How Tragedy Impacts American

Market Returns and Options Volatility

A Thesis

Presented to

The Honors Tutorial College

Ohio University

In Partial Fulfillment

of the Requirements for Graduation

from the Honors Tutorial College

with the degree of Bachelor of Business Administration

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by

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May 2015

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Abstract

This paper expands on prior research by focusing on tragedy in a broad sense and how it impacts market returns and options volatility. Many investors are victims of framing, a concept where they base purely logical decisions on emotion. In a market where the goal is to accurately interpret the price of an asset, this can cause significant inefficiencies that are further exacerbated through arbitrage. The observations from this research indicate that investors react logically to the two categorized types of tragedy: accidental harm and purposeful harm.

Introduction

Tragedy has a variety of definitions. Some define it as a devastating event that evokes feelings of sorrow, while others describe tragic situations as disastrous events that cause serious illness, financial ruin, or fatality. Only one field of study, behavioral finance, truly analyzes how human nature plays a role in decision making with particular regard to financial markets.

Behavioral finance research has uncovered patterns in market reaction following tragic events. These types of tragedy can be classified into two separate categories: accidental harm and purposeful harm.

Accidentally harmful events, hereafter referred to as accidents, occur as a result of negligence, generally that of a specific company or an employee. One example of an accident is a plane crash that occurred due to the failure of a pilot. The second type of accident is natural disasters. Natural disasters include hurricanes, tornados, earthquakes, or any other event that causes large-scale damage or fatality. They are perceived differently than manmade events for two reasons: natural disasters cause relatively more damage and there is no individual entity to blame.

Purposeful harm, the second type of tragedy, is any event where a human deliberately attempts to harm another through physical, mental or emotional means. A primary example of purposeful harm is terrorism. Chang and Zeng define terrorism as "the threatened or actual use of illegal force and violence to attain a political, economic, religious, or social goal through fear, coercion, or intimidation" (2011).

School shootings are also categorized as purposeful harm but are not considered to have a political, religious, or economic motive.

The financial markets react differently to each type of tragedy. This is especially true with regard to market efficiency. Fama categorized market efficiency into three forms: weak-form, semi-strong-form, and strong-form (1970). Weak-form market efficiency asserts that it is impossible for investors to earn above normal returns, or returns that outperform the financial markets, because the market reacts too quickly to historical information and past prices. Weak-form efficiency is supported by the idea that the trading rules developed to take advantage of new information entering the market cannot be executed quickly enough to reap any significant gains. Semi-strong-form market efficiency maintains that investors cannot utilize publicly traded information in order to achieve above normal returns. This includes all information relating to accounting statements, stock split announcements, dividend announcements, sale of stock announcements, block trades, and earnings announcements. Finally, strong-form efficiency theory states that investors cannot utilize any public or private information in order to earn above normal returns. While papers on semi-strong-form and weak-form display fairly consistent results that confirm their legitimacy, studies on strong-form efficiency theory produce more variable results (Newton and Bacon 2012). The root of the controversy surrounding strong-form market efficiency is based in the idea that trading on private information is insider trading and highly illegal. While it’s commonly understood that insider trading occurs from time to time, it is not sensible to believe that all company information is illicitly shared.

The following research provides insight into how financial markets react following accident harm and purposeful harm. To truly understand the impact of these events, it is important to measure market reaction.

Accidental Harm

Accidents are harmful events caused by people that are not intended to inflict harm or cause damage. These events are a result of negligence instead of ill intent. Within the context of a business, the financially detrimental impact of an accident should primarily affect the offending firm. This is due to the firm's inability to properly execute its duties. A firm's failure to operate safely and maximize profitability warrants a devaluation of share price; this is illustrated in Fodor and Stowe's 2012 paper discussing the market's reaction to the BP Oil Spill. Following the spill, BP's shares dropped 50% in value while trading generally increased across the market; trading volume increased 13 fold and option trading volume increased 20 fold. The suspension of the offending firm's cash dividends also contributes to a decrease in consumer confidence, or consumers' optimism about the financial performance of the economy or a particular industry or firm. Immediately following the spill, there was little reaction by financial markets and the media. In the days and weeks following, reactions to the spill became increasingly apparent in the markets and media. This is an example of an early muted response.

Cherin and Hergert's "The Space Shuttle Tragedy and Aerospace Industry Stock Prices" demonstrates how an initial event directly and indirectly affects the value of involved firms (1987). The paper discusses the 29 firms involved in the construction of the Challenger, a vessel that exploded 73 seconds after takeoff. This event caused the deaths of the seven members aboard. When studying the markets' reaction, the researchers divided the involved companies into three groups. The first group includes only Morton Thiokol, the rocket booster and external fuel tank manufacturer that was initially blamed for the crash by the press. Morton Thiokol experienced a noticeable fall in value in the financial markets. The second group of firms received press coverage for the explosion; they experienced relatively fewer detrimental impacts to the firms' value. The third category of firms never received press attention but initially experienced negative effects as well.

Using the Fama Fisher, Jensen, and Roll Cumulative Average Residual (CAR) technique, the researchers observe 60 months' worth of stock price data for each of the companies involved with the Challenger in order to evaluate the firms' value and performance. This was determined through a least-squares regression analysis. During data analysis, the researchers found no distinguishable discounting in share prices in the days prior to the shuttle launch. In the fifteen day period following the launch, all three groups experience CARs that are significantly negative. The first group of firms, including only Morton Thiokol, experienced the largest negative effect, while the remaining two groups of firms experienced a relatively muted negative effect. Following the explosion, the difference between the CARs of firms covered by the press and those that were not was insignificant, though the firms that were not covered by the press experienced a quicker recovery. In its conclusion, the study suggests that the press plays a significant role in how firms are affected by tragic events.

For the purposes of this study, accidental harm is a plane crash. It is difficult to use historical information when analyzing plane crashes because many papers on the impact of plane crashes on stock prices and financial markets do not differentiate between accidental and purposeful crashes.

Kaplanski and Levy, for instance, describe their sample as "large-scale aviation disasters in a 58-year period with 14,768 trading days, from January 1950 to December 2007" (2010). Their sample does not differentiate between accidental or intentional crashes. Failure to make that distinction detracts from their results. However, their usage of Garner's statement, "Airplane crashes shake the peaceful foundation of our everyday life...it reminds us that the system can fail and people die," implies that many of the crashes are accidents (1996). The paper also notes that out of the 288 crashes used, only 23 are classified as hijacking, incident, or criminal occurrence. Removing those events from the sample has a minimal impact on the study’s results. A significant portion of the impact of removing hijackings is easily explained by the terrorist attacks of September 11, 2001, which led to incalculable damage and loss.

Nevertheless, their research does provide some fascinating insight regarding market reaction to plane crashes. It pertains particularly to this paper because they only included crashes with 75 fatalities or more. While the researchers suggest that this number is arbitrary, its magnitude is significant enough to allow readers to assume that the included accidents are severe and warrant significant media coverage.

Following an aviation disaster, Kaplanski and Levy observe average market loss to be $60 billion. An event study methodology is used to calculate returns following the crashes. Returns are quite high considering the actual estimated loss of a crash is closer to $1 billion. It should be noted that these declines experience a reversal effect in the three days following the event. Media research suggests that severe overreaction is a result of the high amount of publicity airline crashes receive. On average, New York Times front page stories relating to aviation crashes are much larger than stories that depict images other than death. The rate of return following crash coverage was obtained from the NYSE Composite Index. Main regressions were retested using the Equally Weighted Index against the Dow Jones Transportation Index for robustness. They observe a significantly lower average rate of return following an airline disaster in comparison to other non-event days. After three days, the average rate of return rises, signifying a market correction. Fama and French's (1992) ten value-weighted portfolios constructed by size (VIX), as well as ten value-weighted portfolios constructed by industry and volatility (VXO), are analyzed in order to determine a possible differential effect corresponding to any of the previously listed variables.

Both the VIX and VXO see significant changes following the plane crashes. As described by Whaley, this is relevant to volatility because the VIX acts as an Investor Fear Gauge (2000). Set by investors, this index expresses consensus about future stock market volatility. Greater uncertainty caused by fear of future market uncertainty causes the value of the index to rise. When looking at the actual volatility, there was not a significant change in volatility in the days leading up to or following the events.

American crashes have a greater effect on stock market reaction than those that occur outside of the United States. This effect is magnified for firms that are smaller, riskier, or in less stable industries. Researchers also notice a historical correlation between cases of 100 casualty crashes with demand for other airline companies. When 100 people die in one plane crash, demand for rivals increases about 1%. Ho, Qiu, and Tang observe a similar trend, except that rivals actually benefit when the number of fatalities is less than ten (2012). Their work also suggests that greater numbers of fatalities lead to larger and lengthier negative impacts for airlines than crashes with fewer fatalities.

The other type of accidental harm tragedy discussed in this paper is natural disaster. The term "natural disaster" is fairly self-explanatory and describes hurricanes, tornados, earthquakes, or any other event that causes large-scale damage or fatality. These tragedies often have specific rating systems used to estimate or classify the occurrence's potential for harm. For example, hurricanes are categorized by wind speeds, surges, and a 5-point scale for severity. By assigning a numerical value, people can better prepare for the expected impact. Although this paper studies the effects of hurricanes, earthquakes, and tornados, it will only reference hurricane-based studies due to the limited availability of research surrounding the other two disasters.

Lamb's 1998 paper compares market reactions from property and casualty firms following Hurricane Hugo and Hurricane Andrew. While many other tragedy-based papers focus on multiple events, most hurricane papers focus on a few specific events because the available sample size is so small. Focusing primarily on the financial impact of property damage, Hurricane Andrew caused over $21.5 billion in property damage in Florida and Louisiana. Hugo caused only $7 billion in damage in North and South Carolina. Despite varying degrees of severity, it could be assumed that the damage caused by both hurricanes have negatively influenced the value of insurance firms, especially those that derive substantial portions of their revenue from the affected areas.

In order to better test the validity of that assumption, Lamb classifies each of the 34 insurance firms as either exposed or unexposed; exposed firms had written direct premiums for the area and unexposed firms did not. Stock data was gathered from the Chicago Research in Security Prices. Similar to other market reaction papers, a standard event study methodology is used to estimate return performance. Estimated parameters are based on a 150-trading day period leading up to the hurricane. The period ends 10 days before the actual event day. Data from the 10 days leading up to the event day are intentionally omitted because investors could anticipate the path and subsequent level of destruction, which could lead to abnormal returns before the hurricane touches down. The goal of analyzing a 150-trading day period is to calculate expected returns. The Average Excess Returns (AERs) for the 10-day period leading up to the event day are used to see if the government, media, or general public has any significant abnormal influence. In addition, a Cumulative Average Excess Return (CAER) is calculated for the event day and the following day.

When looking at returns surrounding Hugo, no significant AER or CAER is found. Andrew, on the other hand, caused significantly negative returns, especially on the event day and the day after. The severity of physical damage caused by a hurricane directly influences its stock price in the days following the event but not the day leading up to the event. Despite the significance of these results, it should be noted that these results are not measured against any sort of benchmark index.

