MARKET RESPONSE OF US EQUITIES TO DOMESTIC NATURAL DISASTERS: INDUSTRY-BASED EVIDENCE

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Abstract

This study investigates US industry-based price response to domestic natural disasters over the period 1960-2015. Using an event study methodology, we estimate pre, during and post disaster impacts. We document a slower response in pre-disaster period than in post-disaster period. We further find that industries react differently to the same disaster and that reactions are not always negative. For example, meteorological disasters have a positive (negative) market impact on Gold (Banking). Moreover, we provide evidence that not every industry responds similarly to different disasters e.g. Gold reacts positively (negatively) to meteorological (geophysical) disasters. As such, we identify key "winner" and "loser" industries in the event of respective natural disasters, which is suggestive of safer investment opportunities to investors sensitive to the prospect of future similar scenarios.

Keywords: Natural disasters, Industry portfolios, Market Reaction

JEL Classification: G10, G14, Q54

1. Introduction

In this paper, we investigate US industry-based market reaction to domestic natural disasters classified into four categories: hydrological, meteorological, climatological and geophysical, over the period 1960-2015.[1] In so doing, we enhance the stock of knowledge regarding the nature and extent of association between natural disasters and industries' returns. Moreover, by taking a broad and comprehensive perspective, our study captures the pre and post disaster behavior of industry portfolios across all major classes of natural catastrophes; thereby enhancing investors' understanding in mitigating disaster risk from a financial investment point of view.

One broad motivation for our research comes from the immense economic consequences that typically attach to such freak occurrences of nature. Most notably, over the past two decades, natural disasters have caused USD1.3 trillion of financial losses and affected more than 2.7 billion people around the world, with the numbers going up every day (UNSDR, 2016). Moreover, scientists predict that the frequency of natural disasters, particularly extreme weather events, will increase in the future due to increasing greenhouse emissions (see, for example, Rahmstorf and Coumou, 2012 and Field, 2012).

While a number of studies have examined the economic impacts of natural disasters, the literature remains inconclusive and suggests varying effects of natural calamities on the aggregate economy (Hornbeck and Keniston, 2014; Noy, 2015). Bower (2011) implies that different classes of natural disasters affect the country's economy differently i.e. impacts from

[1] The Centre for Research on the Epidemiology of Disasters (CRED) defines natural disasters as "naturally occurring physical phenomena caused either by rapid or slow onset events which can be meteorological (extreme temperatures, cyclones and storms/wave surges), hydrological (avalanches and floods), climatological (drought and wildfires), geophysical (earthquakes, landslides, tsunamis and volcanic activity) or biological (disease epidemics)". See http://www.emdat.be/classification#Meteorological

earthquakes and extreme temperature evolve in a different way as compared to landslides, floods and windstorms. Only a few studies (including Carleton and Hsiang, 2016 and Loayza et al., 2012) discuss the impacts of natural disasters, at a disaggregated level, on sectoral economic value. They suggest that the type of disaster and the sector investigated matters for determining the impacts. Interestingly, the natural disaster-equity literature is limited to aggregate stock market impacts (Wang and Kutan, 2013; Worthington, 2008) or firm-level impacts (Bourdeau-Brien and Kryzanowski, 2017).

A handful of studies do examine the impacts of natural disaster on equity sectors but they exclusively focus either on a particular natural disaster event (see e.g. Hood et al., 2013, Hosono et al., 2016) or consider a specific industry (see, e.g., Fink and Fink, 2013 and Wang and Kutan, 2013). However, the behavior of respective industries in the event of different types of natural disasters remains unclear. We fill the void by comprehensively examining the impact of all natural disaster classes, as defined by CRED, namely meteorological, hydrological, climatological and geophysical disasters. We do this on a broad set of US industries – 49 industry portfolios using Fama French Standard Industry Classification (SIC) codes, over a long sample period from 1960 to 2015.

According to the Centre for Research on the Epidemiology of Disasters and the United Nations Office for Disaster Risk Reduction, weather-related disasters including hurricanes, extreme heat, excessive rainfall, and drought constitute 90% of all natural disasters. Scientists argue that modern forecasting systems can predict such disasters, with reasonable accuracy, several days in advance (see, e.g., Muarakami et al., 2015 and Webster et al., 2015). However, existing studies are limited to the performance of equities in the "aftermath" of natural disasters and ignore the pre-disaster impacts of aforementioned predictable disasters.

Pappenberger et al. (2015) and Cools et al. (2016) argue that early earning warning systems are useful tools for savings lives and making society more resilient in the event of predictable natural disasters. Smith et al. (2010) and Webster et al. (2015) advocate the predictability of hydro-meteorological disasters several days in advance. In contrast, studies including Geller et al. (1997) and Geller (2011) strongly argue the unpredictability of geophysical disasters specifically earthquakes. Skidmore and Toya (2002) suggest that predictability of hydro-meteorological disasters makes it easier to prepare and take some steps to reduce the adverse effects. With this in mind, we also examine the impacts of the predictable disasters (hydro-meteorological disasters) on industries prior to the disasters taking place. That is, we estimate abnormal returns to examine the speed (number of days) and pattern (positive, negative or zero) in which industries price natural disasters.[2]

We document several notable findings in our study. First, different industries respond differently to the same disaster class. Second, a given industry can respond differently to different natural disasters i.e. an industry responds in different fashion to meteorological disasters than it responds to geophysical disasters. Third, there is good performance of some industries, regardless of the type of natural disasters. This might provide profitable investment opportunities to investors. Fourth, industries can show sluggish response in the pre-disaster period (for predictable disasters) as compared to the post-disaster period. Scientists argue that false flags in the past and the technical content of the forecasts create uncertainty and can decrease the credibility of the information (see, for example, Gigerenzer et al., 2005 and Allen, and Stainforth, 2002). This lack of clarity make investors less confident in considering the relevant information to address the natural disaster risk.

[2] SIC codes comprising each industry portfolio available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html to construct portfolios.

The remainder of our study is organised as follows. Section 2 briefly outlines the prior relevant literature and proposes several predictions about the expected market reactions of industry portfolios. Section 3 presents the data and research method, while Section 4 presents and discusses the results of our analysis. Section 5 concludes.

2. Prior literature and predictions

Studies on the stock market-natural disaster relationship are not only scarce, but there is a significant disagreement concerning the economic outcomes of natural disasters. Wang and Kutan (2013) relate natural catastrophes in Japan with the performance of insurance stocks and composite indices. They find positive wealth effects on the insurance stocks but composite indices are not effected significantly. While Ewing et al., (2006) find negative impact of Hurricane Floyd on the stock price of insurance companies; they also suggest that the impacts are not always negative over the synoptic life cycle of the disaster. Fink and Fink (2013) study the reaction of oil refinery equities in the Gulf of Mexico to hurricane forecast revisions and find increasing return for the oil refineries.

Keeping in mind the contradictory findings of the aforementioned literature and the sparsity of studies relating natural disasters to the performance of different industry portfolios, we predict that:

P_1**: The market impact of natural disasters varies across different industry portfolios.***

Although the literature does not give us a clear indication of industries' behavior in case of respective natural disasters, prior studies do assist in developing specific intuitive predictions for several specific industries. Orth (1998) evidence insolvency of several insurance companies in the aftermath of Hurricane Andrew in the US Similarly, Hosono et al. (2016) suggest that earthquakes adversely affect lending capacity of banks in the disaster-hit area and make them less attractive for customers. Following the aforementioned literature, we conjecture a second prediction:

P$_{2a}$: *Natural disasters have a negative market impact on insurance and banking industries.*

On the other hand, Fox et al. (2009) and Gu and Nyak (2016) suggest natural disasters as a major reason for drug shortages and Mark and Jason (2017) relate the shortage of drugs with increasing drug prices. Accordingly, we predict that demand for medical equipment and related products increase due to injuries to human and livestock and conjecture our next prediction[3]:

P$_{2b}$: N*atural disasters have a positive market impact on health-related industries*.

Natural disasters cause huge property damage and after a disaster buildings and infrastructures need to be repaired or/and reconstructed –see, e.g., Skidmore and Toya (2002), McCaughey et al. (2018). Accordingly, we predict that such situations increase the demand for construction related products and services and, hence, we conjecture:

P$_{2c}$: N*atural disasters have a positive market impact on the construction industry.*

Moreover, keeping in mind the hedging property of gold (Sari et al., 2010; Draper et al., 2006; Jaffe, 1989) we predict:

P$_3$: N*atural disasters have a positive market impact on gold and precious metals industries.*

[3] Natural disasters have increased over the last few decades affecting 1.7 billion people around the globe including 277.78 million in the U.S (The International Disaster Database, 2016).

It is worth noting that we examine the reaction of industries to each class of natural disasters.[4] Carleton and Hsiang (2016) suggest varying effects of natural disaster on respective economic sectors depending on the severity/class of natural disasters and the industry type. Similarly, Bower (2011) implies that different classes of natural disasters affect the country's economy differently i.e. impacts from earthquake and extreme temperature evolve in a different way as compared to landslides, floods and windstorms.

According to the US Climate Prediction Center, weather related catastrophes such as hurricanes, extreme heat, excessive rainfalls, and drought can be predicted several days in advance with reasonable accuracy. Miller and Chase (1966) discuss several tools for hydro-meteorological forecasts including SGS (surface geostrophic steering) and changes in atmospheric pressure levels. Hope and Neumann (1970) also discuss different methods used in 1950s and 1960s for weather forecasting. Launch of NASA's first weather satellite in 1960 is a major breakthrough in forecasting weather and related disasters. Modern forecasting systems system recorded twenty-four hour forecasts for the first time in 1958 and three-day forecasts in 1960s. Number of studies, including Smith et al. (2010), Webster et al. (2011) and Casse et al. (2015) also discuss the predictability of hydro-meteorological disasters.

Cao and Huang (2018) suggest that "Geophysical disasters are particularly traumatic because they occur without explicit and timely warning and therefore are extremely difficult, if at all possible, to detect timely" (p.1). Over the past few decades, scientists have been trying to develop some mechanism for predicting geophysical disasters (see, for example, Florido et al., 2015) but success of these efforts is still a question mark. We also categorize wildfires

[4] CRED categorise natural disasters into different classest: geophysical (earthquakes, landslides, tsunamis and volcanic activity), hydrological (avalanches and floods), climatological (extreme temperatures, drought and wildfires), meteorological (cyclones and storms/wave surges) and biological (disease epidemics and insect/animal plagues)

(climatological disasters) unpredictable. Although some warning mechanisms use extreme temperature, humidity and wind speed, Pickell et al. (2017) suggest human involvement and thunder/lightning as two main sources igniting wild fires. This makes the prediction of such disasters hard for the scientists. However, certain computer models predict the scale of burning fire and estimate days/weeks for which it might stay ignited (Andrews et al., 2007). These models assists the relevant agencies monitor and control these disasters by allocating resources accordingly.

Given the above discussion, our final intuitive prediction relates to the subset of natural disasters that have a degree of meaningful predictability. Specifically:

***P*$_4$**: *Predictable natural disasters have an evolving market impact in the short window leading up to their "signature" event.*

3. Data and Research Method

3.1 Data Description

The sample period in this study covers from January 1, 1960 to December 31, 2015. We obtain data for US natural disasters from Emergency Disaster Database (EM-DAT) maintained by CRED. Many researchers, including Cavallo et al. (2013) and Loayza et al. (2012), consider it a reliable source of disaster related-information.

Table 1 summarises the huge losses (human and financial) caused by respective classes of natural disasters over the last five decades across four broad types of natural disaster: Meteorological disasters (Extreme temperature and tropical, extra-tropical & convective storms), Hydrological disasters (coastal floods, flash floods and riverine floods), Climatological disasters (drought and wildfires), Geophysical disasters (earthquake, mass movement and volcanic activity) and Biological disasters (epidemic). Most notably, the table indicates that weather-related disasters, specifically hydro-meteorological, are the largest contributors.

