Erasmus University Rotterdam
Erasmus School of Economics

Bachelor Thesis [International Bachelor of Economics and Business Economics]

International Market Integration's Role in Stock Market's Responses to Disaster Events

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Date final version: 25/06/2020

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Abstract

As a result of the increased frequency and severity of terrorism and natural disaster events in the world, investment’s disaster risks are higher than ever. As global supply chains influence the level of such risk for a company, as well as its ability to recover from events, the question is raised as to what extent market integration impacts financial markets in the occurrence of disaster events. The empirical analysis of disaster events and international stock market indices between 1990 and 2018, includes event studies and regression analyses. It was found that market integration causes positive long run returns for markets that are highly correlated to the event country in case of natural disaster events, providing profitable investment opportunities.

Keywords: Finance, Financial Crisis, Stock Market Integration, Financial Risk, Financial Markets

JEL Classification: F3, F4, G1, G4, O05,

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Introduction

On January 29th, 2020, the first person in Europe was diagnosed with COVID-19, a virus that started in China, and on March 17th, every European country had dealt with at least one case. As a response, multiple different measures were taken by governments all over the world, including total lockdowns of economies and social life in a great number of countries. Other measures were less severe, such as "intelligent" lockdowns, where the liberty for companies to continue operations depended on their activity or industry (BCC, 2020). These measures and the spread itself had a large negative impact on the world's economy and the financial stock markets, as March 9th in the same year marked the largest one-day price drop in history in the Dow Jones Industrial Average (DJIA)[1] index.

At the time of conducting this research, the first countries, like China, Denmark and Norway, had already started to loosen the previously taken measures, and to reopen economies up to a certain extent (National Public Radio, 2020, Norwegian Government Security and Service Organisation, 2020, Financial Times, 2020). Meanwhile, other countries such as Spain and Italy, continued their complete lockdown measures (Dirección General de Gobernanza Pública, 2020, The Guardian, 2020). One could expect Chinese, Danish and Norwegian stock markets to react more positively to these policy decisions than Spanish and Italian ones. However, due to globalization, the extent to which firms, and thus markets, can benefit or suffer from such national policy measures, depends on their level of international market integration. This is because, in this scenario, Danish firms that import goods from Spain will have to wait until the Spanish government loosens its restrictions, while the same goes for Chinese firms with Italian customers, as they keep missing out on revenues even after Chinese regulations have allowed them to operate again. On the other hand, Italian firms that operate in Norway can benefit from the Norwegian regulations, which unintegrated Italian competitors cannot. So, in short, as companies and investors can experience great losses caused by disaster events, the degree of international market integration of their supply chains affects the extent of damage. Of course, besides the increased chance of possible damage along the line, global supply chains also provide several competitive advantages. For example, international price differences allow for arbitrage opportunities and cheap production, while financial benefits can be provided by certain governments in order to attract capital (Kogut & Kulatilaka, 1994). These benefits encourage investors to invest in highly internationally integrated companies and markets. However, as indicated by the abovementioned example of China, Norway, Denmark, Spain and Italy, as well as stressed by Barry (2004), these investments raise the risk of value losses due to disruptions somewhere along the operating chain. In examining the role that market integration plays in times of these disruptions, this research focuses on historical data and analyses the behavior of stock markets in relation to disaster events and market integration levels. The question that this research tries to answer is: *How does global market integration impact financial markets' reactions to disaster events?*

Studying these losses due to disruptions has become more relevant than ever due to the increased worldwide frequency and severity of disaster events in the past thirty years, as well as the large financial impact they have imposed. Currently, the world is dealing with the COVID-19 pandemic, while from 1981 until 2016, the number of loss-relevant natural catastrophes worldwide had increased by a factor of about three within the period of 1981

[1] Among other factors, the oil price trade war between Russia and OPEC countries led by Saudi Arabia may also have played a role in this price drop.

until 2016. This is expected to increase even more in the future due to the large global levels of CO2 emissions driven by globalization, which increases global temperatures and the likeliness of extreme heatwaves, precipitation and intense tropical storms, differing per geographic region (Masson-Delmotte, 2018). Besides natural disasters, similar trends can be found for terrorism events, as Brounen and Derwall (2010) found that from 1990 until 2010, the average initial price reaction to major terrorist attacks in world markets was found to be minus 0.34%, while after that period, from 2010 until 2014, the global death toll from terrorism had increased by more than 500% (National Consortium for the Study of Terrorism and Responses to Terrorism, 2019). These trends can be problematic for companies, financial markets and its investors as the events impose great financial losses. Therefore, analyzing the role of international market integration in financial markets' reactions to such events can provide answers in how to react on future events, as well as to strategically reduce the increasing risk of such financial capital losses.