A similar study observes Lamb's results and adds an additional hurricane, Hurricane Floyd, to the research. Ewing, Hein, and Kruse argue that the "accuracy of and public access to information concerning the expected magnitude of a tropical system has expanded significantly over the ten years since Andrew" (2005). They note that more widespread access to superior information influences how investors react to the hurricane in the days leading up to its arrival. An event study was deemed to be the most appropriate methodology. Assuming efficient market theory is valid, it is sensible to speculate that a sharp rise in claims caused by a hurricane would negatively impact the value of insurer stock prices.

The event study methodology is divided into two parts. In the first, a day-by-day study compares market response (S&P Insurer's index) to the storm's characteristics. This study considers the severity of the storm, each day’s potential damage, wind speed, and location. Therefore, multiple event days better suit this study's goal of seeing how the markets interpret hurricane data. The first day exhibiting significantly negative returns is the day Floyd's wind speed increases to 60 MPH and makes a directional change towards the United States, a change CNN reported. After receiving an upgrade to hurricane status, Floyd again caused significantly negative returns in insurer stock prices. This trend continues and results in a 10-day CAER of negative 2% in the days leading up to the hurricane. As it approaches land, its severity lessens. When it finally touches down, there are positive returns associated with the event day. Yet the negative 2% on the days leading up still outweighs the positive event day impact. Similar methodology is used to analyze market returns on the day leading up to Andrew. As Andrew moves closer or picks up speed, relative returns drop. The consistency in findings between two completely separate events invites the possibility that the markets are constantly observing and interpreting data in order to best predict the impact of an expected event.

Most recently, Blau, Ness, and Wade examine short-selling activity surrounding Hurricanes Katrina and Rita (2008). A sample of 72 insurance firms is gathered and divided by business exposure to Gulf states and non-Gulf states. An event study is again used to test the effects of Katrina and Rita on short-selling activity. The short activity of a certain stock on a certain day decreases by the stock's expected short activity and divided by the sample's standard deviation. Finally, a t-test is used to test the significance of these results.

Starting first with short volume around Katrina, there is no significant increase until three days after landfall. Rita, however, sees a significant overall increase in the surrounding days. Considering the proximity of these two events, it could be assumed that the short-sellers became more sophisticated by interpreting the negative returns surrounding Katrina. Furthermore, Gulf state prices leading up to Katrina decline while non-Gulf state prices do not. When Rita touches down, both Gulf and non-Gulf states see negative impacts. This trend supports a scenario in which investors observe general insurance price declines leading up to Katrina. However, they do not realize that only Gulf states decline significantly. Instead, they generalize all insurance companies, which results in a sell-off of all insurance companies. Nevertheless, the concept of investor adaption to historical information creates difficulty when predicting how market reactions to hurricanes will transform over time.

Purposeful Harm

Instances of purposeful harm occur when an individual or group of individuals inflicts or attempts to inflict pain onto another individual or group of individuals. In order to be considered an event of purposeful harm, the event must lead to at least one fatality. This paper considers school shootings and acts of terror. Little research exists to describe the relationship between school shootings and market returns; as a result, the referenced literature primarily concerns terrorist attacks.

When defining terrorism, Chang and Zeng describe it as "the threatened or actual use of illegal force and violence to attain a political, economic, religious, or social goal through fear, coercion, or intimidation" (2011). Drakos uses the Global Terrorism Database to measure the psychological impact of terrorist attacks (2009). The GTD classifies terrorist attacks by three main categories. The first is major events, which influence the behavior of an entire nation. The second is moderate events, which create general unease but have a specifically large effect on a single subset or minority. Lastly, minor events create some anxiety but do not lead to significant behavioral changes. Events are classified into one of these three categories based on numerous variables including changes in behavior and increases in symptoms such as PTSD. It should be noted that this system does not distinguish between events that do or do not lead to casualties.

Researchers who focus on terrorism and its impact on financial markets, specifically stock markets, have observed trends that give investors insight into how to best position oneself following a terrorist attack. Chen and Siem find that US capital markets tend to recover from terrorist attacks sooner than other global capital markets (2004). Despite this, Karolyi and Martell observe a larger impact on stock prices in countries that are more democratic and wealthier (2005). Considering this information, one could assume that the initial impact of terrorist attacks on stock returns is greater because wealthy countries that run democracies are generally more politically stable than countries that are not. Additionally, more politically stable nations are less terrorized than countries that are experiencing political upheaval or difficult economic times. Therefore, the negative returns following attacks are attributed to domestic investors who overreact to a shocking event because they are less familiar with acts of terror. Lo and Lin address this overreaction and find that investor sentiment has the propensity to override true economic costs of an event. Wealthier nations, such as the United States of America, have more liquid markets that enable institutional investors to create market corrections more quickly.

Chesney, Reshetar, and Karaman notice a similar trend (2010). They observe a pattern of extreme event day movements following acts of terror. The post-event effect is minimal in the days following the terrorist attack. Researchers assume that the negative effect is mainly attributable to overreaction of investors as opposed to efficient markets. However, researchers have not reached full agreement on this assumption of causation. The Chesney, Reshetar, and Karaman paper found that one of the most wealthy, democratic nations in the world, the United States of America, is most resilient to acts of terror. The researchers justify this resilience with the stability of America's financial sectors, leaving the possibility of anomalies. Generally, markets as a whole respond negatively to acts of terror, as they weaken consumer confidence and drive many of them from the market. Drakos' findings suggest that returns on indices are lower by an average of 0.049% following acts of terror (2009). His methodology classified terror as a one-sided risk that produces potentially adverse market returns. These results are determined through a GARCH model. He found that terrorist events that cause minor and major psychosocial impacts generate significant returns of .07% and .6%, respectively. Events of moderate psychosocial impact do not produce significant results. There is potential to consider a correlation between psychosocial impact and market returns following an act of terror, though it is difficult to justify why moderate psychosocial impact did not produce significant results. Regardless, it is assumed that terrorist attacks that cause more severe psychosocial impact also have a greater effect on market returns.

Chesney, Reshetar, and Karaman have a similar conclusion regarding market return measured by indices. Using data that covers 77 acts of terror in 25 countries over 11 years, they implement an event study methodology as well as a non-parametric conditional distribution approach and a GARCH model similar to Drakos' model. While the event study methodology approach is most commonly used for this type of statistical analysis, it imposes restrictive requirements on the behavior of indices'. The non-parametric methodology provides a degree of flexibility because parametric assumptions are not required. The GARCH-EVT method allows researchers to account for volatility background, possible dependence among returns, and the fat-tail nature of their distribution, though it should be noted that this method is only implemented on the event day. Each methodology finds 55, 56, and 45 of the 77 events cause significantly negative returns on either a Swiss, American, or European index. America appears to be most resilient to attacks of terror; the researchers note that only four of the attacks take place in the United States. This information provides evidence of greater impact on stock market returns when the act of terror is domestic. Additionally, it appears that all broad-based indices are negatively affected by acts of terror, with the exception of those focused on industries.

Chesney, Reshetar, and Karaman's 2010 paper also analyzes how acts of terror affect industries. Returns within the banking industry prove to be the most resilient to acts of terror because their operations are not tied to physical events. Conversely, insurance and airline returns were most significantly affected. When considering those industries' revenue streams, the correlation is easy to understand. Physical acts of terror virtually always cause harm to both people and property. Investors conclude that insurance companies will pay out large claims for property and casualty insurance.

With regard to airlines, many people associate terrorism with airplane hijackings. Therefore, when investors hear about terrorism, they often assume that it is associated with an airline or that an airline is the potential target. This overreaction is amplified by the unpredictability of terror attacks. Raby 2003 notes that airlines' negative returns often coincide with negative returns in travel and tourism. However, Chang and Zeng's examination of hospitality stocks following acts of terror gather contrary results.

With a sample of 2,578 acts of terror that occur on American soil, target at least one American, or result in at least one American casualty between January 1, 1973 and April 14, 2003, the researchers use a t-test to analyze the significance of the mean difference between aggregate returns of the Travel and Leisure Index on event days versus non-event days. They inspect one, five, ten, twenty, and forty day aggregate returns and find that 40 day returns of the Travel and Leisure Index on event days outperformed non-event days by 1.8% and the S & P 500 by 1.52%. While these results are statistically significant, it is noted that there is a small number of data points of event days. A characteristic regression produced similar results and also observes that long-term returns of larger events (measured by the number of casualties) are more volatile. However, the 40-day period following events exhibits significantly positive returns. While the researchers acknowledge that index returns are not ideal measurements of consumer sentiment, they still pontificate on the idea that acts of terror actually cause citizens to rally and come together, which is the opposite of the attackers' intentions.

Chesney, Reshetar, and Karaman observe inconsistent returns in pharmaceuticals and defense, as well. Following some acts of terror, those industries are negatively affected. More often than not, both industries exhibit positive returns. In addition, pharmaceutical and defense indices tend to have correlated responses. It can be assumed that this is a result of government spending. Generally, when terrorism occurs, a government's reaction is to boost defense and increase R+D on subsidies to combat pathogenic warfare. Assuming efficient markets exist, government spending boosts impacted revenue streams. Negative returns, on the other hand, exhibit a behavioral bias towards a lack of confidence that has nothing to do with business operations.

Data, Variable Definitions, and Methodology

In order to measure the impact of tragedy on stock returns and options volatility, this study's data sets incorporate S&P 500 returns, VIX returns, and damage and fatality results from tragedies. All of this data is available to the public and is easily imported into Microsoft Excel. The time frame for the data ranges from January 2, 1992 to December 30, 2014. The reason for this time frame is that the VIX did not start trading publically until January 1992. The pricing is gathered from Yahoo Finance. Additionally, the tragedy data is pulled from various terrorist, school shooting, aviation crash, and weather-related databases. Criteria for each disaster include at least one fatality and more than $1 million of damage.