Insert Table 1 about here

Of all natural disasters reported in Table 1, we use only those disasters for which specific start and end dates are available We also drop all the drought events due to their long lasting nature (i.e. for months/years). To be included in our sample as a "major" event, the events meet a minimum criteria related to human loss (at least 10 fatalities or at least 100 people are severely affected) and/or economic loss of USD 1 million and above.[5] In this way, our analysis is limited to a sample of 728 U.S. natural disasters. Additionally, we collect data for U.S.-listed common stocks from the Centre for Research in Security Prices (CRSP) over the period 1960-2015, to construct equally weighted industry portfolios.[6] Low volatility and large market capitalization stocks tend to dominate the value-weighted stocks (Kothari et al., 1995). Since we are estimating abnormal returns at stock level, by adopting equally weighted portfolios, we have findings that more meaningfully represent the entire industry and not just the small number of large cap stocks.

3.2 Event Study Setup

We test our predictions using a standard event study method by calculating pre and post natural disaster abnormal returns for a wide range of industry portfolios.[7] Specifically, we use the definition of Kenneth French equally weighted 49 industry portfolios to construct the

[5] L. Sheehan and K. Hewitt. *A Pilot Survey of Global Natural Disasters of the Past Twenty Years*. Working Paper No. 11. Boulder CO: Institute of Behavioral Science, University of Colorado, 1969; quoted in Smith 1996, 20.
[6] SIC codes comprising each industry portfolio available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html to construct portfolios.
[7] There is a wide body of literature employing the event study approach to estimate the stock price impact of all types of event, see, e.g., Bird et al., (2013) and Gao et al. (2012).

portfolios. We use the widely accepted Boehmer, Musumeci and Poulsen (1991) standardized cross-sectional z score to test the significance of the estimates as it is robust to the event induced variance. Marks and Musumeci (2017) examine the statistical power of alternative significance tests used in event studies and find that Boehmer, Musumeci and Poulsen (1991) performs well across a diversity of scenarios. Moreover, we also report non-parametric tests by computing generalized z scores (Cowan, 1992) as a robustness check.[8]

Following many previous event studies (see, e.g., Dong et al., 2016; Coelho, 2015; MacKinlay, 1997), we use the Fama French three-factor model as our benchmark model to calculate abnormal returns and analyse the market impact of natural disasters at stock level.[9] We use all trading days prior to the start of the disaster seasons (December 01 to May 31) announced by the state departments.[10] National Oceanic and Atmospheric Administration, U.S. tracks the hurricane seasons, which normally starts in June and lasts until November every year. We use this estimation method to avoid the influence of multiple disasters, in the same season(s), on our parameter estimates.

We use different windows for respective disasters such that for any disaster, the pre-disaster period includes three days (-3) to one trading day (-1) prior to the event occurrence day (0). If the event happens on a non-trading day, we take the next trading day as event day (0). The post-event period starts trading day +1 through to day thirty (+30).[11] Few studies (see, for example, Cooper et al., 2001) advocate the importance

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[8] Prior studies, including Corrado (2011), suggest the prudent application of non-parametric tests to accommodate any non-normality in the empirical distribution of abnormal returns.
[9] In an unreported experiment, we also use Market Model to calculate abnormal returns and find that results are qualitatively the same. Details are available from the authors upon request.
[10] The updates are available at http://www.noaa.gov/media-release/atlantic-hurricane-season-still-expected-to-be-strongest-since-2012.
[11] Although Modern systems currently release five days advance forecasts for hydro-meteorological disasters, due to our sample dating back to 1960, when only three-day forecasts were available, we examine three days pre-disaster reaction of equities. Fink and Fink (2013) mentions the availability of five day hurricane forecast revisions after 2001.Simlarly National Oceanic and Atmospheric Administration also confirms the availability of 5 day

of confounding events in the event studies. However, Kothari and Warner (2007) argue that such events are troublesome for long-horizon event studies (typically one year). Our event window durations are only several days around the event (maximum of thirty days), hence we do not expect confounding events driving our results.[12]

4. Results

4.1 Short-Window Market Reactions Leading up to Predictable Disasters

This section discusses the abnormal performance of US industry portfolios in the pre-disaster period for hydro-meteorological disasters referred to as predictable disasters. Table 2 presents the Cumulative Average Abnormal Returns (CAAR) for 49 Fama French Industry portfolios for three day pre-disasters event window. [13,14]

Insert Table 2 about here

We use the three day pre-disaster window (-3,-1) to capture the behavior of equities in the pre-disaster period for meteorological disaster and find little evidence that industries price such information. Results for Insurance show small but statistically significant negative abnormal return (-0.02%) in the pre-disaster period conforming to our prediction ($\boldsymbol{P_{2a}}$) for insurance industry i.e. natural disasters have a negative impact on Insurance. Other adversely affected industries include Aero-Aircraft, Transport, Chips-Electronics and Financial Trading. However, we find statistically significant positive pre-disaster abnormal returns for Medical

(120 Hourly) forecast revisions for meteorological disasters after 2001 (https://www.nhc.noaa.gov). Chronology of changes in NHC forecast procedures is available at https://www.nhc.noaa.gov/verification/verify2.shtml

[12] In an unreported experiment, we conduct a further sensitivity analysis. Specifically, following Zhu (2017), we include the event happening earlier in the month and drop the event(s), happening later, in the same month. We find that results are qualitatively the same. In another experiment, we include disaster events that are at least one month apart from other disaster(s) and drop all disaster happening in the same month. We find that results are qualitatively the same. Details are available from the authors upon request.

[13] Using CRED's definition, meteorological disasters in our study refer to tropical storms, extra tropical storms and convective storms and hydrological disasters refer to floods.

[14] We report CAARs that are statistically significant at least at 10% level.

Equipment (0.10%) and Drugs (0.05%) suggesting some "creative destruction" prospects leading into the meteorological natural disasters. We also find positive pre-disaster reactions for Chemicals, Oil and Petroleum and Real Estate industries to such disasters.

Moreover, the findings reveal that more industries tend to react in the pre-disaster period for hydrological cases and reactions are different from those to meteorological disasters. Results support Bower (2011) who suggests that different classes of natural disasters affect the economy differently. We find positive price reaction of Gold and healthcare related industries in the pre-disaster period for hydrological disasters conforming to our predictions (***P_{2b}*** and ***P_3)*** i.e. these natural disasters have positive "lead-in" impact on healthcare related and gold industries. Specifically, we see a price run up for Gold in anticipation of hydrological disasters with a statistically significant abnormal return of 0.22%. Medical Equipment and Drugs also react positively and earn statistically significant pre-disaster abnormal returns (0.08% and 0.06%, respectively). We argue that the expected increase in demand of these industries' products increases stock prices, consequently earning above average returns. Fox et al. (2009) and Gu and Nyak (2016) suggest drug shortages as a consequence of natural disasters, whereas Mark and Jason (2017) imply that shortage of drugs leads to an increase in drug prices. Some other industries including Beer, Household Consumer, Clothes and Apparel, Chemicals and Retail also earn statistically significant short-term abnormal returns when hydrological disasters are about to happen.

Counterintuitively, Insurance and Banking sectors generate significant positive abnormal returns (0.15% and 0.07%) during the pre-disaster time period. Wang and Kutan (2013, p. 673) explain the gain as follows: "… investors tend to demand more insurance coverage during times of natural disasters to maximize their protection and hence insurance sector profits increase yielding higher stock returns in this sector". Table 3 further shows that

Oil and Petroleum equities plunge the most in the pre-hydrological disaster period with pre-disaster CAAR (-3, -1) of -0.20% followed by Utilities (-0.18%) and Textiles (-0.15%).[15]

Results support our generic intuitive prediction (***P*$_4$**) that equities respond to predictable disasters prior to them taking place. We also find that industries are not quick to price the natural disaster forecasts. Furthermore, variation in the industries' reactions to respective natural disasters support our first prediction (***P*$_1$**), however, we find mix indications for industry specific predictions.

4.2 Immediate Market reactions to Natural Disasters

This section discusses the immediate reaction of various industries to different types of natural disasters. Specifically, we examine the industries' response in the first two days (0, +1) of the disasters to capture any abnormal performance.

Insert Table 3 about here

Table 3 presents the cumulative abnormal returns of U.S. industry sectors for meteorological, hydrological, climatological and geophysical disasters. Results show that equities do not show a great response to hydro–meteorological and geophysical disasters, unlike climatological disasters that responsively affect quite a number of industries. Interestingly, we observe a diversity of immediate reaction in most industries to different types of natural disasters but few industries react in a similar fashion. Notably, the Transport Industry generates positive abnormal returns. A plausible explanation is that, due to the increased number of people fleeing quickly from the disaster-hit area, demand for transport generally increases and consequently the stock prices of transportation firms go up. Insurance earns

[15] Reported CAARs are statically significant at least at 10% level.

statistically significant abnormal returns over the first two days of hydrological (0.08%), climatological (0.17%) and geophysical disasters (0.13%), while price reaction to meteorological disasters is insignificant. These results counter our prediction (***P*$_{2a}$**) of negative impacts of natural disasters. Increased demand in the insurance plans and premiums in the disaster prone areas support the gains for the insurance industry in the disaster situation (Wang and Kutan, 2013; Shelor et al., 1992). The Banking sector responds negatively to meteorological and climatological disasters but geophysical disasters have a positive impact. Gold and precious metals do not react immediately to most of the disasters, however, a negative impact of 0.22% occurs in the first two days of hydrological disasters, contrary to our prediction i.e. natural disasters have a positive impact on the gold and precious metals industry. Similarly, reactions of Drugs and Medical equipment are not statistically significant except for climatological disasters, where both these industries yield negative cumulative average abnormal returns (-0.26% and -0.06%, respectively). As such, these latter findings negate our intuitive prediction of positive impacts of natural disasters. The Construction industry earns statistically significant abnormal returns for climatological and hydrological disasters and, thus, conforms to our prediction **(*P*$_{2c}$)** i.e. natural disasters have a positive market impact on construction-related industries. However, the results for meteorological and geophysical disasters negate this prediction.

4.3 Post-Event Market Reactions to Natural Disasters

In this section, we discuss the post-disaster market impact of different types of natural disaster on U.S equities over different post-disaster event widows ranging up to thirty days.

4.3. 1 Meteorological Disasters

Table 4 reports the post-event response to U.S. meteorological disasters across U.S. industry portfolios. We find an increasing trend in the number of industries responding to meteorological disasters over the subsequent days/weeks. Initially, a day after disaster, only a few industries respond but by the end of the fourth week, half of industries react significantly. Kaplanski and Levy (2010), who examine the impact of aviation disasters on stock returns, argue that stocks respond more to the later news carrying (the more disturbing) details of the damage caused, than to the initial news announcing the event's occurrence.

Insert Table 4 about here

Post disaster abnormal returns, as predicted, suggest varying impacts across industries in the wake of meteorological disasters. We discuss in detail the industries with statistically significant CAARs for most of the post disaster windows.[16] Gold and precious metals generate the highest thirty-day cumulative abnormal return of 0.69%. Positive abnormal returns for Medical equipment and Drugs also support our intuitive predictions i.e. natural disasters have positive impact on health related industries ($\boldsymbol{P_{2b}}$). Cumulative Abnormal returns for Medical Equipment and Drugs show an increasing trend over the weeks after the meteorological disasters, with CAAR (0,+5) of 0.13% increasing to CAAR (0,+30) of 0.33% and 0.21%, respectively. Chips-Electronics, Rubber and Construction industries also reveal positive abnormal returns in the post disaster period. In contrast, negative thirty-day cumulative abnormal returns for Banking (-0.23%) and Insurance (-0.09%) support our intuitive prediction ($\boldsymbol{P_{2a}}$) of an adverse effect on these sectors. Utilities and Financial Trading react in a similar fashion and follow a decreasing trend in the weeks after the disasters hit. A few other industries

[16] Reported CAARs are statistically significant at least at 10% level.

also generate significant abnormal returns during certain event window but significance diminishes for the remaining windows, e.g., Books show statistically significant response only in the first week of meteorological disaster. As predicted (***P_{2c}***), natural disasters have a positive market impact on the Construction industry that accumulates positive abnormal return in first post-disaster week. Figure 1 presents the variations in daily cumulative abnormal returns of the aforementioned industries in the event of meteorological disasters.

Insert Figure 1 about here

4.3.2 Hydrological Disasters

Table 5 reports the post-event response to U.S. hydrological disasters across U.S. industry portfolios. We find mix responses of industry portfolios to hydrological disasters: 35% of the portfolios experience negative impacts and 65% positive impacts.

