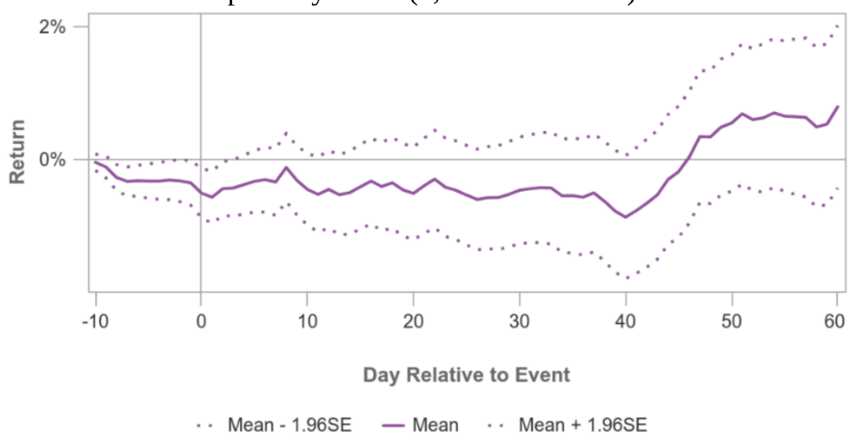
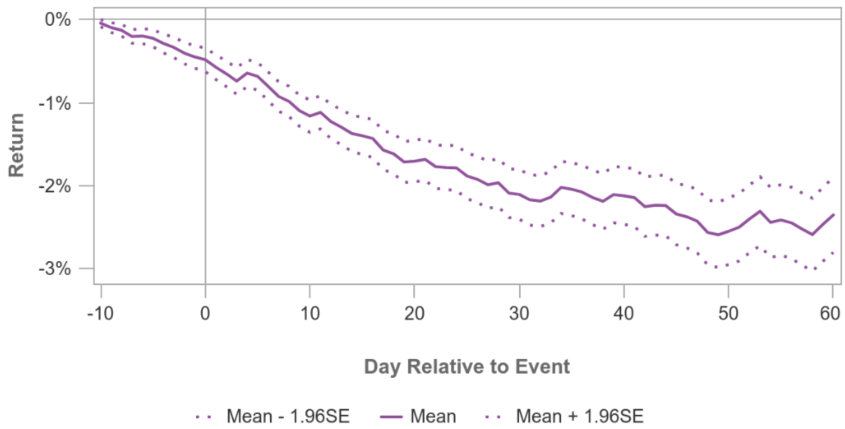


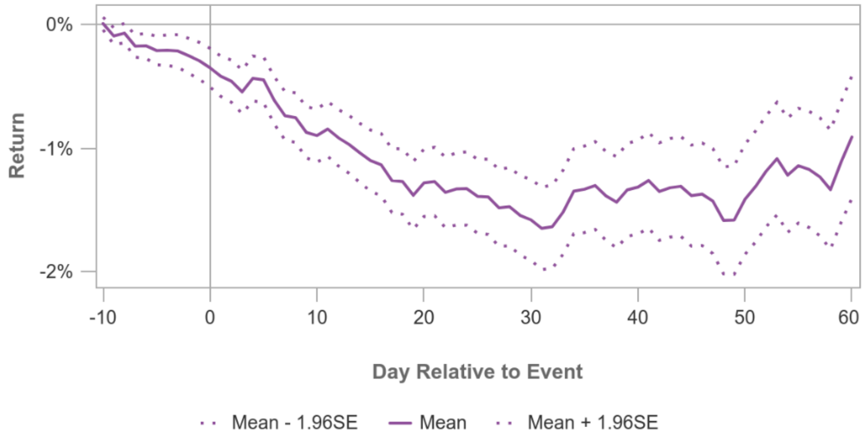
Figure 7. CARs of (Landfall) Tropical Cyclones: Alternative Day 0

This figure plots the cumulative abnormal returns (CARs) from day -10 to day +60, where day 0 is the disaster end date, for the landfall tropical cyclones over 1980-2023. We use the Fama-French three factors plus momentum to calculate the abnormal returns. The solid line graphs the mean CARs, and the top and bottom dotted lines plot the upper and lower 95% confidence limits, respectively. Panel A is for all the tropical cyclone strikes. Panels B and C are for the tropical cyclones that occur pre-Hurricane Sandy (included) and post-Hurricane Sandy, respectively. Panels D and E are for the tropical cyclones that strike pre-Hurricane Katrina (included) and post-Hurricane Katrina, respectively. Panels F and G are respectively for the “mild” and “severe” tropical cyclones, whereas a tropical cyclone is severe (mild) if it causes losses over (below) 60 billion 2024 dollars. The severe cyclones are Hurricanes Katrina, Harvey, Ian, Maria, Sandy, Ida, Irma, and Andrew, listed in a decreasing order of loss amount. Quantities in parentheses are the number of firm-events with non-missing returns used in the CAR calculations in each panel.