Methodology is based around a multiple linear regression that includes the type of tragedy, amount of damage (in millions), and number of fatalities as the independent variables. All of the considered events occurred on American soil. This is to ensure that the included events garner significant media attention that would be relayed to American exchanges and indices. The S&P 500 and VIX are American indexes and therefore less likely to react to tragedies abroad. The type of tragedy is categorized in a binary format where 1 indicates an event day and 0 indicates a non-event day. The dependent variable is either S&P 500 or VIX returns. Day 0 is the event day and the range extends to the fourth day following the event. Returns are calculated by subtracting Day 0's opening price from its closing price and dividing the result by Day 0's opening price. For Day 1, or the first day following the event, returns are calculated by taking subtracting Day 0's opening price from Day 1's closing price and dividing the result by Day 0's opening price. This trend continues up until Day 4, or the fourth day following the event. This determines how or if the event's effect lasts through the next four days. For simplicity's sake, only the longest two regressions are featured below. All of the others can be found within the section of the paper where they are interpreted and discussed. Below is the basic format for the regression:

$$SPDAYn_t = b_0 + b_1(AVI_t) + b_2(AVIFAT_t) + b_3(TER_t) + b_4(TERFAT_t) + b_5(SS_t) + b_6(SSFAT_t) + b_7(HUR_t) + b_8(HURFAT_t) + b_9(HURDAM_t) + b_{10}(EAR_t) + b_{11}(EARFAT_t) + b_{12}(EARDAM_t) + b_{13}(TOR_t) + b_{14}(TORFAT_t) + b_{15}(TORDAM_t)$$

and

$$VIXDAYn_t = b_0 + b_1(AVI_t) + b_2(AVIFAT_t) + b_3(TER_t) + b_4(TERFAT_t) + b_5(SS_t) + b_6(SSFAT_t) + b_7(HUR_t) + b_8(HURFAT_t) + b_9(HURDAM_t) + b_{10}(EAR_t) + b_{11}(EARFAT_t) + b_{12}(EARDAM_t) + b_{13}(TOR_t) + b_{14}(TORFAT_t) + b_{15}(TORDAM_t)$$

The dependent variable is either *SPDAYn* or *VIXDAYn*, where "*n*" represents the day following the event. *b0* is the intercept. *AVI* represents the binary variable indicating whether there is a plane crash on the day and *AVIFAT* represents the amount of fatalities caused by the accident on the day. *TER* represents the binary variable indicating whether there is an act of terror on the day and *TERFAT* represents the amount of fatalities caused by the attack. *SS* represents the binary variable indicating whether there is a school shooting on the day and *SSFAT* represents the amount of fatalities caused by the attack. *HUR* represents the binary variable indicating whether there was a hurricane on the day, *HURFAT* represents the amount of fatalities caused by the disaster, and *HURDAM* represents the amount of damage caused by the disaster. *EAR* represents the binary variable indicating whether there was an earthquake on the day, *EARFAT* represents the amount of fatalities caused by the disaster, and *EARDAM* represents the amount of damage caused by the disaster. *TOR* represents the binary variable indicating whether there is a tornado on the day, *TORFAT* represents the amount of fatalities caused by the disaster, and *TORDAM* represents the amount of damage caused by the disaster. Two other independent variables that occur in various equations are DAM and FAT. *DAM* represents the total amount of damage caused on the event day, regardless of the type of tragedy. *FAT* represents the total amount of fatalities caused on the event day, regardless of the type of tragedy.

Univariate Results

[Insert Table 1]

Table 1a displays the univariate results related to Day 0 for the S&P 500. The total sample of disasters is 534. While most coefficients have appropriate sample sizes, both Hurricane and Earthquake only have 24 and 5, respectively. The mean reaction to event days is 0.07% compared to an average of 0.04% for all other days. Additionally, the median return on disaster days is 0.10% compared to a median of 0.06% for all other days. These results imply that financial markets experience higher returns on days with tragic events than on days without tragic events. A standard deviation of 1.18% for event days versus 1.13% for all days implies slightly higher volatility on event days as well. The All Days category also includes event days; consequently, the mean, median, and standard deviation for non-event days are all lower than what is presented. Moreover, the absolute value of statistically significant coefficients cited in the research is virtually always larger than 0.1%, suggesting some events lead to abnormal returns.

When analyzing individual tragedies, aviation tragedies have a negative skew at (-0.409) and school shootings have a positive skew of (0.422). These results are similar to later regression coefficients. School shootings typically cause positive market returns while aviation disasters typically cause negative market returns. This indicates that the school shootings with subsequent, atypically high returns caused the actual impact of the tragedy to increase, and vice versa for plane crashes.

Table 1b displays the univariate results related to Day 0 for the VIX. The total sample of disasters is 534. While most coefficients have appropriate sample sizes, both Hurricane and Earthquake only have 24 and 5 respectively. The mean reaction to event days is -0.06% compared to an average of -0.09% for all other days. Additionally, the median return on disaster days is -0.76% compared to a median of -0.60% for all other days. These results imply that days on which tragedy occur do not necessarily see higher or lower returns. Historically, the VIX has been considered a more volatile index, so these results are not surprising. Considering the lack of consistently, statistically significant coefficients associated with the VIX regressions, it is expected that these results are slightly more varied. Event days that have normal samples also have standard deviations close to or less than the All Days number of 5.11%. This further indicates a lesser volatility related to tragedies, which goes against standard logic relating to these events. As a note, the All Days category also includes event days, so the mean, median, and standard deviation for non-event days are all probably higher for the median and standard deviation and lower for the mean than what is presented.

[Insert Table 2]

Table 2 displays how many fatalities are associated with each event. The skews here are all positive because one of the main criteria for event days is at least one fatality. More strict criteria requiring more fatalities could lead to results with even greater statistical significance.

[Insert Table 3]

Table 3 lists damage in millions of USD is associated with each tragedy. The skews here are all positive because one of the main criteria for event days is at least one fatality. More strict criteria requiring more damage could lead to results with even greater statistical significance. Additionally, no data is available for how much damage is caused by plane crashes, school shootings, or acts of terror.

*Univariate results for Days 1, 2, 3, and 4 are also available upon request

Empirical Results

[Insert Table 4]

$$SPDAYn_t = b_0 + b_1(AVI_t) + b_2(AVIFAT_t)$$

Regarding S&P 500 returns following aviation disasters, the intercept is consistently significant at 1% from Day 0 through Day 4, suggesting that the average non-event day would exhibit returns starting around 0.041% and cumulatively grow to 0.177% by Day 4. The two independent variables in the regression clarify the question of how aviation disasters affect market returns. The *AVI* coefficient (-0.207%) and the *AVIFAT* coefficient (0.006%) are significant at 1% and 5% on the actual event day, respectively. On Day 1 (-0.285%) and Day 2 (-0.261%), the *AVI* coefficients are significant at 1% and 5%, indicating additional market loss on the following days before the information has been fully integrated into investor perception. *AVIFAT* loses statistical significance after the event day. Past research observes negative market returns following plane crashes, particularly attributable to airline manufacturing and operating equities. Those samples typically include large-scale disasters, even though the sample for the research presented here includes any crash that caused a fatality.

The findings in this paper appear counterintuitive to previous publications. While estimates indicate a market reaction of -0.165%, the *AVIFAT* coefficient estimates that any crash with over 28 fatalities would lead to a positive market reaction. This is only statistically significant on the event day, but the phenomenon stimulates interesting discussion. It should be noted that the 95th percentile for *AVIFAT* is 22.4, which signifies that the sample lacked many observations close to 28 deaths, as shown in Table 2. As a result, the *AVIFAT* coefficient is acting to minimize the overall impact of the average *AVI* disaster and rarely actually makes the estimated daily return positive. Moving forward, it would be beneficial to add a quadratic *AVI* variable to better estimate the positive *AVI* breaking point. The frequency of single death fatalities indicated by the positive skew in Table 2 could have made *AVIFAT* seem like a binary variable. Additionally, the Adjusted R Square on Day 0 is 0.125%. While this seems low, it merely indicates that there are many other factors that play into S&P 500 returns following an aviation disaster.

$$VIXDAYn_t = b_0 + b_1(AVI_t) + b_2(AVIFAT_t)$$

When analyzing VIX's reactions to aviation crashes, the intercepts are not statistically significant until Day 3 at 5% and Day 4 at 1%. The *AVI* coefficient is significant at 10% on Day 1 (0.976%) and Day 2 (1.16%). Day 0 (-0.027%) and Day 2 (-0.47%) *AVIFAT* coefficients are significant at 5%, and Day 1 (0.051%) is significant at 1%. The implications of these results further support the theories stated in the previous paragraph, though they are not nearly as strong. It would take about 20 fatalities to lead to negative VIX returns following an event. Since that number is in the 90th percentile, it is fairly unlikely that so many fatalities would occur and could point to an anomaly in the data. Instead, most estimated events have a positive, small effect on the VIX. Once again, it would be beneficial to include a quadratic *AVIFAT* variable to see if this is a diminishing effect. For Day 1 and Day 2, the Adjusted R Squares are 0.099% and 0.060%, respectively, implying that there are many more factors in play that influence the VIX.

[Insert Table 5]

$$SPDAYn_t = b_0 + b_1(TER_t) + b_2(TERFAT_t)$$

When analyzing how the S&P 500 reacts to terror attacks, there are few statistically significant results. This is likely attributable to the fact that terror attacks often strike at random, and it is difficult to know on which trading day the impact will occur. Nevertheless, the intercept for the regression is significant at either 5% or 10%, suggesting little activity influenced by acts of terror. The only other independent variable that suggests any sort of statistical significance is the Day 0 *TER* variable (0.324%), which is significant at 10%. This number implies that the market actually reacts positively to acts of Terror on the day following. However, the fact that no surrounding variables possess any statistical significance and a low Adjusted R Square (0.024%) implies that the market effect, if any, is quite temporary. Another likely explanation is that the Day 0 *TER* coefficient is merely a false positive. This denotes that an act of terror should not typically affect market value of any holdings unless the attack has the potential to launch a full-scale war or reveal a significant security breach.

$$VIXDAYn_t = b_0 + b_1(TER_t) + b_2(TERFAT_t)$$

Looking at how the VIX is affected by terror attacks, the intercepts do not become statistically significant until Day 2. Additionally, no coefficient has any statistical significance. This is not surprising, as the goal of most terror attacks is to instill fear in the target's people, not their financial markets. A sample size of 40 may have contributed to the absence of an apparent relationship.

[Insert Table 6]

$$SPDAYn_t = b_0 + b_1(SS_t) + b_2(SSFAT_t)$$

After regressing S&P 500 returns on *SS* and *SSFAT*, results indicate a relatively interesting relationship. Day 1 through Day 4 intercepts are significant 1%, and the Day 0 intercept (0.028%) is only significant at 10%. In conjunction, the Day 0 *SS* (0.348%) is significant at 1% and continues significance on Day 2 (0.473%), Day 3 (0.410%), and Day 4 (0.448%). This implies that there is a strong positive relationship between market returns and school shootings that endures throughout the following days. When an attack occurs, the data suggests that the market on that day will have returns above the norm. This is attributable to the timing of the event and the lack of physical damage caused. Instead, shootings often stimulate dialogue about firearm restrictions, which can lead to panic from pro-gun advocates. This has historically caused abnormal sales growth for firearm manufacturers, which makes gun companies attractive, medium-term investments and helps sustain the increased stock price on the days following. As a result, the market effect remains because investors maintain their investment in the firearm utilities until further litigation can be processed. *SSFAT*, on the other hand, is not statistically significant because it only takes one death or incident of gun violence to spark the discussion regarding future restrictions and spurs pro-gun demand. An Adjusted R Square of 0.165% is relatively low, but indicates that there are many more, unassociated market factors in effect on event days. Most shootings occur before the market closes, which results in interesting data for future market-related research.

$$VIXDAYn_t = b_0 + b_1(SS_t) + b_2(SSFAT_t)$$

Upon regressing the VIX on *SS* and *SSFAT*, the results appear relatively inconclusive. Like many of the other regressions, the Day 2 through Day 4 intercepts are statistically significant. Day 3 (-2.466%) and Day 4 (-2.294%) *SS* estimates are significant at 5% and 10%. This could be a result of an anticipation of lower market volatility, but is more likely a false positive.