Insert Table 5 about here

Gold standouts yet again showing 3.31% abnormal return over the thirty days post disaster period. This finding is consistent with the finance literature (Sari et al., 2010; Hillier et al. 2006; Jaffe, 1989) advocating diversification/ hedging roles of gold and precious metal in times of market turbulence. Medical equipment (0.20%) continues to earn significant abnormal returns in the aftermath of hydrological disasters. This conforms to our intuitive prediction (***P_{2b}***). We argue that due to injuries to humans and livestock, demand for medical equipment and related products increases, suggesting abnormal profits for the industry.[17] Autos & Trucks, Meals-restaurants and Chips also react positively. On the other hand, hydrological disasters initially have a negative impact on the Insurance and Banking industries but recovery

[17] Natural disasters have increased over the last few decades affecting 1.7 billion people including 277.78 million in the U.S (The International Disaster Database, 2016)

is evident at the end of the 30-day period. Coal and Business Services are among the industries responding negatively to these disasters. The Construction industry initially responds positively to hydrological disaster with CAAR (0, +5) of 0.38% but later, abnormal return (0, +30) drops to -0.23%. Figure 2 shows daily cumulative abnormal returns of the respective industries that respond significantly for most of the event windows under study.

Insert Figure 2 about here

4.3.3 Climatological Disasters

Table 6 reports the post-event response to U.S. climatological disasters across U.S. industry portfolios. We expect the responses of industries to climatological disasters (wildfires) to be different from those for meteorological and hydrological disasters (due to differences in the nature of the disasters). Loayza et al. (2012) and Carleton and Hsiang (2016) suggest varying effects of natural disaster on respective economic sectors depending on the severity/class of natural disasters and the industry type. We find most of the industries respond significantly to the disaster within the first week, unlike the alternative disaster categories discussed earlier. After ignition of climatological disaster (wildfires), National Weather Services, FEMA and other relevant agencies take an active part in managing the wildfires and continuously provide updates on the damage and control measures. This detailed information gives investors more confidence in making their investment decisions.

Insert Table 6 about here

Table 6 shows that climatological disasters seem to act as a blessing in disguise for most of the industry portfolios. Confirming our predictions ($\boldsymbol{P_{2b}}$, $\boldsymbol{P_3}$) of positive impacts of natural disasters, Gold, Medical Equipment and Drugs generate thirty-day cumulative abnormal returns of 2.44%, 0.65% and 0.24%, respectively.[18] Computer related stocks particularly Computer Hardware and Chips also earn statistically significant cumulative abnormal returns of 1.35% and 1.30%, respectively. Similarly, Telecom, Building Materials, Aero-Aircraft, Steel, Ships Rail Roads, Machinery, Autos & Trucks and Coal industries react positively to such natural disasters.

Results show that the Banking industry is adversely affected (CAAR of -0.58%) at the end of thirty days. Insurance stocks also show a decreasing trend over the weeks after climatological disasters; however, the response is statistically insignificant, except for the initial two post-disaster weeks. Underperformance of Banking and Insurance stocks supports our intuitive prediction ($\boldsymbol{P_{2a}}$) where we conjecture that these industries react negatively to natural disasters. Other negatively affected industries include Textiles, Retail and Financial Trading with significant negative thirty day CAARs. The Construction sector shows statistically insignificant response, contradicting our prediction ($\boldsymbol{P_{2c}}$) that natural disasters have a positive market impact. Figure 3 shows daily cumulative abnormal returns of the aforementioned industries in the event of climatological disasters.

Insert Figure 3 about here

4.3.4 Geophysical Disasters

Table 7 reports the post-event response to U.S. meteorological disasters across U.S. industry portfolios. We find an increasing trend in the number of industries responding to such disasters over the thirty-day period. Counterintuitively, Gold and Precious metals experience a substantial negative impact to such disasters i.e. CAAR (0, +30) of -4.08%. We suggest that the nature of geophysical disasters (earthquakes and landslides) hinder the mining activities

[18] Reported CAARs are statically significant at least at 10% level.

and slowdown the performance of Gold and allied metals. Pullen et al. (2014) find little evidence of gold stocks being safe haven, however they suggest gold bullions a better investment. Similarly, Clothes, Oil & Petroleum and Financial Trading show declining trend.

Insert Table 7 about here

Results for Insurance and Banking sectors support the "gaining from loss" hypotheses and both industries earn significant abnormal returns in the aftermath of such disasters. Hence, this opposes our predictions (***P_{2a})*** that natural disasters have a negative impact on insurance and banking industries. Drugs generate a statistically significant CAAR (0, +30) of 1.23%. Utilities, Food and Hardware industries also reveal statistically significant and positive abnormal returns in the post-event window of geophysical disasters in the U.S. Results for the Construction industry contradict our prediction (***P_{2c}***) of positive impacts for geophysical disasters. Figure 4 plots daily cumulative abnormal returns of the discussed industries for the period under study.

Insert Figure 4 about here

5. Conclusion

This study examines the response of equities to different types of natural disasters in the U.S. We partition the equity market into forty-nine industry sectors to examine the price reaction of stocks at semi-disaggregated level. We classify the natural disasters into hydrological, meteorological, climatological and geophysical disasters (CRED definitions). We provide evidence that equities are slow to respond in the pre-disaster period for hydro-meteorological disasters. We argue that false flags in the past, for respective disasters, and the technical content of the forecasts make the investors unclear and less confident in considering the relevant information to address the natural disaster risk.[19]

For the post-disaster period, we find varying behaviour across industries implying diversification benefits for investors. We find that reactions are more industry and disaster specific i.e. several industries do not show similar responses to different types of natural disasters and different industries do not react in a similar fashion to the same natural disaster. We identify the key "winner" and "loser" industries in the event of certain disasters in the US; which is suggestive of safer investment options in such catastrophic situations. While our study analyses the market impact of domestic natural disasters on US industries, factors driving the variations in the disaster impacts across different industries remains an open question for future research.

[19] Gigerenzer etl. (2005) and Joslyn and Savelli (2010) suggest that general public finds content of the forecasts hard to understand whereas Allen and Satiforth (2002) and Kendon et al. (2014) discuss the uncertainty attached to some weather forecasts.

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Figure 1: Meteorological Disasters and Daily Cumulative Abnormal Returns for Industry Portfolios

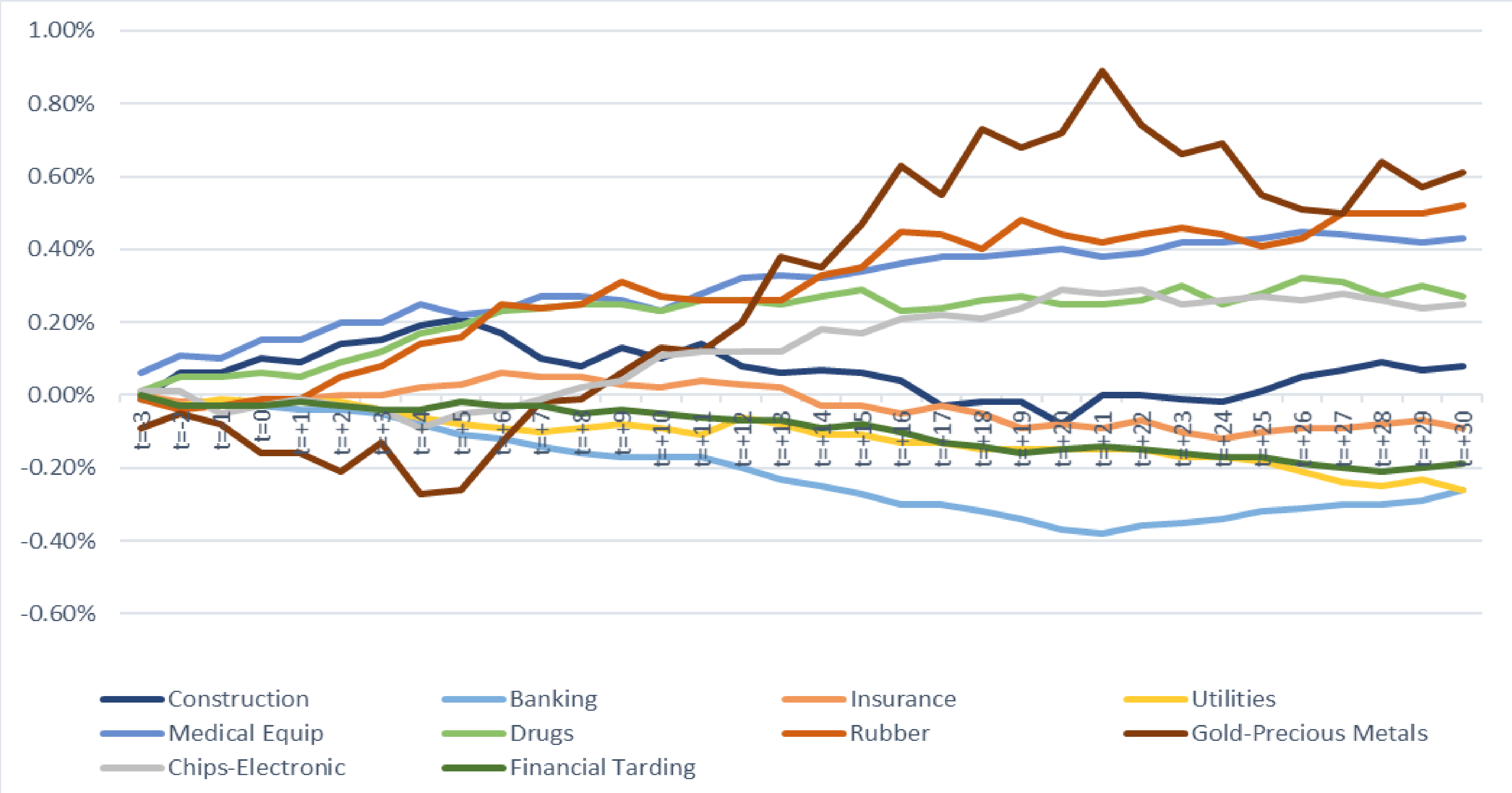

Figure shows daily cumulative average abnormal returns for different equity industries (showing statistically significant response atleast at 10% level) in the event of meteorological disasters.

Figure 2: Hydrological Disasters and Daily Cumulative Abnormal Returns for Industry Portfolios