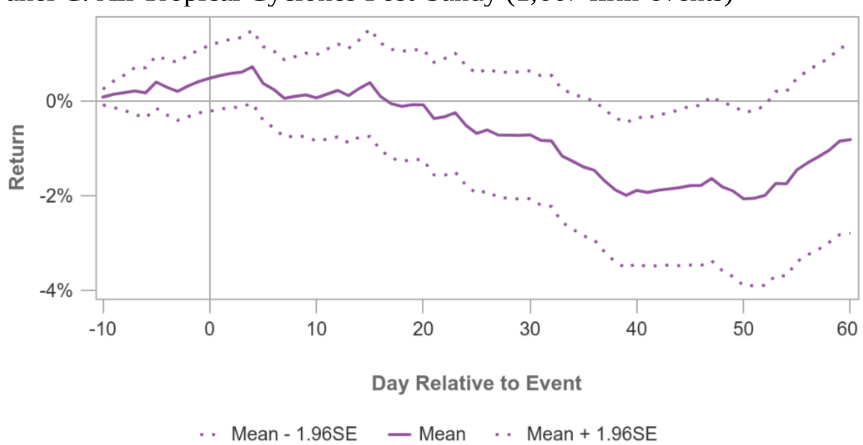
Panel A. All Tropical Cyclones (33,476 firm-events)



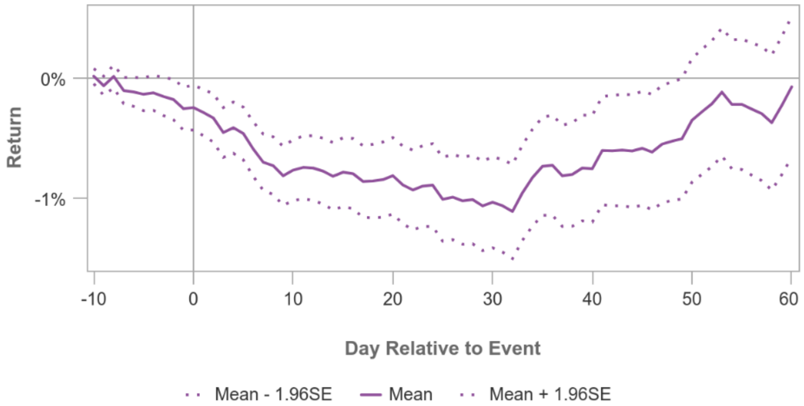
Panel B. All Tropical Cyclones Pre-Sanday (including Hurricane Sandy, 24,929 firm-events)



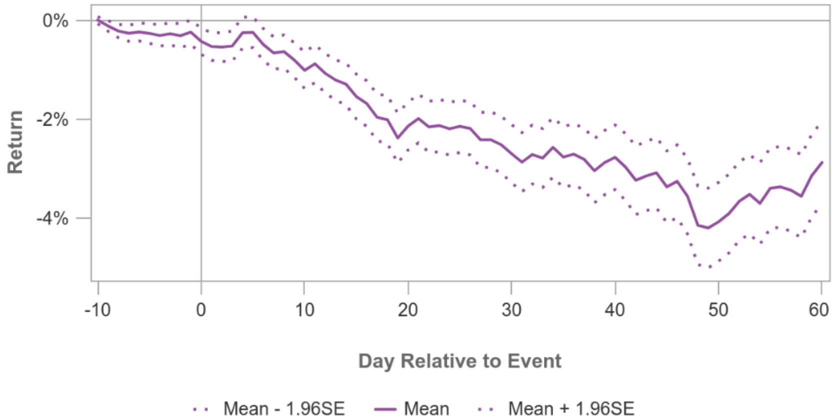
Panel C. All Tropical Cyclones Post-Sandy (1,667 firm-events)



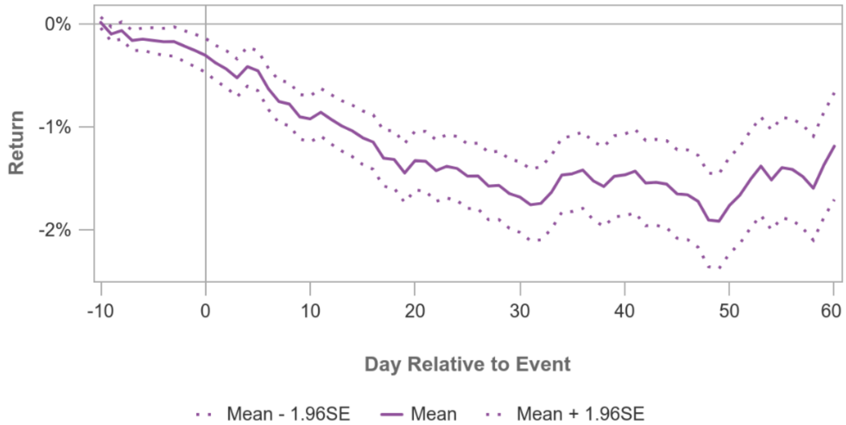
Panel D. All Tropical Cyclones Pre-Katrina (Hurricane Katrina included; 18,700 firm-events)



Panel E. All Tropical Cyclones Post-Katrina (7,896 firm-events)



Panel F. Mild Tropical Cyclones (23,746 firm-events)



Panel G. Severe Tropical Cyclones (2,850 firm-events)