[Insert Table 7]

$$SPDAYn_t = b_0 + b_1(HUR_t) + b_2(HURFAT_t) + b_3(HURDAM)$$

The regressions for S&P 500 returns on *HUR*, *HURFAT*, and *HURDAM* support this study's trend in the data that the Day 0 intercept is significant at 5% and the intercepts through Day 1 to Day 4 are significant at 1%. No other coefficients are statistically significant, and four of five Adjusted R Squares are negative. Looking back at the data set, this lack of significance is likely attributable to the loose criteria for the small hurricane sample. While there are minimum death and damage criteria for the events, there is no specification for the hurricane's classification on the

Hurricane Severity Scale. In future research, it is advisable to add this criterion in order to control for smaller hurricanes that do not garner significant media attention. As past research has shown, there is often significant anticipation for hurricanes. This could cause the expected volatility of the event to be priced-in by the actual event day, when the hurricane touches down on American soil.

$$VIXDAYn_t = b_0 + b_1(HUR_t) + b_2(HURFAT_t) + b_3(HURDAM)$$

After regressing VIX returns on *HUR*, *HURFAT*, and *HURDAM*, the Day 0 through Day 2 intercepts are statistically insignificant. Day 3 and Day 4 intercepts are significant at 5% and 1%. On Day 2, both *HURFAT* (-0.032%) and *HURDAM* (0.0003%) are significant at 10%. Applying the mean of each variable to the estimates suggests an approximate 2% increase in expected volatility following the event day. Estimates on Hurricane damage are not released until several days after the event, and the information inflow to the market is not consistent from event to event. This could explain why the statistical significance is so weak. Since these estimates only suggest statistically significant relationships, it would be beneficial to gather a larger sample and include quadratics for *HURFAT* and *HURDAM* in order to see if they would counteract the seemingly negative relationship between the two. This lack of significance could also be attributed to the loose criteria for the hurricane sample, as there is no specification for the hurricane's classification on the Hurricane Severity Scale. In future research, it is advisable to add this criterion in order to control for smaller hurricanes that do not garner significant media attention.

[Insert Table 8]

$$SPDAYn_t = b_0 + b_1(EAR_t) + b_2(EARFAT_t) + b_3(EARDAM)$$

The regressions for S&P 500 returns on *EAR*, *EARFAT*, and *EARDAM* support this study's the trend that the Day 0 intercept is significant at 5% while the intercepts through Day 1 to Day 4 is significant at 1%. No coefficients are statistically significant and all of the Adjusted R Squares are negative. The limited number of earthquake data points (5) is likely the primary cause of statistical insignificance. Large-scale, American earthquakes are not particularly common; as a result, it is difficult to draw a justified conclusion from these results.

$$VIXDAYn_t = b_0 + b_1(EAR_t) + b_2(EARFAT_t) + b_3(EARDAM)$$

After regressing VIX returns on *EAR*, *EARFAT*, and *EARDAM*, the results support the trend that Day 0 and Day 1 intercepts are statistically insignificant and Day 2, Day 3, and Day 4 are significant at 10%, 5%, and 1%. Otherwise, there are no statistically significant coefficients. As previously mentioned, it is difficult to draw any kind of observation from a data sample of 5 observations. All of the Adjusted R Squares are either negative or virtually 0.

[Insert Table 9]

$$SPDAYn_t = b_0 + b_1(TOR_t) + b_2(TORFAT_t) + b_3(TORDAM)$$

Upon regressing S&P 500 returns on *TOR*, *TORFAT*, and *TORDAM*, the trend of the Day 0 intercept being significant at 5% and Day 1 to Day 4 intercepts being significant at 1% continues. No coefficients are statistically significant, and all of the Adjusted R Squares are negative. This lack of significance is likely attributable to the loose criteria for the tornado sample. There are death and damage criteria for the event, but no specification for the tornado's minimum on the Fujita scale. For future research, it is advisable to create a minimum rank on the Fujita Scale in order to control for less severe tornados. Unlike the other types of natural disasters, the sample size of 130 would enable the narrowing of scope.

$$VIXDAYn_t = b_0 + b_1(TOR_t) + b_2(TORFAT_t) + b_3(TORDAM)$$

Upon regressing VIX returns on *TOR*, *TORFAT*, and *TORDAM* the trend of Day 0 and Day 1 intercepts' statistical insignificance and Day 2, Day 3, and Day 4 intercepts' statistical significance at 10%, 5%, and 1% continues. The Day 1 (-1.568%) and Day 2 (-1.550) *TOR* variables are significant at 5% and 10% with Day 1 and Day 2's Adjusted R Squares at 0.034% and 0.024%. Those R Squares are fairly powerful considering the circumstances, but it is difficult to explain why implied 30-day volatility would drop following a tornado. Unlike hurricanes, tornados are not anticipated as far in advance and typically do not cause damage on the same scale. It is even more surprising that there is no significance surrounding the level of damage caused by these hurricanes. Looking back at the data set, this lack of significance is likely attributable to the loose criteria for the tornado sample. While there are death and damage criteria for the event, there is no specification for the tornado's minimum on the Fujita scale. In future research, it would be sensible to add this criterion in order to control for smaller tornadoes that may not have garnered significant media attention.

[Insert Table 10]

$$SPDAYn_t = b_0 + b_1(AVI_t) + b_2(AVIFAT_t) + b_3(TER_t) + b_4(TERFAT_t) + b_5(SS_t) + b_6(SSFAT_t) + b_7(HUR_t) + b_8(HURFAT_t) + b_9(HURDAM_t) + b_{10}(EAR_t) + b_{11}(EARFAT_t) + b_{12}(EARDAM_t) + b_{13}(TOR_t) + b_{14}(TORFAT_t) + b_{15}(TORDAM_t)$$

The results of regressing the S&P 500 on all of the previously mentioned independent variables are fairly predictable. The Day 0 and Day 1 through Day 4 intercepts are significant at 5% and 1%, respectively. Additionally, the Day 0 *AVI* coefficient (-0.209%) and Day 0 *AVIFAT* coefficient (0.006%) were significant at 1% and 5% respectively. Consistent with the aviation specific regression, the *AVI* coefficient remains statistically significant over time while the *AVIFAT* coefficient does not. It can be inferred that the market reacts positively to any crash with 28 or more fatalities. The occurrence of 28 fatalities falls above *AVIFAT*'s 95th percentile shown on Table 1a, causing rarity within the sample of events with that degree of impact. It is assumed that that data is hardly conclusive and the calculated estimates are intended to represent aviation disasters with few fatalities. *AVI* should instead be interpreted as the result of a decline in airplane operator and manufacturer stock. This also has implications for the S%P 500 data.

The Day 0 *SS* coefficient (0.355%) continues to be significant at 1%, likely predicting an increased demand for firearms following a shooting. This increased demand is also reflected in the following days' estimators, which have declining levels of statistical significance. The declining levels of significance indicate that, while the market remembers the event day, it becomes less and less of a factor into returns over time.

The Day 0 *TER* variable (0.325%) is significant at 10%. While 10% significance is only suggestive of a relationship between S&P 500 returns and terror attacks, it does pose an interesting question. Why would the market respond favorably to a domestic act of terror? The likely answer is that this coefficient is a false positive.

One final note is that the Day 0 Adjusted R Square is 0.191%, higher than any of the other singular event days.

$$VIXDAYn_t = b_0 + b_1(AVI_t) + b_2(AVIFAT_t) + b_3(TER_t) + b_4(TERFAT_t) + b_5(SS_t) + b_6(SSFAT_t) + b_7(HUR_t) + b_8(HURFAT_t) + b_9(HURDAM_t) + b_{10}(EAR_t) + b_{11}(EARFAT_t) + b_{12}(EARDAM_t) + b_{13}(TOR_t) + b_{14}(TORFAT_t) + b_{15}(TORDAM_t)$$

Table 10b exhibits findings unique to the current results. The *AVIFAT* coefficients on Day 0 (-0.027%), Day 1 (-0.051%), and Day 2 (-0.048%) are significant at 5%, indicating slightly less expected market volatility over the next 30 days. The *AVI* coefficient is significant at 10% on Day 1 (1.007%) and Day 2 (1.182%). Between those and the Day 2 (0.025%), Day 3 (0.038%), and Day 4 (0.051%) significance at 10%, 5%, and 1%, it appears that the aviation disasters tend to garner more media attention; therefore, a few days of positive VIX returns makes sense. The initial response is that a crash can lead to increased anticipation of future volatility and

AVIFAT acts in place of a quadratic *AVI* variable. On Day 3 (-2.499%) and Day 4 (-2.340%), the intercepts are significant at 5% and 10%. This is consistent with historical analysis and demonstrates a possibility for lower implied volatility following a school shooting. Once again, this could be attributed to the fact that people buy and hold firearm equities instead of buying and selling immediately off of a singular event.

[Insert Table 11]

$$SPDAYn_t = b_0+b_1(AVI_t)+b_2(TER_t)+b_3(SS_t)+b_4(HUR_t)+b_5(EAR_t)+ b_6(TOR_t) + b_7(FAT_t) + b_8(DAM_t)$$

With an Adjusted R Square of 0.259%, Table 11a offers predictions for how the market might react to aviation disasters, terror attacks, and school shootings. It is also the highest Adjusted R Square for all of the regressions. At 5%, the Day 0 *AVI* coefficient (-0.178%) is slightly less impactful than previous coefficients despite its implication for negative reactions on the event day. The impact becomes more severe on Day 1 (-0.261%) and Day 2 (-0.241%). Observing smaller *AVI* coefficients when *AVIFAT* is removed from the regression supports the theory that the variable is significant as a false positive to lower the initial *AVI* impact. Fears of financial and legal consequences for airplane manufacturers and operators likely drive this decline. During the following days, the market is more aware of the consequences of the tragedy and the return hovers around -.25% for the remainder of the time frame. The trend toward selling aviation-related holdings could be contributing to a long-term drop in market value. A similar theory could be proposed regarding the Day 0 *SS* coefficient (0.368%). Significant at 1%, this estimate supports the theory that the market experiences positive gains following a school shooting because buyers will purchase more firearms in fear of pending legal restrictions. Following this market gain, the market stays up around .508%. The increase can be attributed to the fact that investors will hold these firearm equities until information comes to the market regarding regulations. Once again, this effect is active on the event day, but its impact is overlooked by other information in the days following. Other than intercepts, the only other coefficient that is statistically significant is the Day 0 *TER* (0.311%), which is significant at 10%. Like the *TOR* and *EAR* coefficients in Table 10b, this is one of the only instances when the Day 0 *TER* coefficient is statistically significant. This may be a false positive because positive market returns following an act of terror is not consistent with past research.

$$VIXDAYn_t = b_0+b_1(AVI_t)+b_2(TER_t)+b_3(SS_t)+b_4(HUR_t)+b_5(EAR_t)+ b_6(TOR_t) + b_7(FAT_t) + b_8(DAM_t)$$

Day 0 *AVI* (0.636%) and Day 1 *AVI* (0.904%) are significant at 10%, supporting the hypothesis that media attention garnered by plane accidents causes their impact to last longer than all tragedies, other than school shootings. This is not typically seen with weather- or terror-related variables because it is hard to determine exactly who will be impacted. Aviation disasters, on the other hand, cause volatility because there is uncertainty about which firm or firms will actually be punished for the accident. Day 1 (-1.428%) and Day 2 (-1.584%) *TOR* estimates exhibit temporary losses for the market following the event day. The VIX falls after tornados, an interesting result due to the unpredictability of tornados.