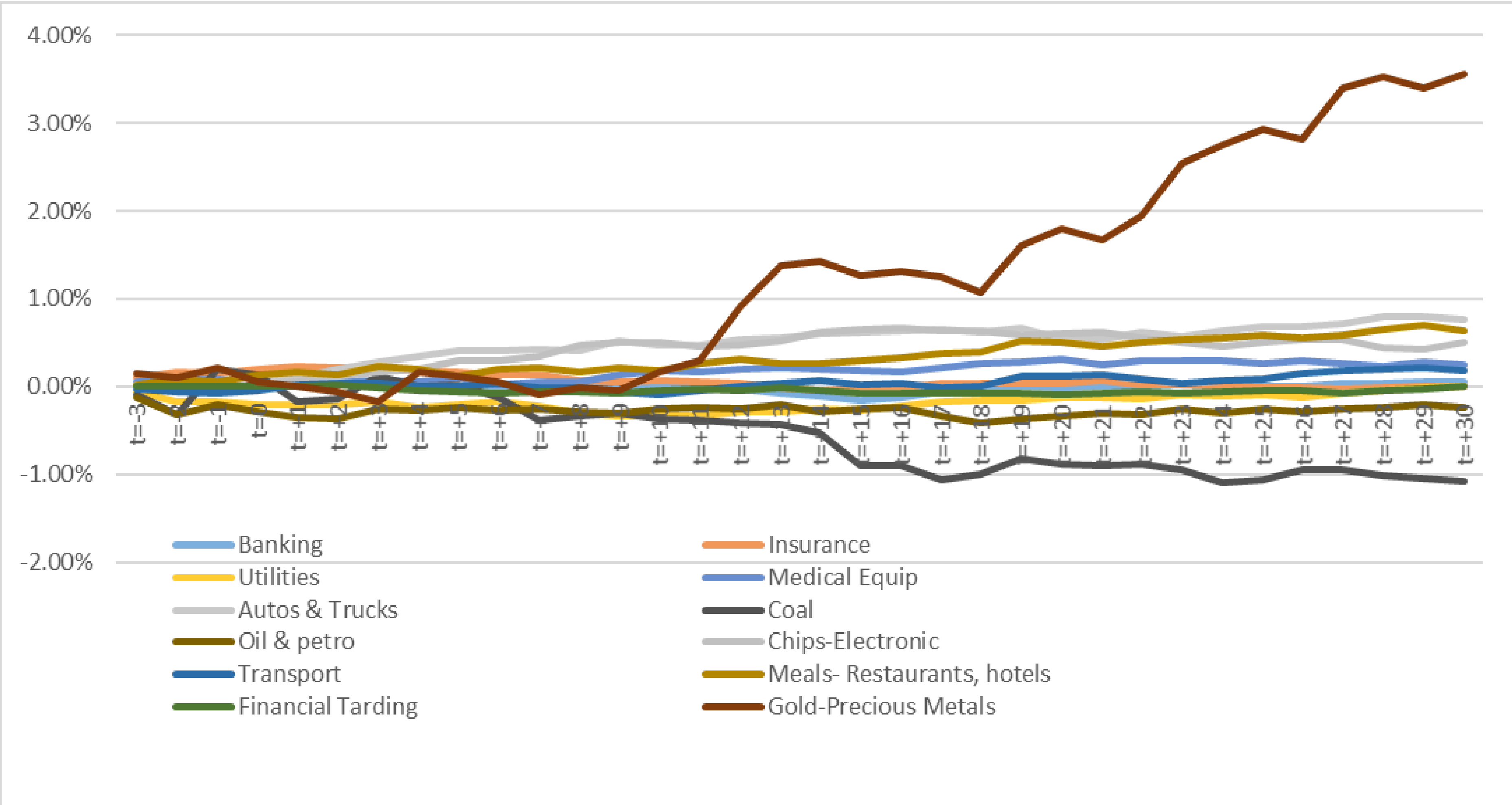

Figure shows daily cumulative average abnormal returns for different equity industries(showing statistically significant response atleast at 10% level) in the event of hydrological disasters.

Figure 3: Climatological Disasters and Daily Cumulative Abnormal Returns for Industry Portfolios

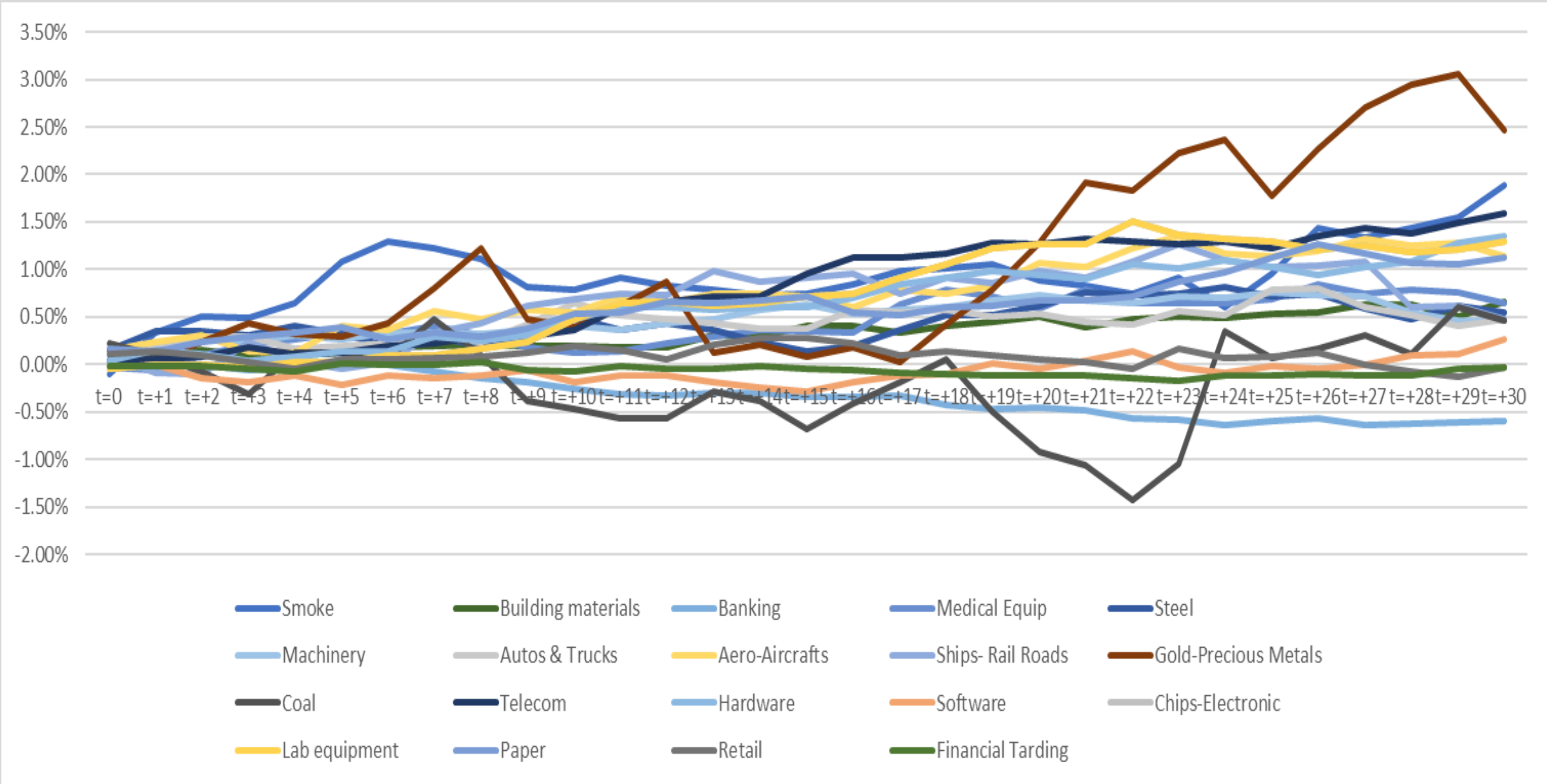

Figure shows daily cumulative average abnormal returns for different equity industries(showing statistically significant response atleast at 10% level) in the event of climatological disasters.

Figure 4: Geophysical Disasters and Daily Cumulative Abnormal Returns for Industry Portfolios

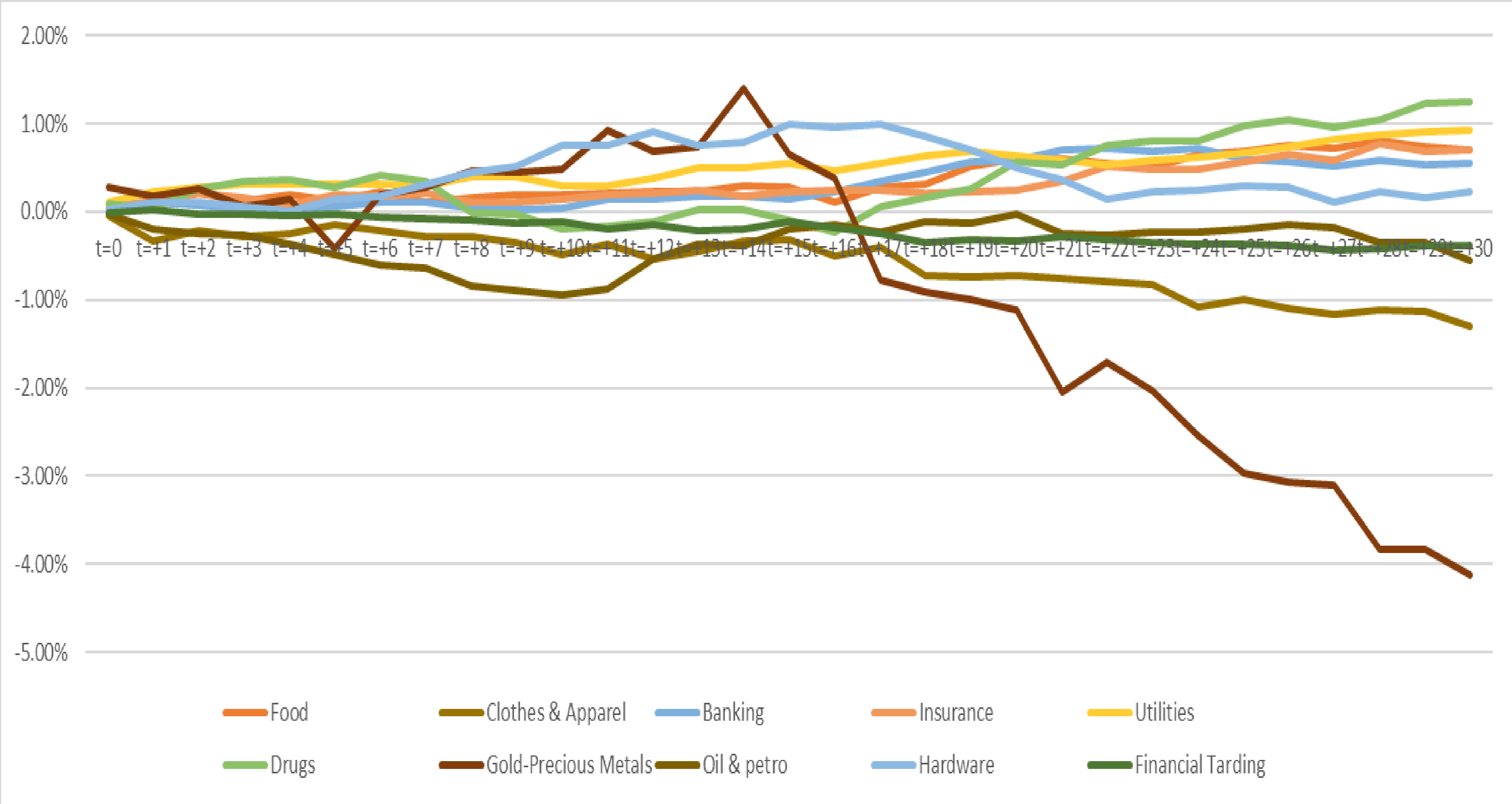

Figure shows daily cumulative average abnormal returns for different equity industries(showing statistically significant response atleast at 10% level) in the event of geophysical disasters.

Table 1 Summary of Impact Measures across natural Disaster classes in the United States (1960-2015)

Disaster Class	Occurrence(s)	Deaths	Total # people affected	Total damage(billion $)	Share in Financial Damage
Meteorological	559	17216	14.1 million	615.41	79.21%
Hydrological	166	2272	12.3 million	60.49	7.78%
Climatological	82	147	0.8 million	59.25	7.62%
Geophysical	30	500	0.08 million	41.75	5.37%
Biological	5	317	0.4 million	0	0%
Total	842	20,452	27.8 million	776.9	

Source: Centre for Research on the Epidemiology of Disasters-CRED available at http://www.emdat.be/

Table 2 Pre-Disaster Market Reactions of Industry portfolios to Hydro-Metorological Disasters

This table presents Cumulative Average Abnormal Retuns of 49 FF Industry Portfolios for pre-disaster period of 3 days in event of meteorological and hydrological disasters (**Prediction 4)**.We divide industry portfolios into three subsets such that Panel A includes industries predicted to have negative impacts of natual disasters **(Prediction 2a)**, Panel B includes industries predicted to have positive impacts **(Predictions 2b, 2c & 3)** and Panel C includes industries predicted to have no specific impacts (**Prediction 1**). We report Boehmer, Musumeci and Poulsen (1991) standardized cross-sectional z score **(BMP)** and Cowan (1992) non parametric significance score **(Sign z)** where ,*,**,*** present 10%, 5%, and 1% significance levels.