This paper examines the main worldwide disaster events, separated into terrorism and natural ones, that occurred in the period of 1990 until 2018. Historical market price data allow to determine market integration levels between markets, as well as observe their differences in stock markets' return behavior. This research examines event study methodology to observe stock market reactions to disaster events in little-, medium- and highly integrated markets separately, while conducting linear regression analyses to find the effect that market integration has on post-event stock returns. Using this methodology, it was found that for terrorism disaster events, the event country does not experience any market reactions, while highly correlated foreign countries show negative initial price reactions and positive returns in the long run. However, market integration was not found to impact these reactions. Furthermore, it was found that in the occurrence of a natural disaster event, the event country faces negative returns on the second trading day after the event date, and abnormal volatility up until five trading days following the day the event occurred. In foreign countries, although no initial reactions were found, the study shows evidence for market integration and market capitalization to drive positive abnormal returns in the long run, indicating that they benefit from a correlated country's recovery. The research was followed by the incorporation of these findings into an investment strategy and compared to a well-diversified investment portfolio, in order to test the applicability and validity of the results. Evidence was found for the last result in foreign countries at times of natural disaster events to provide profitable trading strategies.

This research stands out from previous research, because existing disaster event studies mainly focus on economic characteristics, such as wealth, foreign direct investment, market structures and market capitalization (Karolyi, 2006, Chen & Siems, 2003, Kollias, Manou, Papadamou, & Stagiannis, 2011), while the impact of market integration in disaster recoveries is only studied on individual disasters and certain firms and industries (Pankratz and Schiller, 2019, Todo, Nakajima, & Matous, 2015, Carvalho, Nirei, Saito, & Tahbas-Salehi, 2016), instead of aggregating events and focus on national markets. Regarding studies on incorporating disaster risks into investment decisions, much attention has been paid to divesture and diversifying risks (Anderson, Bolton & Samama, 2016, Fang, Seng, & Wirjanto, 2019, Narayan & Sriananthakumar, 2018), while little results have been published about possible profitable strategies that are provided by possible disaster event market reactions. The focus on market integration in the analysis of multiple worldwide disaster events, together with the application of the results in investment strategies on historical market indices will thus contribute to the existing literature and the general understanding of stock market behavior and globalization.

The rest of this paper is structured as follows. In section 2, the literature directly related to this study will be discussed. First economic theory is assessed, followed up with empirical literature on disasters and disaster risk management in investment portfolios, from which multiple hypotheses are derived and formulated. Section 3 will describe the data and methodology used to test these hypotheses, while the results of these tests will be presented and discussed in section 4. In section 5, the main findings are summarized, from which a conclusion about the research question will be derived. Furthermore, the Appendix discloses information of the sample, data analyses, and robustness tests.

Literature Review

The following section discusses literature and states the hypotheses that will be tested in order to answer the research question. First, economic theory on disaster risks and financial and economic disaster event effects are discussed, followed by empirical literature on differential impacts of disasters per country, region and event, as well as the role of market integration. Lastly, the existing literature on disaster risk management in investment portfolios is discussed.

Economic Theory

Disaster Risk Theory

Sharpe (1964) developed an asset pricing model, which stated that uncertainty in financial markets, implying investment risk, is compensated with high stock returns and volatilities. However, his theory was not able to provide an explanation for the large observed stock returns and volatilities that US common stocks have in excess of the Treasury Bill rate. These unexplained observations were labeled as “The Equity Risk Premium Puzzle” and “The Volatility Premium Puzzle”, respectively. Subsequently, in 1988, Thomas A. Rietz was the first to explain the first of these puzzles, with the use of little probable, severe market crashes. He applied the Arrow-Debreu model (Mehra and Prescott, 1985) and incorporated, according to his paper, reasonable degrees of time preference and risk-aversion in order to solve it. However, many researchers criticized this model to depend on counterfactually high probabilities and sizes of economic disasters. In response to the criticism, Barro (2006) applied the model to the United States in the twentieth century, and found that it performed well in explaining returns when using a disaster probability of around 1.5-2% per year. However, one could still argue that this probability is too high and not reliable, as it is highly determined by the large disasters that characterized the beginning of that century, namely World War I, the Great Depression, and World War II. Nevertheless, more support for this theory was found by Wachter (2013), who built further on Rietz’ model by addressing “The Volatility Puzzle” with time-varying implied disaster probabilities over the period 1890 until 2010. In her work, she labeled disasters as events that cause a large negative shock to aggregate consumption and finds that the probability of their occurrence is highly skewed. This implies that there are times that disasters can occur with high probability, although unusual. Her model was able to solve the puzzle for US stocks in the analyzed period. However, it only incorporated disasters caused by mankind, while natural disasters were excluded. Due to the increased probabilities of such natural disasters happening, as explained in the introduction, it is highly relevant to assess the effect of those time-varying probabilities on stock return volatilities as well.

Economic theory on disaster event impacts

The fact that volatilities increase due to probabilities of disaster risks can be explained by Sharpe's model (1964). The effect of the actual occurrence of these events were studied by Benson and Clay (2003), who focused on short- and long run impacts. They argued that disasters can represent a multifaceted shock to welfare, namely through physical integrity, assets and income. Physical integrity includes fatalities, injuries, sickness and violence, while assets include housing and income-generating assets, which can be damaged or destroyed by disasters. Due to the loss of physical-integrity (human capital) and assets, income can be lost. These effects are both on individual households and companies. When direct damage (the financial cost of visible physical damage) and indirect damage (resulting from the transmissions of a disaster shock through the economy) occur on an aggregate level, they include losses of synergies, common assets and resources, with as a result, a decline in economies and entire financial markets. Following the Efficient Market Hypothesis (EMH), stock prices immediately adjust to such events towards their most efficient prices. However, as De Bondt & Thaler (1986) explain, investor's over- and underreactions can prevent this from happening and cause inefficient pricing after the occurrence of such unanticipated events. Since inefficient pricing leads to abnormal return activities, disaster events can provide profitable investment strategies following the occurrences of such events.