[Insert Table 12]

$$SPDAYn_t = b_0 + b_1(AVI_t) + b_2(TER_t) + b_3(SS_t) + b_4(HUR_t) + b_5(EAR_t) + b_6(TOR_t) + b_7(FAT_t)$$

By regressing S&P 500 returns on the binary coefficients and *FAT*, the analysis produced results that are similar to previous observations. Aviation and school shootings are consistent with previous results, both in coefficients and significance levels. The only difference is that the Day 1 *TER* coefficient (0.406%) is significant at 10%. While this is suggestive of a relationship, there are still questions as to where an act of terror would lead to positive market returns of any sort.

$$VIXDAYn_t = b_0 + b_1(AVI_t) + b_2(TER_t) + b_3(SS_t) + b_4(HUR_t) + b_5(EAR_t) + b_6(TOR_t) + b_7(FAT_t)$$

By removing Damage from the regression of VIX returns on the predicting variables, *AVI* seems to lose its statistical significance. This is especially interesting considering the fact that there is no variable for aviation damage. This change in results suggests that the *AVI* statistical significance in Table 11b is a false positive and that aviation disasters do not materially impact volatility. Another theory for this occurrence is that the *AVIFAT* variable needs to be present in order to truly have an impact. *TOR* for Day 1 (-1.474%) and Day 2 (-1.655%) remain constant at 5% and 1%. As previously mentioned, there is little research about how tornados impact the financial markets, though one would assume that the results found here are unexpected. Intuitively, tornados should not lead to less expected volatility. One possible exception is if large-scale tornados in the data set signified an end to tornado season, which is a fairly far-fetched theory.

[Insert Table 13]

$$SPDAYn_t = b_0 + b_1(HUR_t) + b_2(EAR_t) + b_3(TOR_t) + b_4(DAM_t)$$

When regressing S&P 500 returns on independent variables, only *HUR*, *EAR*, *TOR*, and *DAM* are included because the other tragedies do not have any damage-related data listed with them. Consistent with past regressions, the intercepts are all statistically significant. The explanatory variables, on the other hand, have no statistical significance and all of the Adjusted R Squares are negative. While these findings technically fail to reject any sort of null hypothesis, it should be noted that the earthquake sample only has five observations and hurricane only has 24. Over a 22-year observation period, these samples are comparatively small. Until more data can be gathered the current findings will have to stand.

$$VIXDAYn_t = b_0 + b_1(HUR_t) + b_2(EAR_t) + b_3(TOR_t) + b_4(DAM_t)$$

The regression of VIX returns on *HUR*, *EAR*, *TOR*, and *DAM* variables is consistent with the similarly structured regressions. The main difference is that *TOR* is statistically significant on Day 0 (-0.820%) and Day 1 (-1.551%) to Day 2 (-1.717%) at 10%, 5%, and 5%. With Adjusted R Squares hovering around .045%, there is not a strong justification for an explanation regarding VIX variation by tornado occurrences. However, it is another consideration for further research.

Conclusion

This paper expands upon prior research by focusing on tragedy and how it impacts market returns and options volatility. Tragedy can have negative implications for investors' objective decision-making, market efficiencies, and overall confidence in the financial markets. By identifying tragedy-induced inefficiencies, the market can "price them in," or control for them, so that the market can return to a more trustworthy and efficient state.

As with any research, the data and methodology can be improved. Regarding the data set, it would be beneficial if there were a larger available sample. This is difficult to achieve because most of the tragedies occur at random and cannot be prompted legally. By growing the data sets, a researcher could be more selective about which events to choose based on the number of fatalities, amount of damage, or degree of disaster. Methodology could be improved by creating quadratic independent variables in order to determine if there is a diminishing impact from increasing severity of an event. Setting the intercept to zero could also improve the validity of the data.

The observations from this research have shown that, in a broad sense, investors react logically to the two categorized types of tragedy: accidental harm and purposeful harm. When an aviation crash occurs, the S&P 500 tends to decline slightly. As new information enters the market, investors infer that the affected airline or airplane manufacturer is worth less than what investors had previously perceived. The affect decreases over time, which is due to the fact that the market is constantly flooded with new information and aviation-related companies only comprise a small portion of the index. In addition, there is a possibility that when one aviation equity loses value, another gains the value. Simply stated, investors see value in the airline industry but do not want to own a company that has frequent crashes. As a reaction, they move their capital into another aviation-related holding. The number of aviation fatalities, on the other hand, does not typically have a significant effect on the price of these assets because financial markets do not typically have any regard for human life.

Another example of phenomenon is school shootings. The market reacts positively to a school shooting. The fatality of a child does not have a direct impact on a company's value in the eyes of a truly efficient market. Instead, it signals pending legislation that will increase firearm restrictions. When gun owners and enthusiasts fear they will lose their right to a firearm, they rush to the store to purchase more weapons, resulting in abnormal sales for firearm-related equities.

The VIX tracks near-term, expected market volatility. When regressed against the VIX, the independent coefficients rarely have any significant impact. This is consistent with market efficiency theory. It predicts future market fluctuation; however, if the event being analyzed has already occurred, then there is little left to buy into or sell off moving forward.

In every case, there are sure to be extremely large-scale events that will prove to disagree with the previously suggested theories. However, those are seen as anomalies and not something that even the most active investor can trade for regularly. As always, it is hopeful that there is some validity to these theories and by bringing them to the market, another step toward market efficiency is achieved.

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Table 1: This table displays all of the univariate results associated with the respective variables from S&P and VIX Day 0. Aviation, Terror, School Shooting, Hurricane, Earthquake, and Tornado are all binary variables that reflect the returns associated with their event days. "SD" stands for standard deviation, "P5" stands for the 5th percentile, and "P95" stands for the 95th percentile.

Table 1a: S&P and VIX Day 0 Univariate

S&P Day 0	N	Mean	Median	SD	P5	P95
Aviation	247	-0.11%	0.04%	1.10%	-2.17%	1.50%
Terror	41	0.36%	0.22%	0.88%	-0.68%	2.17%
School Shooting	107	0.40%	0.19%	1.49%	-0.99%	2.13%
Hurricane	24	-0.10%	0.03%	1.28%	-2.06%	1.35%
Earthquake	5	0.22%	0.20%	0.33%	-0.14%	0.63%
Tornado	130	0.09%	0.18%	0.99%	-1.74%	1.37%
All Disasters	534	0.07%	0.10%	1.18%	-1.80%	1.59%
All Days	5794	0.04%	0.06%	1.13%	-1.75%	1.66%
All Disasters-All Days	-5260	0.04%	0.04%	0.05%	-0.05%	-0.07%

Table 1b: VIX Day 0 Univariate

VIX Day 0	N	Mean	Median	SD	P5	P95
Aviation	247	-0.06%	-0.62%	5.13%	-7.25%	9.29%
Terror	41	0.80%	0.00%	5.73%	-5.45%	7.32%
School Shooting	107	-0.24%	-1.34%	5.12%	-6.20%	8.79%
Hurricane	24	-1.30%	-1.73%	4.22%	-6.97%	5.20%
Earthquake	5	3.88%	-0.70%	9.50%	-4.37%	16.49%
Tornado	130	-0.15%	-0.50%	4.70%	-8.21%	6.89%
All Disasters	534	-0.06%	-0.76%	5.11%	-7.20%	8.45%
All Days	5794	-0.09%	-0.60%	5.43%	-7.46%	9.24%
All Disasters-All Days	-5260	0.03%	-0.15%	-0.32%	0.27%	-0.79%

Table 2: Aviation, Terror, School Shooting, Hurricane, Earthquake, and Tornado are all binary variables that reflect the fatalities associated with their event days. It differs from the previous charts in that "N" stands for the total number of fatalities. "SD" stands for standard deviation, "P5" stands for the 5th percentile, and "P95" stands for the 95th percentile.

Fatality	N	Mean	Median	SD	P5	P95
Aviation	2047	8.29	2.00	25.79	1.00	22.40
Terror	254	6.20	1.00	26.07	1.00	13.00
School Shooting	271	2.53	1.00	4.27	1.00	6.70
Hurricane	1809	75.38	22.00	241.84	1.00	144.40
Earthquake	68	13.60	2.00	25.95	1.20	48.60
Tornado	1180	9.08	2.00	20.76	1.00	33.20
All Disasters	5629	10.54	2.00	56.61	1.00	30.35
All Days	5629	0.97	0.00	17.45	0.00	2.00
All Disasters-All Days	0	9.57	2.00	39.15	1.00	28.35

Table 3: Aviation, Terror, School Shooting, Hurricane, Earthquake, and Tornado are all binary variables that reflect the damage associated with their event days. It differs from the previous charts in that "N" stands for the total number of fatalities. "SD" stands for standard deviation, "P5" stands for the 5th percentile, and "P95" stands for the 95th percentile.

Damage	N	Mean	Median	SD	P5	P95
Hurricane	$375,929.00	$15,663.71	$7,280.00	$24,122.19	$943.75	$59,678.00
Earthquake	$ 42,399.50	$ 8,479.90	$ 300.00	$17,639.13	$ 24.40	$32,400.00
Tornado	$ 17,950.16	$ 138.08	$ 15.00	$ 493.79	$ 1.00	$ 335.19
All Disasters	$436,278.66	$ 817.00	$ -	$ 6,204.16	$ -	$ 1,085.88
All Days	$436,278.66	$ 75.30	$ -	$ 1,898.26	$ -	$ -
All Disasters-All Days	0	741.70	0.00	4305.90	0.00	1085.88
*In Millions						

Table 4: This table displays how the S&P 500 and VIX react to aviation crashes. Day 0 tracks how the market reacted on the day the event occurred, Day 1 tracks how the market has reacted since the opening of Day 0, etc. Aviation is a binary variable while Aviation Fatality measures the number of fatalities. To the left of each coefficient are asterisks used to denote the level of significance of each coefficient. "***" indicates significance at 1%, "**" indicates significance at 5%, and "*" indicates significance at 10%. Below each coefficient is the standard error.

Table 4a: Aviation S&P Returns

S&P	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	0.41929	***	0.79292	***	1.10860	***	1.42359	***	1.76803	***	*Thousandths
	(-0.15112)		(-0.20931)		(-0.25044)		(-0.28578)		(-0.31651)		
Aviation	-2.06636	***	-2.84663	***	-2.60543	**	-2.16620	-	-2.86863	*	*Thousandths
	(-0.76723)		(-1.06269)		(-1.27152)		(-1.45092)		(-1.60693)		
Aviation Fatality	6.00805	**	3.95671	-	3.69252	-	0.91923	-	3.84516	-	*Hundred-Thousandths
	(-2.77676)		(-3.84609)		(-4.6019)		(-5.25119)		(-5.81581)		
Adjusted R Square	0.00125		0.00090		0.00039		0.00005		0.00021		
Observations	5794		5794		5794		5794		5794		

Table 4b: Aviation VIX Returns

VIX	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	-0.91325	-	0.55525	-	1.81091	-	3.10107	**	4.32575	***	*Thousandths
	(-0.72855)		(-1.08071)		(-1.29727)		(-1.47174)		(-1.61318)		
Aviation	0.25067	-	0.97594	*	1.16120	*	0.94550	-	0.62969	-	*Hundredths
	(-0.36989)		(-0.54868)		(-0.65863)		(-0.74721)		(-0.81902)		
Aviation Fatality	-2.66767	**	-5.12184	***	-4.77131	**	-3.30615	-	-2.97699	-	*Ten-Thousandths
	(-1.33871)		(-1.9858)		(-2.38372)		(-2.70432)		(-2.9642)		
Adjusted R Square	0.00034		0.00099		0.00060		0.00007		-0.00013		
Observations	5794		5794		5794		5794		5794		

Table 5: This table displays how the S&P 500 and VIX react to acts of terror. Day 0 tracks how the market reacted on the day the event occurred, Day 1 tracks how the market has reacted since the opening of Day 0, etc. Terror is a binary variable while Terror Fatality measures the number of fatalities. To the left of each coefficient are asterisks used to denote the level of significance of each coefficient. "***" indicates significance at 1%, "**" indicates significance at 5%, and "*" indicates significance at 10%. Below each coefficient is the standard error.