	Meterological disasters			**Hydrorological disasters**		
Industries	**CAAR (-3, -1)**	**BMP**	**Sign z**	**CAAR (-3, -1)**	**BMP**	**Sign z**
Panel A						
Banking	-0.02%	-0.667	-0.077	0.05%	4.270***	4.092***
Insurance	-0.02%	-3.660***	-0.798	0.15%	5.268***	4.934***
Panel B						
Construction	0.06%	0.901	1.351	0.06%	0.319	0.616
Drugs	0.05%	2.231**	-0.378	0.06%	3.450***	2.868***
Gold-Precious Metals	-0.08%	-3.269***	0.594	0.22%	3.037***	2.607***
Medical Equip	0.10%	2.656***	-0.114	0.08%	2.828***	1.775*
Panel C						
Agriculture	-0.03%	0.550	-0.529	0.04%	1.518	0.507
Aero-Aircrafts	-0.07%	-1.709*	0.022	0.02%	-0.215	-0.509
Autos & Trucks	0.05%	1.228	1.643	0.03%	0.186	0.988
Beer	-0.03%	-0.342	-0.219	0.19%	2.692***	1.031
Books	0.04%	0.583	-0.762	-0.02%	-0.593	0.438
Boxes- Shipping	-0.03%	-0.133	-1.622	0.00%	-0.082	0.095
Building materials	-0.05%	-0.909	-0.907	-0.01%	-0.468	0.563
Business Services	0.01%	0.050	0.796	-0.01%	0.604	0.922
Candy and Soda	-0.03%	-0.568	0.644	0.00%	1.612	0.639
Chemicals	0.11%	2.162**	0.611	0.08%	2.964***	3.090***
Chips-Electronic	-0.05%	-2.395**	-2.366**	0.00%	0.412	0.691
Clothes & Apparel	0.09%	1.160	1.160	0.10%	1.701*	3.227***
Coal	0.20%	1.409	0.558	0.20%	0.485	0.401
Electric Equipment	-0.03%	-0.844	-1.033	0.00%	0.395	0.406
Fabricated Products	0.16%	1.131	-0.032	-0.09%	-0.946	-0.691
Financial Tarding	-0.03%	-6.250***	3.785***	0.01%	-0.093	3.596***
Food	-0.06%	-1.353	-0.829	0.05%	2.149*	2.430**
Fun & Entertainment	0.11%	1.322	1.843*	0.20%	2.441**	1.014
Guns-Defense	0.06%	1.221	0.738	-0.15%	-0.213	0.224
Hardware	-0.02%	-0.542	-0.630	-0.07%	-1.114	-0.998
Healthcare	0.08%	1.523	0.936	0.01%	1.204	1.398
Household-Consumer	-0.01%	-0.770	-0.472	0.13%	2.520**	2.578***
Lab equipment	0.02%	0.465	-1.004	0.00%	0.809	-0.291
Machinery	-0.03%	-1.031	-2.166**	-0.14%	-2.120**	-2.243**
Meals- Restaurants, hotels	0.06%	0.764	-0.789	0.05%	2.107**	2.151**
Mines	0.05%	0.860	0.080	0.13%	0.930	1.366
Oil & petro	0.10%	2.488**	2.282**	-0.20%	-7.566***	-2.884***
Others	0.01%	1.064	0.173	-0.13%	-1.641	-0.042
Paper	-0.04%	-1.184	-0.968	0.09%	2.062**	1.434
Personal Services	0.10%	1.035	1.759*	0.03%	0.190	1.225
Real Estate	0.07%	2.193**	1.440	0.05%	1.421	0.469
Retail	0.02%	0.322	0.704	0.07%	3.018***	4.380***
Rubber	-0.03%	-0.759	-0.049	0.04%	0.876	0.195
Ships- Rail Roads	-0.03%	0.249	0.751	-0.03%	-1.001	0.243
Smoke	-0.03%	-1.605	-1.412	0.07%	0.135	-0.805
Software	-0.03%	-1.610	0.479	-0.01%	0.964	1.852*
Steel	-0.02%	-1.502	-1.498	0.12%	1.945*	2.403**
Telecom	-0.01%	-0.010	0.183	-0.01%	-0.092	-0.779
Textiles	0.03%	0.246	-0.358	-0.15%	-1.679*	0.024
Toys	-0.03%	-0.496	-0.177	0.04%	1.314	0.108
Transport	-0.06%	-4.128***	-2.442**	-0.07%	-1.550	-0.122
Utilities	-0.01%	-1.236	-0.775	-0.18%	-8.788***	-6.000***
Wholesale	0.02%	0.413	0.390	-0.13%	-1.909*	-2.020**

Table 3 Market Reactions of Industry Portfolios to Different Classes of Natural Disasters

This table presents immediate reaction of 49 FF Industry Portfolios to respective classes of natural disasters. We divide industry portfolios into three subsets such that Panel A includes industries predicted to have negative impacts of natual disasters **(Prediction 2a)**, Panel B includesindustries predicted to have positive impacts **(Predictions 2b, 2c & 3)** and Panel C includes industries predicted to have no specific impacts **(Prediction1).** We report Boehmer, Musumeci and Poulsen (1991) standardized cross-sectional z score **(BMP)** and Cowan (1992) non parametric significance score **(Sign z)** where*,**,*** present 10%, 5% and 1% significance levels.

	Meterological disasters			Hydrorological disasters			Climatological disasters			Geophysical disasters		
Industries	**CAAR (0, +1)**	**BMP**	**Sign z**	**CAAR (0, +1)**	**BMP**	**Sign z**	**CAAR (0, +1)**	**BMP**	**Sign z**	**CAAR (0, +1)**	**BMP**	**Sign z**
Panel A												
Banking	-0.02%	-2.915***	2.600***	0.00%	4.184***	2.997**	-0.03%	2.110**	3.810***	0.11%	3.107***	5.933***
Insurance	0.01%	-0.980	0.176	0.08%	6.364***	5.163***	0.17%	6.69***	8.018***	0.13%	2.825***	2.916***
Panel B												
Construction	0.03%	0.245	1.227	0.19%	3.074***	3.106***	0.05%	2.373**	3.830***	0.01%	0.536	0.405
Drugs	0.00%	-0.395	-0.980	0.01%	1.138	0.875	-0.26%	-1.700*	-1.038	0.04%	1.474	0.342
Gold-Precious Metals	-0.08%	-0.117	1.813*	-0.22%	-3.527***	-1.797*	0.02%	0.173	-0.373	0.17%	1.551	-0.075
Medical Equip	0.05%	0.860	-0.324	-0.01%	0.964	-0.151	-0.06%	2.074*	1.546	-0.19%	-0.478	-0.549
Panel C												
Agriculture	0.00%	0.443	-0.580	0.05%	1.277	0.507	0.25%	1.532	2.658***	-0.25%	-0.269	0.339
Aero-Aircrafts	0.07%	1.958*	0.495	0.15%	1.648	0.400	0.24%	3.768***	4.144***	-0.20%	-1.238	-0.667
Autos & Trucks	-0.01%	0.081	1.472	0.07%	2.649***	2.370**	0.16%	2.382**	1.480	-0.08%	-0.658	-0.552
Beer	0.00%	0.222	-0.395	0.16%	1.704*	1.585	-0.06%	1.311	0.541	-0.25%	-0.816	0.055
Books	0.06%	0.139	0.727	-0.07%	0.479	0.154	0.19%	2.370**	3.864***	-0.07%	0.000	0.013
Boxes- Shipping	0.08%	0.814	0.113	0.05%	1.262	0.917	0.06%	0.818	0.726	0.05%	1.357	1.939*
Building materials	-0.03%	0.428	0.418	0.07%	1.937*	2.864***	0.11%	2.031**	2.6255***	0.06%	1.611	1.775*
Business Services	0.02%	0.738	0.771	-0.03%	-0.089	-0.362	-0.03%	0.482	3.118***	-0.01%	0.530	1.583
Candy and Soda	-0.03%	0.343	0.260	0.06%	1.764*	1.182	-0.07%	1.047	-0.194	-0.10%	-0.266	0.419
Chemicals	0.00%	1.685*	0.655	0.10%	3.121***	2.846**	0.33%	6.290***	3.808***	0.48%	3.238***	3.043***
Chips-Electronic	0.04%	1.519	1.821*	0.05%	2.837***	1.797*	0.02%	1.660*	1.695*	-0.06%	0.448	0.114
Clothes & Apparel	0.02%	0.801	-0.039	-0.08%	0.213	1.120	0.12%	2.946***	3.276***	-0.34%	-3.118**	-1.425
Coal	-0.05%	-0.578	-0.822	-0.37%	-0.827	0.135	0.10%	1.178	0.728	-0.20%	0.240	0.873
Electric Equipment	-0.02%	0.057	-0.612	-0.02%	0.620	1.540	0.24%	2.301*	1.700*	0.16%	2.128*	2.103*
Fabricated Products	0.00%	0.156	1.904*	-0.25%	-1.756*	-0.444	0.29%	0.777	1.418	0.07%	0.000	0.964
Financial Tarding	0.01%	5.408***	8.654***	-0.01%	2.536**	3.379***	-0.02%	6.222***	7.608***	0.02%	0.951	3.133***
Food	0.01%	1.495	0.916	-0.02%	-0.118	0.112	0.22%	4.829***	4.060***	0.08%	1.888*	1.300
Fun & Entertainment	-0.05%	-0.581	1.540	0.07%	0.803	0.873	-0.05%	1.471*	0.433	0.12%	-0.296	1.549
Guns-Defense	-0.04%	0.111	-0.178	-0.04%	0.501	0.163	0.26%	2.600**	1.614	-0.01%	-0.044	-0.689
Hardware	-0.01%	0.431	2.078**	0.01%	1.059	1.842*	0.15%	3.382***	3.958***	0.11%	1.195	2.907***
Healthcare	0.07%	0.879	0.986	-0.01%	0.674	0.519	-0.02%	2.103**	2.491**	-0.22%	-0.615	-0.698
Household-Consumer	0.02%	0.451	1.528	0.07%	0.646	1.791*	0.13%	3.357***	4.292***	0.16%	1.555	1.392
Lab equipment	0.02%	0.440	0.916	0.05%	1.291	0.826	0.12%	2.206**	3.205***	-0.27%	-1.344	-0.580
Machinery	0.01%	-0.046	0.978	-0.02%	1.333	1.392	0.20%	4.718***	4.085***	-0.06%	0.016	0.986
Meals- Restaurants, hotels	0.03%	0.959	1.481	0.11%	2.653***	1.666*	-0.14%	-0.987	0.279	0.02%	0.639	0.267
Mines	-0.03%	0.614	-0.457	-0.29%	-1.377	-1.177	-0.05%	0.495	0.256	0.12%	1.061	0.155
Oil & petro	0.01%	2.255**	3.663***	-0.15%	-5.421***	-4.031***	-0.01%	-3.651***	-2.744***	-0.20%	-1.371	0.615
Others	-0.11%	-1.976**	-0.210	-0.02%	1.089	-0.042	-0.37%	-1.004	-0.347	0.01%	-0.166	0.052
Paper	0.02%	-0.329	0.210	0.03%	1.729*	1.401	0.14%	2.991***	2.816***	0.09%	1.737*	0.753
Personal Services	-0.06%	-2.193**	-0.389	0.18%	2.136**	1.515	-0.03%	0.848	1.654*	-0.43%	-0.136	-0.334
Real Estate	-0.02%	-0.478	-0.656	0.01%	1.732*	1.061	-0.08%	-0.991	0.159	-0.04%	-0.718	0.496
Retail	0.04%	0.522	2.296**	0.01%	1.663*	2.309**	0.14%	4.469***	7.344***	-0.08%	-2.330**	-1.650*
Rubber	0.02%	1.820*	1.767*	-0.01%	1.095	1.944*	-0.20%	0.791	-0.453	-0.04%	0.904	0.650
Ships- Rail Roads	-0.01%	-0.932	-0.471	-0.16%	-0.299	-1.854*	-0.09%	-0.265	0.703	0.41%	1.278	0.416
Smoke	0.03%	-0.718	0.060	-0.11%	-0.844	-0.587	0.34%	2.196*	0.975	0.20%	1.176	0.558
Software	-0.03%	-2.109**	2.268**	0.01%	0.401	1.955*	-0.01%	3.665***	7.437***	0.06%	0.238	1.287
Steel	0.00%	1.170	1.560	0.00%	0.805	1.093	0.35%	4.001***	3.034***	0.24%	3.487***	4.573***
Telecom	0.03%	1.121	0.007	-0.04%	1.420	0.630	0.06%	3.625***	4.285***	0.05%	1.198	1.252
Textiles	-0.11%	-1.423	-1.782*	-0.02%	0.333	0.891	0.20%	0.645	0.427	-0.03%	-0.022	1.177
Toys	-0.02%	-0.689	-1.589	0.12%	1.592	1.782*	-0.02%	1.298	0.488	-0.14%	-0.447	-0.088
Transport	0.06%	2.955***	2.038**	0.09%	2.767***	2.032**	0.15%	2.533**	3.842***	-0.11%	-0.915	-0.587
Utilities	-0.01%	0.159	1.062	-0.03%	-0.993	-1.291	0.09%	3.334***	2.879***	0.22%	6.507***	5.471***
Wholesale	0.00%	-0.134	0.276	0.08%	2.753***	1.791*	0.15%	2.492**	1.970**	-0.02%	1.220	0.745

Table 4 Post-Event Market reactions of Industry Portfolios to Meteorological Natural Disasters

This table presents Cumulative Abnormal Retuns of 49 FF Industry Portfolios over different post-disaster event windows in the event of meteorological disasters. We divide industry portfolios into three subsets such that Panel A includes industries predicted to have negative impacts of natual disasters **(Prediction 2a)**, Panel B includes industries predicted to have positive impacts (**Predictions 2b, 2c & 3**) and Panel C includes to industries predicted to have no specific impacts (**Prediction 1**). We report Boehmer, Musumeci and Poulsen (1991) standardized cross-sectional z score **(BMP)** and Cowan (1992) non parametric significance score **(Sign z)** where *,**,*** present 10%, 5% and 1% significance levels.