Table 5a: Terror S&P Returns

S&P	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	0.32943	**	0.65646	***	0.97657	***	1.29894	***	1.62324	***	*Thousandths
	(-0.14846)		(-0.20561)		(-0.24594)		(-0.28061)		(-0.31082)		
Terror	3.24543	*	3.87954	-	4.28157	-	4.59612	-	4.62456	-	*Thousandths
	(-1.81488)		(-2.51344)		(-3.00652)		(-3.43035)		(-3.79961)		
Terror Fatality	0.07442	-	3.73689	-	8.44572	-	6.89657	-	7.66496	-	*Hundred-Thousandths
	(-6.83021)		(-9.45919)		(-11.31486)		(-12.90993)		(-14.29959)		
Adjusted R Square	0.00024		0.00017		0.00022		0.00010		0.00003		
Observations	5794		5794		5794		5794		5794		

Table 5b: Terror VIX Returns

VIX	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	-0.98160	-	0.76443	-	2.14476	*	3.39878	**	4.59447	***	*Thousandths
	(-0.71552)		(-1.06175)		(-1.27428)		(-1.44532)		(-1.58409)		
Terror	1.22275	-	0.74024	-	0.33249	-	0.25985	-	-1.28124	-	*Hundredths
	(-0.87469)		(-1.29794)		(-1.55775)		(-1.76684)		(-1.93648)		
Terror Fatality	-1.26899	-	-6.03855	-	-7.05360	-	-6.80507	-	-3.37536	-	*Ten-Thousandths
	(-3.29184)		(-4.88474)		(-5.86249)		(-6.64941)		(-7.28783)		
Adjusted R Square	-0.00001		-0.00007		-0.00009		-0.00016		-0.00020		
Observations	5794		5794		5794		5794		5794		

Table 6: This table displays how the S&P 500 and VIX react to school shootings. Day 0 tracks how the market reacted on the day the event occurred, Day 1 tracks how the market has reacted since the opening of Day 0, etc. School Shooting is a binary variable while School Shooting Fatality measures the number of fatalities. To the left of each coefficient are asterisks used to denote the level of significance of each coefficient. "***" indicates significance at 1%, "**" indicates significance at 5%, and "*" indicates significance at 10%. Below each coefficient is the standard error.

Table 6a: School Shooting S&P Returns

S&P	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	0.28378	*	0.61791	***	0.91610	***	1.24017	***	1.56641	***	*Thousandths
	(-0.14922)		(-0.20673)		(-0.24726)		(-0.28213)		(-0.31254)		
School Shooting	3.48339	***	2.73716	-	4.73316	**	4.09668	*	4.48330	*	*Thousandths
	(-1.27326)		(-1.764)		(-2.1099)		(-2.40745)		(-2.66693)		
School Shooting Fatality	0.92268	-	3.65287	-	1.50976	-	3.99074	-	2.16292	-	*Ten-Thousands
	(-2.5452)		(-3.52618)		(-4.2176)		(-4.81241)		(-5.33109)		
Adjusted R Square	0.00165		0.00084		0.00104		0.00082		0.00051		
Observations	5794		5794		5794		5794		5794		

Table 6b: School Shooting VIX Returns

VIX	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	-0.86138	-	1.00925	-	2.38343	*	3.75761	***	4.84899	***	*Thousandths
	(-0.71977)		(-1.06783)		(-1.28159)		(-1.45331)		(-1.59295)		
School Shooting	-0.24253	-	-1.21322	-	-1.31903	-	-2.46556	**	-2.29490	*	*Hundredths
	(-0.61418)		(-0.91119)		(-1.09358)		(-1.24011)		(-1.35927)		
School Shooting Fatality	0.11827	-	0.10989	-	-0.05296	-	1.81823	-	1.36478	-	*Thousandths
	(-1.22772)		(-1.82143)		(-2.18604)		(-2.47894)		(-2.71714)		
Adjusted R Square	-0.00032		0.00005		0.00000		0.00035		0.00018		
Observations	5794		5794		5794		5794		5794		

Table 7: This table displays how the S&P 500 and VIX react to hurricanes. Day 0 tracks how the market reacted on the day the event occurred, Day 1 tracks how the market has reacted since the opening of Day 0, etc. Hurricane is a binary variable while Hurricane Fatality and Hurricane Damage measure the number of fatalities and amount of damage, respectively. To the left of each coefficient are asterisks used to denote the level of significance of each coefficient. "***" indicates significance at 1%, "**" indicates significance at 5%, and "*" indicates significance at 10%. Below each coefficient is the standard error.

Table 7a: Hurricane S&P Returns

S&P	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	0.35789	**	0.69074	***	1.03273	***	1.35697	***	1.68341	***	*Thousandths
	(-0.14828)		(-0.20536)		(-0.2456)		(-0.28024)		(-0.31039)		
Hurricane	3.27764	-	-0.89273	-	-32.42742	-	-74.65774	-	-81.13496	-	*Ten-Thousands
	(-30.05848)		(-41.62777)		(-49.78417)		(-56.80609)		(-62.91789)		
Hurricane Fatality	1.48950	-	2.23758	-	3.91695	-	-0.32999	-	0.56020	-	*Hundred-Thousandths
	(-1.94811)		(-2.69792)		(-3.22654)		(-3.68164)		(-4.07775)		
Hurricane Damage	-1.76900	-	-1.82000	-	-3.23000	-	1.45900	-	1.19900	-	*Ten-Millionths
	(-1.953)		(-2.705)		(-3.235)		(-3.691)		(-4.088)		
Adjusted R Square	-0.00032		-0.00037		0.00008		-0.00018		-0.00015		
Observations	5794		5794		5794		5794		5794		

Table 7b: Hurricane VIX Returns

VIX	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	-0.89204	-	0.76978	-	2.05477	-	3.32147	**	4.32956	***	*Thousandths
	(-0.71455)		(-1.06026)		(-1.27213)		(-1.44336)		(-1.58146)		
Hurricane	-1.31927	-	-0.18254	-	-0.55826	-	1.05892	-	2.29185	-	*Hundredths
	(-1.44844)		(-2.14923)		(-2.57872)		(-2.92581)		(-3.20575)		
Hurricane Fatality	-0.93879	-	-1.76757	-	-3.17316	*	-0.80508	-	-2.58257	-	*Ten-Thousandths
	(-0.93875)		(-1.39293)		(-1.67128)		(-1.89624)		(-2.07766)		
Hurricane Damage	1.16160	-	1.28400	-	3.15630	*	0.72650	-	2.23720	-	*Millionths
	(-0.9411)		(-1.3965)		(-1.6755)		(-1.9011)		(-2.0829)		
Adjusted R Square	-0.00025		-0.00020		0.00032		-0.00040		0.00017		
Observations	5794		5794		5794		5794		5794		

Table 8: This table displays how the S&P 500 and VIX react to earthquakes. Day 0 tracks how the market reacted on the day the event occurred, Day 1 tracks how the market has reacted since the opening of Day 0, etc. Earthquake is a binary variable while Earthquake Fatality and Earthquake Damage measure the number of fatalities and amount of damage, respectively. To the left of each coefficient are asterisks used to denote the level of significance of each coefficient. "***" indicates significance at 1%, "**" indicates significance at 5%, and "*" indicates significance at 10%. Below each coefficient is the standard error

Table 8a: Earthquake S&P Returns

S&P	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	0.35081	**	0.68291	***	1.00718	***	1.32513	***	1.65218	***	*Thousandths
	(-0.14805)		(-0.20502)		(-0.24526)		(-0.27979)		(-0.3099)		
Earthquake Damage	-0.10400	-	-4.50130	-	-2.07200	-	-1.25620	-	3.15030	-	*Millionths
	(-4.5349)		(-6.2799)		(-7.5123)		(-8.5698)		(-9.4924)		
Earthquake	0.18712	-	0.01220	-	0.27756	-	1.25954	-	1.44408	-	*Hundredths
	(-0.67413)		(-0.93353)		(-1.11674)		(-1.27395)		(-1.41109)		
Earthquake Fatality	0.06477	-	3.02257	-	1.37714	-	0.65462	-	-2.41709	-	*Thousandths
	(-3.08276)		(-4.26897)		(-5.10674)		(-5.82566)		(-6.4528)		
Adjusted R Square	-0.00049		-0.00039		-0.00047		-0.00025		-0.00033		
Observations	5794		5794		5794		5794		5794		

Table 8b: Earthquake VIX Returns

VIX	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	-0.86694	-	0.83035	-	2.18489	*	3.43498	**	4.52587	***	*Thousandths
	(-0.71328)		(-1.05848)		(-1.27038)		(-1.44079)		(-1.57896)		
Earthquake Damage	-0.41739	-	-0.91673	-	-1.72222	-	-4.43203	-	-7.72926	-	*Hundred-Thousandths
	(-2.18477)		(-3.24211)		(-3.89116)		(-4.41315)		(-4.83634)		
Earthquake	-0.52234	-	-0.68267	-	-0.70351	-	-0.89092	-	-1.10507	-	*Tenths
	(-0.32478)		(-0.48196)		(-0.57844)		(-0.65604)		(-0.71895)		
Earthquake Fatality	0.35723	-	0.73266	-	1.18613	-	3.01259	-	5.31787	-	*Hundredths
	(-1.48518)		(-2.20395)		(-2.64516)		(-3)		(-3.28768)		
Adjusted R Square	0.00002		-0.00013		-0.00020		-0.00012		0.00005		
Observations	5794		5794		5794		5794		5794		

Table 9: This table displays how the S&P 500 and VIX react to tornadoes. Day 0 tracks how the market reacted on the day the event occurred, Day 1 tracks how the market has reacted since the opening of Day 0, etc. Tornado is a binary variable while Tornado Fatality and Tornado Damage measure the number of fatalities and amount of damage, respectively. To the left of each coefficient are asterisks used to denote the level of significance of each coefficient. "***" indicates significance at 1%, "**" indicates significance at 5%, and "*" indicates significance at 10%. Below each coefficient is the standard error.

Table 9a: Tornado S&P Returns

S&P	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	0.34039	**	0.66887	***	1.00060	***	1.32130	***	1.65397	***	*Thousandths
	(-0.14967)		(-0.20728)		(-0.24795)		(-0.28289)		(-0.31333)		
Tornado	6.84627	-	7.91122	-	1.47100	-	2.97377	-	-2.65003	-	*Ten-Thousands
	(-10.91958)		(-15.1221)		(-18.08892)		(-20.63802)		(-22.85884)		
Tornado Fatality	-1.03507	-	1.48421	-	8.12829	-	6.92579	-	8.40944	-	*Hundred-Thousandths
	(-7.41737)		(-10.27203)		(-12.28731)		(-14.01884)		(-15.52739)		
Tornado Damage	-0.39390	-	-1.32120	-	-3.19100	-	-2.45120	-	-1.88200	-	*Millionths
	(-3.1189)		(-4.3192)		(-5.1666)		(-5.8947)		(-6.529)		
Adjusted R Square	-0.00044		-0.00045		-0.00042		-0.00046		-0.00046		
Observations	5794		5794		5794		5794		5794		

Table 9b: Tornado VIX Returns

VIX	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	-0.72618	-	1.13562	-	2.50627	*	3.73223	**	4.73423	***	*Thousandths
	(-0.72107)		(-1.06984)		(-1.28404)		(-1.45654)		(-1.5965)		
Tornado	-0.72658	-	-1.56816	**	-1.54998	*	-1.47550	-	-0.99022	-	*Hundredths
	(-0.52606)		(-0.78051)		(-0.93677)		(-1.06263)		(-1.16473)		
Tornado Fatality	-2.97713	-	-1.52534	-	-4.40362	-	-2.94817	-	-5.37776	-	*Ten-Thousandths
	(-3.57336)		(-5.30176)		(-6.36324)		(-7.21814)		(-7.91169)		
Tornado Damage	1.58806	-	1.21501	-	2.21268	-	1.49129	-	2.79134	-	*Hundred-Thousandths
	(-1.50254)		(-2.22931)		(-2.67564)		(-3.03511)		(-3.32674)		
Adjusted R Square	0.00013		0.00034		0.00024		-0.00004		-0.00021		
Observations	5794		5794		5794		5794		5794		

Table 10: This table displays how the S&P 500 and VIX react to the various events listed in the regression. Day 0 tracks how the market reacted on the day the event occurred, Day 1 tracks how the market has reacted since the opening of Day 0, etc. The singular terms describe the binary variables while the Fatality and Damage terms measure the number of fatalities and amount of damage, respectively. To the left of each coefficient are asterisks used to denote the level of significance of each coefficient. "***" indicates significance at 1%, "**" indicates significance at 5%, and "*" indicates significance at 10%. Below each coefficient is the standard error.

Table 10a: Full Data S&P Returns

S&P	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	0.31838	**	0.68205	***	0.98808	***	1.29088	***	1.64846	***	*Thousandths
	(-0.15487)		(-0.21461)		(-0.2567)		(-0.29298)		(-0.32454)		
Aviation	-2.09244	***	-2.86941	***	-2.61947	**	-2.14547	-	-2.84786	*	*Thousandths
	(-0.76736)		(-1.06334)		(-1.27189)		(-1.45166)		(-1.60807)		
Aviation Fatality	6.01547	**	3.97689	-	3.73180	-	1.05103	-	3.97210	-	*Hundred-Thousandths
	(-2.77625)		(-3.84708)		(-4.60159)		(-5.252)		(-5.81787)		
Terror	3.25033	*	3.81749	-	4.25106	-	4.49607	-	4.57558	-	*Thousandths
	(-1.81498)		(-2.51504)		(-3.0083)		(-3.4335)		(-3.80344)		
Terror Fatality	-0.13329	-	3.39780	-	8.15717	-	6.51985	-	7.34647	-	*Hundred-Thousandths
	(-6.8254)		(-9.45802)		(-11.31299)		(-12.912)		(-14.3032)		
School Shooting	3.55083	***	2.83986	-	4.83516	**	4.20143	*	4.59632	*	*Thousandths
	(-1.27348)		(-1.76468)		(-2.11078)		(-2.40912)		(-2.66869)		
School Shooting Fatality	0.70177	-	3.34412	-	1.12772	-	3.61069	-	1.76286	-	*Ten-Thousands
	(-2.54769)		(-3.53035)		(-4.22275)		(-4.8196)		(-5.33889)		
Hurricane	5.35843	-	2.82744	-	-28.61138	-	-70.68909	-	-76.97378	-	*Ten-Thousands
	(-30.0452)		(-41.63389)		(-49.79939)		(-56.83821)		(-62.96221)		
Hurricane Fatality	1.43699	-	2.22675	-	3.94989	-	-0.30030	-	0.63420	-	*Hundred-Thousandths
	(-1.94824)		(-2.69969)		(-3.22917)		(-3.6856)		(-4.0827)		
Earthquake	0.19037	-	0.01228	-	0.27946	-	1.26296	-	1.44445	-	*Hundredths
	(-0.67334)		(-0.93305)		(-1.11605)		(-1.2738)		(-1.41104)		
Earthquake Fatality	0.06477	-	3.02257	-	1.37714	-	0.65462	-	-2.41709	-	*Thousandths
	(-3.07905)		(-4.26667)		(-5.10347)		(-5.82482)		(-6.45241)		
Tornado	7.34999	-	7.70213	-	1.35742	-	3.19980	-	-3.10607	-	*Ten-Thousands
	(-10.95502)		(-15.18047)		(-18.15776)		(-20.72424)		(-22.95716)		
Tornado Fatality	-0.70560	-	2.01110	-	8.70325	-	7.38560	-	9.05999	-	*Hundred-Thousandths
	(-7.41148)		(-10.27015)		(-12.2844)		(-14.02071)		(-15.53137)		
Hurricane Damage	-1.78800	-	-1.90400	-	-3.30800	-	1.36900	-	1.11100	-	*Ten-Millionths
	(-1.951)		(-2.704)		(-3.234)		(-3.692)		(-4.089)		
Earthquake Damage	-0.10400	-	-4.50130	-	-2.07200	-	-1.25620	-	3.15030	-	*Millionths
	(-4.5294)		(-6.2765)		(-7.5075)		(-8.5686)		(-9.4918)		
Tornado Damage	-0.51760	-	-1.48730	-	-3.37330	-	-2.60500	-	-2.07420	-	*Millionths
	(-3.1154)		(-4.3171)		(-5.1638)		(-5.8936)		(-6.5286)		
Adjusted R Square	0.00191		0.00068		0.00081		0.00004		-0.00021		
Observations	5794		5794		5794		5794		5794		

Table 10b: Full Data VIX Returns

VIX	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	-0.91463	-	0.99595	-	2.45211	*	3.82511	**	5.13317	***	*Thousandths
	(-0.7471)		(-1.10809)		(-1.33019)		(-1.50868)		(-1.65458)		
Aviation	0.26206	-	1.00660	*	1.18154	*	0.97498	-	0.65133	-	*Hundredths
	(-0.37018)		(-0.54904)		(-0.65909)		(-0.74753)		(-0.81982)		
Aviation Fatality	-2.65488	**	-5.08820	**	-4.75815	**	-3.27131	-	-2.98847	-	*Ten-Thousandths
	(-1.33927)		(-1.98639)		(-2.38454)		(-2.70451)		(-2.96605)		
Terror	1.21034	-	0.69742	-	0.27955	-	0.16578	-	-1.36093	-	*Hundredths
	(-0.87555)		(-1.29861)		(-1.5589)		(-1.76808)		(-1.93906)		
Terror Fatality	-1.25846	-	-5.97841	-	-6.97785	-	-6.78837	-	-3.35442	-	*Ten-Thousandths
	(-3.29258)		(-4.88353)		(-5.86239)		(-6.64901)		(-7.29201)		
School Shooting	-0.23377	-	-1.24084	-	-1.35483	-	-2.49924	**	-2.33987	*	*Hundredths
	(-0.61433)		(-0.91117)		(-1.0938)		(-1.24057)		(-1.36054)		
School Shooting Fatality	0.05103	-	0.12428	-	-0.00303	-	1.87460	-	1.48131	-	*Thousandths
	(-1.22901)		(-1.82285)		(-2.18823)		(-2.48185)		(-2.72185)		
Hurricane	-0.86023	-	-3.20165	-	-2.03003	-	-2.53163	-	-0.92008	-	*Hundredths
	(-1.44938)		(-2.14971)		(-2.5806)		(-2.92687)		(-3.20992)		
Hurricane Fatality	-0.04861	-	-0.16032	-	-0.23066	-	-0.37927	**	-0.14584	-	*Thousandths
	(-0.09398)		(-0.1394)		(-0.16734)		(-0.18979)		(-0.20814)		
Earthquake	0.67117	**	0.10583	-	-0.06637	-	-0.09535	-	-0.31213	-	*Tenths
	(-0.32482)		(-0.48177)		(-0.57834)		(-0.65594)		(-0.71937)		
Earthquake Fatality	-1.27172	-	-2.52774	-	-2.09104	-	-1.61948	-	0.30747	-	*Hundredths
	(-1.48534)		(-2.20304)		(-2.64462)		(-2.99948)		(-3.28954)		
Tornado	0.13372	-	-0.30247	-	-1.10835	-	-1.03138	-	-0.97331	-	*Hundredths
	(-0.52847)		(-0.78382)		(-0.94093)		(-1.06719)		(-1.17039)		
Tornado Fatality	-3.74544	-	-7.14311	-	-5.56127	-	-8.27655	-	-6.71212	-	*Ten-Thousandths
	(-3.57531)		(-5.30287)		(-6.36577)		(-7.21994)		(-7.91815)		
Hurricane Damage	0.17420	-	1.55980	-	1.65800	-	3.60210	*	1.18630	-	*Millionths
	(-0.9413)		(-1.3962)		(-1.6761)		(-1.9009)		(-2.0848)		
Earthquake Damage	1.71615	-	3.68819	-	3.09983	-	2.27228	-	-0.58075	-	*Hundred-Thousandths
	(-2.18501)		(-3.24078)		(-3.89036)		(-4.41238)		(-4.83908)		
Tornado Damage	0.26669	-	1.86181	-	1.47107	-	2.44019	-	1.70119	-	*Hundred-Thousandths
	(-1.50289)		(-2.22907)		(-2.67587)		(-3.03492)		(-3.32841)		
Adjusted R Square	-0.00020		0.00069		0.00021		0.00018		-0.00108		
Observations	5794		5794		5794		5794		5794		

Table 11: This table displays how the S&P 500 and VIX react to the various events listed in the regression. Day 0 tracks how the market reacted on the day the event occurred, Day 1 tracks how the market has reacted since the opening of Day 0, etc. The singular terms describe the binary variables while the Fatality and Damage terms measure the number of fatalities and amount of damage, respectively. To the left of each coefficient are asterisks used to denote the level of significance of each coefficient. "***" indicates significance at 1%, "**" indicates significance at 5%, and "*" indicates significance at 10%. Below each coefficient is the standard error.