Industries	**CAAR (0, +5)**	**BMP**	**Sign z**	**CAAR (0, +10)**	**BMP**	**Sign z**	**CAAR (0,+20)**	**BMP**	**Sign z**	**CAAR (0,+30)**	**BMP**	**Sign z**
Panel A												
Banking	-0.07%	-7.039***	-6.597***	-0.14%	-8.150***	-8.033***	-0.34%	-16.183**	-12.325***	-0.23%	-7.850***	-4.191***
Insurance	0.04%	0.894	2.045**	0.03%	1.003	4.613***	-0.07%	-2.402**	2.901***	-0.09%	-2.169***	5.360***
Panel B												
Construction	0.15%	1.714*	0.930	0.04%	-0.698	0.656	-0.13%	-3.105***	0.565	0.03%	-2.664***	2.214**
Drugs	0.13%	4.022***	2.552**	0.18%	4.713***	5.491***	0.19%	3.311***	7.459***	0.21%	3.433***	9.562***
Gold-Precious Metals	-0.17%	-3.037***	-0.357	0.23%	1.121	0.699	0.81%	5.170***	4.142***	0.69%	3.248***	3.042***
Medical Equip	0.13%	2.971***	0.797	0.14%	2.996***	2.008**	0.32%	3.345***	5.932***	0.33%	2.949***	7.061***
Panel C												
Agriculture	0.02%	0.360	-1.015	0.19%	1.395	-0.864	-0.03%	0.480	-1.391	-0.06%	0.088	-1.467
Aero-Aircrafts	0.02%	0.804	-0.336	0.02%	0.888	0.591	-0.01%	-0.164	1.915*	0.18%	0.128	3.182***
Autos & Trucks	-0.02%	-0.214	0.500	0.07%	1.169	1.322	0.16%	1.315	3.892***	0.24%	1.042	5.023***
Beer	0.00%	0.743	0.699	0.08%	1.159	-0.028	0.16%	2.276**	1.294	0.24%	2.232**	2.683***
Books	0.11%	1.288	2.060**	0.07%	1.367	2.107**	0.04%	1.556	3.362***	0.05%	1.366	3.911***
Boxes- Shipping	0.13%	1.190	-0.380	0.15%	1.265	0.958	0.16%	1.194	1.033	0.31%	1.611	2.792***
Building materials	0.02%	1.445	-0.863	-0.04%	-0.208	-1.094	0.01%	0.087	0.565	0.03%	0.289	1.892*
Business Services	0.03%	0.659	-0.467	0.07%	0.552	2.250**	0.13%	0.533	5.138***	0.11%	0.044	6.880***
Candy and Soda	0.07%	1.764*	-0.121	0.03%	0.407	-0.560	0.09%	0.411	0.950	-0.12%	-0.458	0.209
Chemicals	-0.02%	0.633	-0.440	-0.07%	0.102	0.167	-0.03%	0.002	1.538	0 -0.0	0.156	2.483**
Chips-Electronic	0.00%	0.609	1.022	0.16%	5.908***	7.620***	0.34%	8.102***	13.458***	0.30%	6.779***	13.832***
Clothes & Apparel	0.03%	-0.872	-2.232**	0.02%	-1.024	-1.234	0.07%	-0.401	2.550**	0.14%	0.497	5.100***
Coal	-0.13%	-0.561	-0.043	-0.09%	0.218	0.021	0.29%	1.265	1.078	0.06%	0.694	0.822
Electric Equipment	0.01%	0.916	-1.301	0.06%	2.201**	0.363	0.12%	1.990**	1.874*	0.24%	2.623***	3.746***
Fabricated Products	0.03%	-0.302	0.325	0.20%	1.182	2.250**	0.16%	0.962	1.210	0.43%	1.335	2.250**
Financial Tarding	0.02%	2.699***	13.088***	0.00%	-3.859***	13.903***	-0.11%	-13.973***	11.205***	-0.14%	-16.668***	4.879***
Food	0.02%	1.296	0.494	-0.01%	1.499	0.850	0.05%	3.170***	3.112***	0.12%	3.396***	6.237***
Fun & Entertainment	0.02%	0.444	-0.518	0.06%	0.778	1.579	0.13%	0.004	1.567	0.34%	0.163	3.770***
Guns-Defense	-0.09%	0.374	0.420	-0.01%	1.309	0.556	0.07%	1.152	0.726	0.14%	1.219	0.861
Hardware	-0.08%	-0.964	0.796	-0.02%	0.216	2.648***	0.10%	1.049	6.236***	0.09%	0.323	6.748***
Healthcare	0.16%	1.374	-0.194	0.26%	2.085**	2.826***	0.38%	0.889	3.414***	0.55%	0.917	5.836***
Household-Consumer	0.09%	1.770*	1.952*	0.14%	0.923	1.857*	0.17%	-0.242	3.270***	0.19%	-0.193	3.768***
Lab equipment	-0.01%	-0.873	-1.135	0.13%	2.194**	1.691*	0.30%	3.788***	5.441***	0.27%	2.820***	5.408***
Machinery	-0.05%	-0.899	-1.368	0.02%	0.740	0.685	0.02%	0.448	3.379***	-0.07%	-0.485	5.143***
Meals- Restaurants, hotels	0.06%	-0.346	-0.629	0.03%	-1.930*	-0.892	0.27%	0.523	2.335***	0.33%	0.511	4.017***
Mines	-0.08%	0.904	1.898*	-0.04%	1.490	0.803	-0.08%	1.604	2.622***	-0.34%	0.790	2.696***
Oil & petro	-0.04%	0.705	0.205	-0.02%	2.141**	2.882***	0.11%	5.014***	6.570***	0.01%	3.401***	7.826***
Others	0.02%	-0.675	-2.272**	0.14%	0.257	-0.287	0.22%	-0.032	0.994	0.18%	-0.205	2.165*
Paper	0.06%	0.574	-0.960	0.00%	-0.647	-0.664	-0.11%	-1.461	-0.522	-0.11%	-1.723*	0.296
Personal Services	-0.11%	0.334	-1.922*	0.08%	0.334	-0.480	0.19%	-1.903*	1.777*	0.41%	-0.761	2.102**
Real Estate	0.06%	1.531	-1.196	0.06%	1.145	-1.889*	0.03%	1.442	-0.616	0.22%	2.729***	1.364
Retail	0.00%	-2.168**	-0.221	-0.06%	-4.694***	-0.254	-0.03%	-4.157***	4.473***	0.15%	-1.133	8.015***
Rubber	0.19%	3.002***	1.089	0.30%	3.742***	2.234**	0.49%	3.579***	3.250***	0.57%	3.181***	3.479***
Ships- Rail Roads	-0.07%	-1.198	-1.619	-0.08%	-0.306	-0.956	-0.13%	-0.437	1.002	-0.19%	-0.242	0.943
Smoke	-0.05%	-0.831	-0.295	-0.05%	-1.013	-1.170	-0.21%	-1.965*	-1.170	-0.14%	-1.694*	-0.295
Software	-0.07%	-3.641***	-1.403	0.00%	0.055	5.247***	0.24%	3.274***	11.050***	0.36%	4.312***	13.568***
Steel	0.01%	0.820	1.557	0.04%	1.327	1.662*	-0.02%	-0.255	1.754*	-0.12%	-0.778	3.920***
Telecom	0.06%	1.385	0.198	0.01%	0.006	-0.080	0.12%	2.367**	4.340***	0.19%	3.092***	6.959***
Textiles	-0.08%	-0.838	-2.476**	-0.14%	-1.769*	-1.858*	-0.27%	-2.656***	-1.474	-0.23%	-1.915*	-1.312
Toys	0.09%	0.736	0.799	0.09%	0.382	-0.626	0.16%	0.754	2.434**	0.26%	1.069	3.369***
Transport	0.07%	1.082	0.734	0.06%	-0.696	0.734	0.04%	-1.227	3.172***	0.12%	-0.717	4.740***
Utilities	-0.06%	-4.519***	0.857	-0.08%	-3.574***	3.664***	-0.11%	-1.924*	5.097***	-0.24%	-5.453***	1.561
Wholesale	0.03%	1.117	-0.422	0.05%	1.497	0.994	0.05%	0.863	3.198***	0.08%	1.002	5.570***

Table 5 Post-Event Market reactions of Industry Portfolios to Hydrological Natural Disasters

This table presents Cumulative Abnormal Retuns of 49 FF Industry Portfolios over different post-disaster event windows in the event of hydrological disasters. We divide industry portfolios into three subsets such that Panel A includes industries predicted to have negative impacts of natual disasters (**Prediction 2a**), Panel B includes industries predicted to have positive impacts (**Predictions 2b, 2c & 3**) and Panel C includes industries predicted to have no specific impacts (**Prediction 1**). We report Boehmer, Musumeci and Poulsen (1991) standardized cross-sectional z score (**BMP**) and Cowan (1992) non parametric significance score **(Sign z)** where*,**,*** present 10%, 5% and 1% significance levels.

Industries	CAAR (0, +5)	BMP	Sign z	CAAR (0, +10)	BMP	Sign z	CAAR (0,+20)	BMP	Sign z	CAAR (0,+30)	BMP	Sign z
Panel A												
Banking	-0.04%	-3.212***	-4.630***	-0.06%	-2.051**	-1.012	-0.05%	0.910	3.744***	0.02%	4.927***	9.697***
Insurance	0.01%	1.486	1.536	-0.07%	-0.435	1.969**	-0.11%	-1.099	4.513***	-0.15%	-1.297	4.106***
Panel B												
Construction	0.38%	3.826***	4.000***	0.07%	0.321	1.275	0.03%	1.201	2.504**	-0.23%	0.084	3.655***
Drugs	-0.13%	-1.990**	-4.494***	-0.20%	-1.767*	-3.295***	-0.59%	-2.964***	-1.293	-0.59%	-0.889	2.586***
Gold-Precious Metals	-0.12%	0.263	0.298	-0.06%	1.087	1.526	1.56%	6.736***	5.630***	3.31%	5.037***	4.466***
Medical Equip	0.02%	0.593	0.616	0.10%	1.627	0.171	0.24%	2.233**	3.121***	0.20%	2.153**	4.026***
Panel C												
Agriculutre	-0.14%	0.204	-1.057	-0.11%	0.155	-0.182	0.14%	0.205	0.187	0.60%	0.537	1.893*
Aero-Aircrafts	0.03%	-0.793	0.711	0.21%	1.258	1.340	0.51%	3.401***	4.592***	0.86%	4.615***	5.991***
Autos & Trucks	0.38%	4.273***	3.595***	0.44%	3.751***	2.988**	0.49%	3.106***	4.767***	0.71%	3.945***	5.081***
Beer	0.21%	0.347	0.906	-0.07%	-0.813	-0.282	0.22%	1.015	1.698*	0.59%	2.194**	3.005***
Books	-0.24%	-1.289	-1.007	-0.28%	-2.213**	-0.381	-0.07%	-1.094	0.444	0.07%	-0.957	0.843
Boxes- Shipping	-0.14%	0.081	-0.765	-0.31%	0.024	1.199	-0.22%	1.096	0.970	-0.44%	0.860	2.112**
Building materials	0.00%	0.847	1.929*	-0.02%	-0.066	0.648	-0.05%	0.388	2.727***	-0.06%	0.609	3.107***
Business Services	-0.04%	-0.669	-0.478	-0.13%	-0.895	-0.897	-0.15%	-1.240	2.139**	-0.27%	-1.698*	4.678***
Candy and Soda	-0.12%	-0.372	-0.489	-0.15%	-0.474	0.646	0.16%	-0.198	0.844	0.81%	1.672*	3.263***
Chemicals	-0.01%	0.745	1.090	-0.27%	-3.038***	-1.275	0.10%	1.449	1.884*	0.25%	3.521***	4.637***
Chips-Electronic	0.30%	5.684***	5.785***	0.51%	7.389***	8.224***	0.60%	7.642***	7.607***	0.52%	7.110***	7.551***
Clothes & Apparel	-0.04%	0.021	1.305	-0.29%	-1.515	-1.058	-0.19%	-0.751	1.757*	0.08%	1.219	3.197***
Coal	-0.18%	0.534	0.935	-0.58%	-0.863	0.051	-1.09%	-2.040*	-1.010	-1.27%	-2.121**	-1.717*
Electric Equipment	0.07%	1.443	0.977	0.18%	1.25 1	1.296	0.23%	1.530	2.650***	0.48%	2.495**	5.237***
Fabricated Products	-0.47%	-2.267**	-1.354	-0.43%	-1.772*	-0.202	-0.38%	-0.964	-0.715	-0.71%	-1.521	0.026
Financial Tarding	-0.07%	-4.135***	3.296***	-0.06%	-3.238***	6.295***	-0.10%	-4.007***	4.832***	-0.02%	-2.321**	9.256***
Food	-0.04%	-1.913*	1.570	-0.13%	-2.336**	-2.573**	-0.09%	-1.600	-0.116	-0.09%	-1.345	0.310
Fun & Entertainment	0.24%	0.862	-0.091	0.50%	0.917	0.623	0.74%	1.025	3.251***	1.13%	1.574	4.744***
Guns-Defense	-0.34%	-1.355	-1.303	-0.17%	-0.379	-0.565	-0.38%	0.52	-0.319	-0.26%	0.904	0.111
Hardware	0.08%	1.580	2.531**	0.21%	2.597***	3.608***	0.04%	0.778	3.062***	-0.38%	-0.237	3.624***
Healthcare	0.13%	1.087	-0.417	0.06%	0.782	1.491	-0.02%	-1.252	0.893	0.09%	-1.737*	1.716*
Household-Consumer	0.02%	-2.102**	-1.896*	0.13%	-1.305	0.174	0.35%	0.26 1	1.953*	0.50%	0.415	3.864***
Lab equipment	0.16%	1.071	0.235	0.21%	0.616	-0.487	0.28%	1.175	2.486***	0.42%	2.175**	4.488***
Machinery	-0.10%	0.536	1.379	-0.07%	0.119	1.765*	-0.07%	-0.126	3.470***	-0.08%	0.302	5.254***
Meals- Restaurants, hotels	0.07%	0.899	1.267	0.14%	1.334	0.530	0.47%	3.040**	3.106***	0.60%	3.649***	5.402***
Mines	-0.36%	-0.678	-0.862	-0.54%	-1.167	-2.262**	-0.16%	0.899	-0.350	0.62%	2.902***	2.926***
Oil & petro	-0.05%	0.097	0.887	-0.06%	-0.672	1.319	-0.14%	0.446	3.362***	-0.06%	0.565	3.776***
Others	0.24%	2.767***	0.439	0.24%	1.543	-0.374	0.31%	1.281	0.671	0.55%	1.621	1.164
Paper	-0.02%	-0.904	0.510	-0.01%	-0.742	0.467	0.18%	0.487	1.424	0.41%	1.850*	3.557***
Personal Services	0.15%	0.366	0.820	0.11%	0.366	1.980**	0.60%	1.406	2.138**	1.06%	2.439**	3.562***
Real Estate	0.15%	1.747*	1.794*	0.15%	1.581	2.197**	0.30%	0.862	1.925*	0.37%	0.496	0.999
Retail	-0.06%	-1.744*	-0.057	0.08%	0.362	2.600***	0.22%	0.756	7.112***	0.39%	1.839*	8.079***
Rubber	-0.28%	-1.296	-1.039	-0.28%	-0.979	-0.749	-0.30%	-0.221	0.396	-0.30%	0.536	3.869***
Ships- Rail Roads	-0.20%	-0.474	-1.850*	-0.17%	-0.585	-1.312	-0.14%	0.373	0.139	0.29%	1.087	2.344**
Smoke	0.00%	-0.414	-0.071	0.16%	-0.397	1.018	0.61%	0.319	0.873	1.19%	0.74 2	1.018
Software	0.12%	0.459	1.345	0.24%	2.711***	4.453***	0.17%	1.639	6.054***	0.02%	1.024	7.116***
Steel	-0.11%	-0.264	0.682	-0.01%	-0.475	0.459	-0.05%	-0.127	1.162	0.06%	0.463	2.312***
Telecom	-0.10%	-0.967	-1.433	0.02%	0.742	1.024	-0.04%	0.387	2.114**	-0.04%	1.433	3.742***
Textiles	-0.24%	-0.578	0.940	-0.21%	-0.639	0.891	-0.15%	-0.301	1.958*	0.08%	-0.017	1.642
Toys	0.12%	0.508	-1.232	0.40%	1.987*	0.917	0.67%	2.420**	3.094***	0.59%	2.072**	3.122***
Transport	0.08%	2.638***	2.035**	-0.02%	0.000	0.888	0.19%	1.732*	3.368***	0.26%	2.278**	3.988***
Utilities	-0.02%	0.65	1.899*	-0.16%	-2.338**	-2.479**	0.05%	3.011***	3.163***	0.17%	4.454***	5.715***
Wholesale	0.00%	0.543	-0.843	0.03%	0.408	-0.336	0.02%	0.593	2.043**	-0.13%	-0.648	2.243**

Table 6 Post-Event Market reactions of Industry Portfolios to Climatological Natural Disasters

This table presents Cumulative Abnormal Retuns of 49 FF Industry Portfolios over different post-disaster event windows in the event of climatological disasters. We divide industry portfolios into three subsets such that Panel A includes industries predicted to have negative impacts of natual disasters **(Prediction 2a)**, Panel B includes industries predicted to have positive impacts **(Predictions 2b, 2c & 3)** and Panel C includes industries predicted to have no specific impacts (**Prediction 1**). We report Boehmer, Musumeci and Poulsen (1991) standardized cross-sectional z score **(BMP)** and Cowan (1992) non parametric significance score **(Sign z)** where*,**,*** present 10%, 5% and 1% significance levels.

Industries	CAAR (0, +5)	BMP	Sign z	CAAR (0, +10)	BMP	Sign z	CAAR (0,+20)	BMP	Sign z	CAAR (0,+30)	BMP	Sign z
Panel A												
Banking	0.04%	4.490***	4.074***	-0.24%	-0.377	-1.845*	-0.44%	-0.974	-2.773***	-0.58%	-2.657***	-1.697*
Insurance	0.18%	3.780***	7.264***	0.17%	2.719**	4.609***	-0.14%	-0.536	0.978	-0.04%	-0.478	3.303***
Panel B												
Construction	0.03%	0.611	0.392	0.34%	2.111**	2.402**	0.09%	1.111	1.074	-0.49%	-0.907	0.787
Drugs	0.00%	2.101**	3.188***	-0.55%	-1.593	-0.726	-0.46%	0.299	0.776	-0.24%	1.734*	2.263**
Gold-Precious Metals	0.32%	1.876*	-0.320	0.41%	1.265	-1.404	1.28%	2.640***	0.629	2.44%	4.644***	2.707***
Medical Equip	0.34%	3.712***	3.258***	0.12%	1.496	1.346	0.59%	3.054***	3.726***	0.65%	2.880***	5.103***
Panel C												
Agriculutre	-0.22%	0.655	1.388	-0.45%	-0.412	0.186	-0.29%	-0.390	0.787	1.00%	-0.615	0.110
Aero-Aircrafts	0.41%	2.815***	2.855***	0.55%	3.269***	3.443***	1.09%	3.579***	2.797***	1.18%	3.383***	3.501***
Autos & Trucks	0.19%	2.239**	0.628	0.63%	5.193***	3.115***	0.51%	4.042***	3.183***	0.45%	2.928***	3.081***
Beer	0.01%	2.186**	2.077*	-0.33%	-0.221	0.902	-0.29%	-0.229	-0.025	-0.05%	1.326	1.273
Books	0.23%	1.652*	3.061**	0.37%	2.212**	3.959***	0.34%	1.642	2.162**	0.32%	1.319	4.195***
Boxes- Shipping	0.20%	1.666*	2.295**	0.72%	2.672***	1.475	0.73%	1.988**	2.593***	0.54%	1.318	1.624
Building materials	0.11%	0.848	1.035	0.19%	1.696*	1.787*	0.52%	2.225**	2.977**	0.67%	2.586***	2.915***
Business Services	-0.01%	1.276	3.384***	0.01%	2.386**	4.110***	-0.24%	0.668	2.356**	-0.17%	0.991	4.269***
Candy and Soda	-0.19%	0.143	0.865	-0.06%	0.554	0.034	-0.25%	-0.529	0.185	-0.14%	0.171	0.638
Chemicals	0.40%	4.470***	5.261***	0.68%	6.087***	5.203***	0.93%	5.228***	4.094***	1.40%	5.885***	4.940***
Chips-Electronic	0.02%	3.585***	5.082***	0.47%	7.524***	8.497***	1.25%	2.025**	3.817***	1.30%	8.484***	9.862***
Clothes & Apparel	0.03%	2.104**	2.917***	0.31%	2.903***	5.188***	0.39%	2.592***	3.930***	0.15%	1.296	2.323**
Coal	0.12%	1.335	0.355	-0.47%	-0.711	-1.514	-0.92%	-1.343	-0.673	0.44%	0.143	-0.766
Drugs	0.00%	2.101**	3.188***	-0.55%	-1.593	-0.726	-0.46%	0.299	0.776	-0.24%	1.734*	2.263**
Electric Equipment	0.37%	3.049***	1.929*	0.28%	2.942***	1.252	0.56%	4.064***	3.767***	0.91%	3.897***	3.606***
Fabricated Products	-0.14%	0.439	-0.091	-0.38%	-0.563	-0.307	-0.06%	0.331	1.642	-0.62%	0.387	0.775
Financial Tarding	0.01%	6.379***	13.970***	-0.07%	2.815***	4.746***	-0.14%	-0.273	2.052**	-0.04%	2.328**	4.715***
Food	0.24%	3.362***	2.388**	0.17%	1.275	1.280	-0.10%	-0.112	1.345	-0.06%	0.607	2.193**
Fun & Entertainment	-0.45%	-1.433	0.402	-0.10%	0.666	2.013**	-0.78%	-0.886	0.103	-0.93%	-1.255	0.230
Guns-Defense	0.09%	1.489	1.016	0.03%	1.136	0.816	0.77%	2.489**	1.616	0.41%	2.179*	2.316**
Hardware	0.13%	2.970***	3.720***	0.47%	4.333***	5.268***	0.94%	4.625***	5.939***	1.35%	4.588***	6.094***
Healthcare	-0.15%	0.437	0.815	-0.19%	-0.6	-1.275	-0.26%	-0.449	-0.827	-0.11%	-0.267	1.562
Household-Consumer	0.12%	1.766*	3.472***	0.02%	1.357	2.773***	0.25%	1.507	2.645***	0.14%	0.594	2.089**
Lab equipment	0.44%	4.038***	3.261***	0.74%	4.804***	5.282***	1.07%	4.921***	5.728***	1.25%	4.924***	5.448***
Machinery	0.26%	3.251***	2.962***	0.40%	4.176***	3.531***	0.73%	4.749***	4.276***	0.47%	2.948***	5.372***
Meals- Restaurants, hotels	-0.31%	-0.891	1.102	0.09%	1.248	1.591	-0.60%	-2.214**	-1.098	-0.61%	-1.254	0.552
Mines	0.16%	2.703**	1.714*	-0.09%	1.714*	1.175	-0.21%	0.557	0.852	0.50%	2.101**	1.984**
Oil & petro	0.11%	-1.608	0.386	0.50%	3.745***	2.682***	-0.39%	-2.901***	-0.366	-1.23%	-6.062***	-1.198
Others	-0.15%	-0.518	1.300	-0.33%	-0.589	-0.181	-0.37%	-0.267	0.918	-0.20%	0.122	2.159**
Paper	0.39%	3.550***	2.378**	0.53%	4.817***	3.520***	0.70%	4.314***	3.226***	1.15%	4.384***	5.141***
Personal Services	-0.12%	-2.166**	1.612	0.07%	-2.166**	1.903*	0.26%	0.155	1.820*	0.69%	0.735	2.235**
Real Estate	-0.32%	-1.777*	-0.066	-0.39%	-1.632	-0.418	-0.18%	-0.139	0.051	-0.35%	-1.302	0.129
Retail	0.05%	1.855*	5.880***	0.19%	1.699*	5.275***	0.07%	-0.019	2.864***	-0.03%	-1.710*	1.636
Rubber	-0.32%	-0.287	-0.962	-0.75%	-1.221	-0.369	-1.26%	-1.720*	-0.688	-1.12%	-0.735	0.682
Ships- Rail Roads	-0.04%	-0.207	0.191	0.71%	1.101	1.921*	1.00%	1.278	2.441**	0.50%	0.271	1.748*
Smoke	1.08%	2.881***	3.735***	0.80%	2.065**	3.045**	0.88%	0.614	2.009**	1.88%	1.505	2.700***
Software	-0.21%	2.188**	4.411***	-0.19%	3.470***	6.000***	-0.05%	4.247***	6.559***	0.26%	5.055***	8.052***
Steel	0.32%	3.083***	3.624***	0.48%	2.907***	4.955***	0.62%	2.866***	4.149***	0.56%	2.247**	3.747***
Telecom	0.12%	3.257***	2.511**	0.37%	3.940***	4.532***	1.25%	6.199***	4.884***	1.56%	5.484***	4.730***
Textiles	-0.11%	-1.077	-0.719	-0.61%	-2.554**	-1.865*	-0.46%	-2.211**	-0.418	-0.56%	-2.052**	0.367
Toys	-0.10%	0.604	0.954	0.44%	1.484	1.880*	0.49%	0.946	1.140	0.33%	0.083	0.630
Transport	-0.09%	-0.654	0.031	-0.02%	2.094**	1.757*	0.11%	1.517	1.976**	0.11%	0.259	0.906
Utilities	0.09%	0.196	0.326	0.13%	0.596	2.063**	0.01%	-0.780	-0.990	0.20%	0.646	2.721***
Wholesale	0.10%	1.986**	1.038	0.22%	1.369	0.721	0.23%	0.586	0.608	-0.01%	-0.784	1.015