Table 11a: Summed Damage and Fatality S&P Returns

S&P	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	0.31903	**	0.68179	***	0.98777	***	1.29094	***	1.64937	***	*Thousandths
	(-0.15481)		(-0.2145)		(-0.25655)		(-0.29283)		(-0.32437)		
Aviation	-1.78043	**	-2.75622	***	-2.61850	**	-2.17367	-	-2.76957	*	*Thousandths
	(-0.74212)		(-1.02824)		(-1.2298)		(-1.4037)		(-1.5549)		
Terror	3.10909	*	3.95966	-	4.54375	-	4.92846	-	4.89362	-	*Thousandths
	(-1.76525)		(-2.44584)		(-2.92528)		(-3.33893)		(-3.69859)		
School Shooting	3.67533	***	3.62513	**	5.02536	***	5.08294	**	4.96732	**	*Thousandths
	(-1.09819)		(-1.5216)		(-1.81986)		(-2.0772)		(-2.30095)		
Hurricane	8.09759	-	3.95020	-	-31.79164	-	-56.70097	-	-58.37454	-	*Ten-Thousands
	(-28.16977)		(-39.03065)		(-46.68157)		(-53.28247)		(-59.0219)		
Earthquake	0.35570	-	0.45081	-	0.60069	-	1.09468	-	0.88793	-	*Hundredths
	(-0.51527)		(-0.71393)		(-0.85388)		(-0.97462)		(-1.0796)		
Tornado	3.94083	-	5.25895	-	1.48782	-	5.04723	-	-0.49517	-	*Ten-Thousands
	(-10.12243)		(-14.02513)		(-16.77439)		(-19.14633)		(-21.20872)		
Fatality	2.21480	-	2.56562	-	3.80187	-	1.26696	-	2.88653	-	*Hundred-Thousandths
	(-1.41982)		(-1.96724)		(-2.35286)		(-2.68556)		(-2.97484)		
Damage	-2.30700	-	-2.12000	-	-3.03100	-	-0.28200	-	-1.16300	-	*Ten-Millionths
	(-1.474)		(-2.042)		(-2.442)		(-2.788)		(-3.088)		
Adjusted R Square	0.00259		0.00159		0.00189		0.00101		0.00082		
Observations	5794		5794		5794		5794		5794		

Table 11b: Summed Damage and Fatality VIX Returns

VIX	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	-0.76849	-	1.03591	-	2.53589	*	3.98091	***	4.77902	***	*Thousandths
	(-0.7467)		(-1.10801)		(-1.32982)		(-1.50877)		(-1.65372)		
Aviation	0.63586	*	0.90359	*	0.79083	-	0.35023	-	0.52139	-	*Hundredths
	(-0.35794)		(-0.53113)		(-0.63746)		(-0.72324)		(-0.79273)		
Terror	-1.12188	-	-1.59811	-	-1.60748	-	-2.79823	-	-2.54845	-	*Hundredths
	(-0.85142)		(-1.26339)		(-1.51631)		(-1.72035)		(-1.88563)		
School Shooting	-0.34785	-	-0.52967	-	-1.16938	-	-1.13288	-	-0.81334	-	*Hundredths
	(-0.52968)		(-0.78597)		(-0.94332)		(-1.07025)		(-1.17308)		
Hurricane	-1.40026	-	-0.20120	-	0.48340	-	1.44253	-	3.06185	-	*Hundredths
	(-1.35869)		(-2.01611)		(-2.41972)		(-2.74532)		(-3.00909)		
Earthquake	-0.47795	*	-0.53862	-	-0.67490	-	-0.56468	-	-0.50087	-	*Tenths
	(-0.24852)		(-0.36878)		(-0.4426)		(-0.50216)		(-0.55041)		
Tornado	-0.74018	-	-1.42817	**	-1.58362	*	-1.60237	-	-1.06486	-	*Hundredths
	(-0.48822)		(-0.72446)		(-0.86949)		(-0.98649)		(-1.08127)		
Fatality	-83.56580	-	-128.56160	-	-140.47070	-	7.67350	-	-105.39410	-	*Millionths
	(-68.481)		(-101.6168)		(-121.9598)		(-138.3709)		(-151.6652)		
Damage	1.15440	-	1.06620	-	1.64750	-	0.07150	-	1.00900	-	*Millionths
	(-0.7109)		(-1.0548)		(-1.266)		(-1.4363)		(-1.5743)		
Adjusted R Square	0.00082		0.00079		0.00072		0.00006		-0.00009		
Observations	5794		5794		5794		5794		5794		

Table 12: This table displays how the S&P 500 and VIX react to the various events listed in the regression. Day 0 tracks how the market reacted on the day the event occurred, Day 1 tracks how the market has reacted since the opening of Day 0, etc. The singular terms describe the binary variables while the Fatality term measuring the number of fatalities. To the left of each coefficient are asterisks used to denote the level of significance of each coefficient. "***" indicates significance at 1%, "**" indicates significance at 5%, and "*" indicates significance at 10%. Below each coefficient is the standard error.

Table 12a: Sole Fatality S&P Returns

S&P	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	0.31885	**	0.68162	***	0.98753	***	1.29091	***	1.64928	***	*Thousandths
	(-0.15483)		(-0.2145)		(-0.25656)		(-0.2928)		(-0.32435)		
Aviation	-1.62049	**	-2.60922	**	-2.40837	**	-2.15413	-	-2.68893	*	*Thousandths
	(-0.73514)		(-1.01845)		(-1.21814)		(-1.39021)		(-1.53997)		
Terror	3.21589	*	4.05782	*	4.68408	-	4.94151	-	4.94747	-	*Thousandths
	(-1.76415)		(-2.44403)		(-2.92323)		(-3.33615)		(-3.69555)		
School Shooting	3.71795	***	3.66430	**	5.08136	***	5.08814	**	4.98881	**	*Thousandths
	(-1.09799)		(-1.52114)		(-1.81939)		(-2.07638)		(-2.30007)		
Hurricane	-15.01529	-	-17.29252	-	-62.15939	-	-59.52543	-	-70.02813	-	*Ten-Thousands
	(-23.99105)		(-33.23687)		(-39.75366)		(-45.36894)		(-50.25652)		
Earthquake	0.18354	-	0.29258	-	0.37448	-	1.07364	-	0.80112	-	*Hundredths
	(-0.50345)		(-0.69747)		(-0.83423)		(-0.95207)		(-1.05463)		
Tornado	4.93979	-	6.17709	-	2.80035	-	5.16930	-	0.00851	-	*Ten-Thousands
	(-10.10354)		(-13.99731)		(-16.74178)		(-19.10659)		(-21.16494)		
Fatality	0.49339	-	0.98350	-	1.54013	-	1.05660	-	2.01859	-	*Hundred-Thousandths
	(-0.89791)		(-1.24395)		(-1.48785)		(-1.69802)		(-1.88094)		
Adjusted R Square	0.00234		0.00158		0.00180		0.00119		0.00097		
Observations	5794		5794		5794		5794		5794		

Table 12b: Sole Fatality VIX Returns

VIX	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	-0.76756	-	1.03677	-	2.53722	*	3.98097	***	4.77983	***	*Thousandths
	(-0.74681)		(-1.10801)		(-1.3299)		(-1.50864)		(-1.65364)		
Aviation	0.55581	-	0.82966	-	0.67659	-	0.34527	-	0.45142	-	*Hundredths
	(-0.35458)		(-0.52607)		(-0.63143)		(-0.71629)		(-0.78514)		
Terror	-1.17534	-	-1.64748	-	-1.68377	-	-2.80154	-	-2.59517	-	*Hundredths
	(-0.8509)		(-1.26245)		(-1.51527)		(-1.71891)		(-1.88413)		
School Shooting	-0.36918	-	-0.54937	-	-1.19982	-	-1.13420	-	-0.83198	-	*Hundredths
	(-0.52959)		(-0.78573)		(-0.94309)		(-1.06983)		(-1.17266)		
Hurricane	-0.24351	-	0.86721	-	2.13426	-	1.51419	-	4.07292	-	*Hundredths
	(-1.15716)		(-1.71683)		(-2.06065)		(-2.33759)		(-2.56227)		
Earthquake	-0.39179	-	-0.45904	-	-0.55193	-	-0.55934	-	-0.42555	-	*Tenths
	(-0.24283)		(-0.36028)		(-0.43243)		(-0.49054)		(-0.53769)		
Tornado	-0.79018	-	-1.47435	**	-1.65497	*	-1.60547	-	-1.10856	-	*Hundredths
	(-0.48732)		(-0.72302)		(-0.86782)		(-0.98445)		(-1.07907)		
Fatality	2.58656	-	-48.98837	-	-17.51716	-	13.01060	-	-30.09157	-	*Millionths
	(-43.3087)		(-64.2555)		(-77.1235)		(-87.4885)		(-95.8975)		
Adjusted R Square	0.00054		0.00079		0.00060		0.00024		0.00001		
Observations	5794		5794		5794		5794		5794		

Table 13: This table displays how the S&P 500 and VIX react to the various events listed in the regression. Day 0 tracks how the market reacted on the day the event occurred, Day 1 tracks how the market has reacted since the opening of Day 0, etc. The singular terms describe the binary variables while the Damage term measuring the amount of damage. To the left of each coefficient are asterisks used to denote the level of significance of each coefficient. "***" indicates significance at 1%, "**" indicates significance at 5%, and "*" indicates significance at 10%. Below each coefficient is the standard error.

Table 13a: Sole Damage S&P Returns

S&P	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	0.34320	**	0.67118	***	1.01814	***	1.33419	***	1.67124	***	*Thousandths
	(-0.15002)		(-0.20777)		(-0.24849)		(-0.28349)		(-0.31401)		
Hurricane	-5.80909	-	-12.84245	-	-54.87932	-	-66.72833	-	-77.09484	-	*Ten-Thousandths
	(-27.26731)		(-37.76264)		(-45.16548)		(-51.52544)		(-57.07343)		
Earthquake	0.22977	-	0.30770	-	0.38633	-	1.01776	-	0.72403	-	*Hundredths
	(-0.5102)		(-0.70658)		(-0.8451)		(-0.9641)		(-1.06791)		
Tornado	5.96092	-	7.61753	-	5.03458	-	5.92995	-	2.08825	-	*Ten-Thousands
	(-10.02851)		(-13.88853)		(-16.61119)		(-18.95028)		(-20.99075)		
Damage	-0.49470	-	-0.00828	-	0.07116	-	0.77735	-	1.20699	-	*Ten-Millionths
	(-0.933)		(-1.293)		(-1.546)		(-1.764)		(-1.953)		
Adjusted R Square	-0.00051		-0.00058		-0.00030		-0.00014		-0.00026		
Observations	5794		5794		5794		5794		5794		

Table 13b: Sole Damage VIX Returns

VIX	Day 0		Day 1		Day 2		Day 3		Day 4		
Intercept	-0.67767	-	1.15430	-	2.48199	*	3.71794	**	4.62237	***	*Thousandths
	(-0.72261)		(-1.07224)		(-1.2868)		(-1.45979)		(-1.59993)		
Hurricane	-0.89915	-	0.56036	-	1.30349	-	1.48504	-	3.67785	-	*Hundredths
	(-1.31339)		(-1.94886)		(-2.33884)		(-2.65326)		(-2.90798)		
Earthquake	-0.43232	*	-0.46832	-	-0.59657	-	-0.56557	-	-0.44099	-	*Tenths
	(-0.24575)		(-0.36465)		(-0.43762)		(-0.49645)		(-0.54411)		
Tornado	-0.81972	*	-1.55120	**	-1.71657	**	-1.57221	-	-1.15486	-	*Hundredths
	(-0.48305)		(-0.71676)		(-0.86019)		(-0.97583)		(-1.06951)		
Damage	0.47151	-	0.01709	-	0.50478	-	0.12535	-	0.15235	-	*Millionths
	(-0.4495)		(-0.667)		(-0.8005)		(-0.9081)		(-0.9953)		
Adjusted R Square	0.00040		0.00042		0.00049		0.00006		0.00004		
Observations	5794		5794		5794		5794		5794		