Table 7 Post-Event Market reactions of Industry Portfolios to Geophysical Natural Disasters

This table presents Cumulative Abnormal Retuns of 49 FF Industry Portfolios over different post-disaster event windows in the event of geophysical disasters. We divide industry portfolios into three subsets such that Panel A includes industries predicted to have negative impacts of natual disasters **(Prediction 2a)**, Panel B includes industries predicted to have positive impacts **(Prediction 2b, 2c & 3)** and Panel C includes industries predicted to have no specific impacts **(Prediction 1)**. We report Boehmer, Musumeci and Poulsen (1991) standardized cross-sectional z score **(BMP)** and Cowan (1992) non parametric significance score **(Sign z)** where,*,**,*** present 10%, 5% and 1% significance levels.

Industries	CAAR (0, +5)	BMP	Sign z	CAAR (0, +10)	BMP	Sign z	CAAR (0,+20)	BMP	Sign z	CAAR (0,+30)	BMP	Sign z
Panel A												
Banking	0.06%	-0.498	5.933***	0.03%	-1.801*	0.808	0.57%	2.144**	6.651***	0.54%	2.832***	6.720***
Insurance	0.19%	3.062***	3.945***	0.13%	1.593	2.791***	0.23%	1.737*	4.693***	0.67%	4.730***	7.749***
Panel B												
Construction	0.47%	0.779	1.417	-0.20%	-1.205	-0.418	0.14%	-0.567	0.540	-0.27%	-0.448	0.940
Drugs	0.28%	3.070***	2.127**	-0.18%	-0.786	-0.372	0.56%	2.133**	4.835***	1.23%	3.598***	5.728***
Gold-Precious Metals	-0.41%	-0.204	-0.597	0.48%	2.670***	2.209**	-1.12%	-0.045	-1.446	-4.08%	-3.156***	-4.317***
Medical Equip	-0.06%	1.025	0.895	0.12%	1.031	1.275	-0.47%	-0.447	2.264**	-0.06%	1.083	2.758***
Panel C												
Agriculutre	-0.68%	-0.729	-1.245	-0.46%	0.276	0.656	0.22%	1.434	1.500	-0.19%	-0.484	0.761
Aero-Aircrafts	-0.44%	-1.424	-1.484	-0.68%	-1.837*	-2.598***	-0.69%	-0.520	-0.073	-1.02%	-0.726	-0.964
Autos & Trucks	-0.06%	-0.655	0.029	0.14%	-0.295	1.675*	-0.36%	-0.719	0.561	-0.41%	-1.005	0.803
Beer	-0.07%	0.241	0.653	0.04%	1.069	0.953	-0.02%	1.117	2.249**	0.36%	1.175	2.747***
Books	-0.11%	0.183	1.331	-0.40%	-0.898	0.607	0.12%	0.043	1.200	0.17%	0.043	1.068
Boxes- Shipping	-0.03%	0.339	-0.414	0.44%	1.411	0.098	1.08%	1.392	0.507	1.43%	1.340	1.018
Building materials	0.06%	-0.353	-0.591	0.25%	0.993	1.244	0.39%	2.044**	2.264**	0.12%	1.689*	2.101**
Business Services	-0.10%	0.176	-0.267	-0.07%	0.139	1.998**	-0.30%	-0.979	3.391***	-0.44%	-0.750	3.557***
Candy and Soda	-0.45%	0.42	0.162	-0.62%	-0.312	0.162	0.00%	0.843	1.188	0.38%	1.052	1.701*
Chemicals	0.35%	2.078**	1.665*	0.39%	1.964*	2.656***	0.74%	2.329**	3.259***	0.18%	0.24 0	2.354**
Chips-Electronic	-0.05%	0.255	0.756	0.38%	3.144***	2.743***	0.12%	2.077**	3.472***	0.41%	2.903***	4.377***
Clothes & Apparel	-0.14%	-0.914	-0.131	-0.47%	-1.923*	-1.127	-0.69%	-2.073*	-0.032	-1.25%	-2.857***	-0.530
Coal	-0.65%	-0.359	1.012	0.59%	0.504	1.151	0.80%	-0.176	0.316	0.62%	0.138	0.038
Electric Equipment	0.19%	1.694*	1.301	-0.25%	-0.364	0.356	-0.31%	-0.007	2.292**	-0.63%	-0.435	1.914*
Fabricated Products	0.38%	0.976	0.792	0.48%	0.887	1.910*	0.40%	0.557	0.534	0.96%	1.449	1.566
Financial Tarding	-0.03%	-2.772***	-1.550	-0.09%	-5.785***	-0.762	-0.31%	-9.142**	-2.661**	-0.35%	-8.788***	-3.264***
Food	0.12%	2.360**	2.741***	0.17%	2.427**	1.931*	0.58%	3.164***	3.372***	0.68%	4.079***	5.714***
Fun & Entertainment	0.02%	0.4	0.307	-0.18%	-0.615	0.049	0.19%	-0.062	1.499	0.30%	0.042	1.940*
Guns-Defense	0.05%	0.205	-0.548	-0.13%	0.122	-0.972	-0.03%	0.036	-0.123	-0.16%	-0.276	0.019
Hardware	0.13%	1.658*	1.510	0.74%	4.050***	3.900***	0.49%	2.974***	4.633***	0.22%	2.387**	4.836***
Healthcare	0.15%	0.907	1.725*	-0.25%	-1.521	-0.080	-0.08%	-0.960	1.345	0.69%	0.361	2.296**
Household-Consumer	0.43%	1.914*	1.640	0.39%	1.399	2.094**	-0.19%	0.511	2.711***	-0.44%	-0.216	1.783*
Lab equipment	-0.02%	0.724	0.679	-0.16%	0.765	1.208	-0.50%	0.963	3.133***	-0.48%	1.379	3.458***
Machinery	0.04%	-0.063	0.092	0.02%	0.031	1.109	-0.06%	0.117	1.756*	-0.28%	-0.209	1.940*
Meals- Restaurants, hotels	0.11%	1.731*	0.812	0.21%	2.532**	2.173**	0.52%	2.224**	2.809***	0.64%	2.651***	3.081***
Mines	0.30%	1.226	1.604	1.05%	1.624	1.040	-0.11%	-0.214	0.073	-1.63%	-1.714*	-0.410
Oil & petro	-0.49%	-1.898*	-0.444	-0.95%	-3.157***	-3.076***	-0.02%	1.811*	1.730*	-0.55%	0.960	3.395***
Others	0.42%	0.211	1.352	0.73%	0.409	1.215	0.21%	-0.160	1.078	0.54%	0.022	0.531
Paper	0.15%	1.408	2.114**	0.09%	1.066	0.608	-0.34%	-0.399	0.511	-0.97%	-1.654*	0.316
Personal Services	-0.15%	-0.136	1.202	0.67%	-0.136	2.313**	0.14%	0.51 0	1.660*	0.67%	1.748*	2.117**
Real Estate	-0.16%	-0.411	0.075	-0.31%	-0.628	-0.135	-0.39%	-0.653	-0.188	-0.25%	0.446	0.549
Retail	-0.14%	-1.529	-0.746	-0.09%	-0.320	1.252	-0.53%	-1.454	0.896	-0.29%	-0.336	3.141***
Rubber	0.34%	2.442**	1.875*	0.61%	2.620***	3.809***	0.47%	1.369	3.411***	0.03%	1.088	3.639***
Ships- Rail Roads	0.56%	0.955	-0.263	-0.13%	0.119	-0.635	0.90%	0.525	0.232	0.53%	0.163	-0.139
Smoke	0.09%	1.152	1.742*	-0.02%	0.972	0.219	-0.57%	-0.471	-1.134	-0.38%	-0.337	1.235
Software	-0.45%	-2.259**	-2.069**	-0.08%	0.302	1.778*	0.11%	0.837	4.257***	0.54%	2.069**	5.444***
Steel	0.21%	1.970**	2.026**	0.40%	2.725***	2.891***	0.12%	1.411	3.516***	-0.18%	0.574	2.795***
Telecom	-0.21%	0.251	0.348	0.07%	1.068	1.553	-0.03%	0.955	2.720***	-0.64%	-0.989	2.306**
Textiles	0.19%	1.397	0.836	0.36%	0.804	1.789*	0.50%	1.341	2.470**	0.20%	0.524	2.470**
Toys	0.14%	0.604	1.274	0.28%	1.711*	1.987**	-0.47%	0.674	1.339	0.05%	1.311	2.117**
Transport	-0.23%	-1.249	-0.704	-0.38%	-0.389	-0.199	-0.49%	-0.864	0.811	-0.19%	-0.878	0.850
Utilities	0.32%	6.869***	6.156***	0.31%	5.453***	4.153***	0.63%	4.336***	3.310***	0.92%	5.783***	3.626***
Wholesale	-0.10%	0.734	0.523	0.01%	1.687*	2.495**	-0.20%	1.066	3.707***	-0.24%	1.134	4.121***