Empirical Literature

Terrorism disaster events

In previous studies on disaster risk on stock portfolios, Berkman, Jacobsen & Lee (2011) studied the impact of political crises on world market stock returns. Their results included higher than normal volatilities and negative returns at the start of a crisis, lower than average returns as crises continue, and lower volatilities, combined with positive returns at the end of a crisis. These results cumulate to a total negative post-event return of -4% per annum. In addition, they found that the effect is stronger in times of wars and when strong world powers are involved. Interesting about these results is the impact of changes in disaster probabilities during political crises. However, their study showed no significant predictive power of crisis risk in regressions of future market returns. A possible reason could be that their sample did not exist of actual historical crises, but moments in which the probabilities of threats of disasters increased, which should avoid small sample problems according to the authors. However, the disadvantage of this method is that the over- and underreactions of investors to news releases of actual crises events are not taken into account.

Furthermore, literature on historical terrorism events has been examined extensively. Kollias, Manou, Papadamou & Stagiannis (2011) analyzed whether stock market reactions differ according to their level of market capitalization. Even though they did not find any significant results on abnormal stock returns in their event studies, they did find that small markets are more sensitive to terrorist attacks according to their volatility. Moreover, Tavor (2011), who studied 116 terrorist events that happened in Israel between 2000 and 2010, found that the ones occurring within confronting areas exhibit smaller stock reactions than attacks happening in non-confronting areas. However, from both Kollias' and Tavor's findings, the validity can be questioned as the first paper only compares two stock markets (the London Stock Exchange and the Athens Stock Exchange), while the latter one analyses the Tel Aviv 100 Index Return only. Other interesting characteristics that tend to influence market reactions to terrorism activities were found by Harrigan & Martin (2002) and Karolyi

(2006). The first paper showed that price reactions are larger for countries with more foreign investment, international trade, and larger tourism industries, while the latter one found the same for countries with more wealth and democracy.

Elaborating on these results, Chen & Siems (2004) used an event study methodology in assessing terrorism effects on global capital markets. In their study, they compared recent attacks (Iraq's invasion of Kuwait in 1990 and the 9/11 terrorist attacks), with 14 attacks dating back to 1915. They found that US capital markets were more resilient in more recent years than they were in the past, and also tend to recover quicker than other global capital markets. Evidence for the main cause was not found, but their conclusion suggested that the strong financial sector and high liquidity together with policy measures were the main driving forces. In line with Chen & Siems' results about recent recoveries of financial downfalls is the analysis of Foo and Witkowska (2017) on the financial market recoveries of countries after the 2008 global financial crisis. In this analysis, the authors suggest that developed countries recover quicker from such downfalls, but they fail to give explanations for these observations. This research will elaborate on these findings by assessing the impact of market integration levels on differential market recoveries over time and across developed and undeveloped countries.

Natural disaster events

Unlike terrorism events, results in empirical literature on stock market reactions to natural disasters do not concur. Bourdeau-Brien & Kryzanowski (2017) analyzed natural disasters that occurred in the US between 1990 and 2007 and the associated US common stock reactions. They found that the conditional volatility of stock returns increased significantly for almost all natural disaster types, especially in states where the disaster occurred. In line with this are the results of Worthington & Valadkhani (2007), who analyzed Australian equity markets from 1982 -2002 and found that their returns reacted negatively to national natural disaster events. In addition, they found that price reactions depend on the amount of time it takes for full information about the event to be released publicly.

In contrast to these findings are the results of Wang & Kutan's work (2013), who analyzed natural disasters in both Japan and the US. Like Bourdeau-Brien and Kryzanowski, they found significant effects on return volatility in US common stocks. However, this was not the case for Japanese markets. Also, they did not find any evidence for natural disasters affecting stock returns significantly in either market. This paper will focus on the role of market integration as a possible explanation for the differences in those results, as it includes events in 18 different countries, over more than 27 years.

Market integration's role in disaster consequences

As disasters can cause large economic and financial losses, it is highly relevant for investors to take disaster risks into account when making investment decisions. However, the large globalization growth from 1990 until 2010 (The Economist, 2017), has made it harder to mitigate natural disaster risk exposure through regional diversification, as can be learned from the example of Denmark, Norway, China, Spain and Italy, mentioned earlier in the introduction. Evidence for this effect was found by Barrot & Sauvagnat (2016), who researched the effect of natural disasters on firms, basing the directly hit firm on the location of its headquarters. They found that natural disaster events impose substantial output losses for suppliers that are hit, which spill over to other suppliers and customers, causing substantial damage to the entire supply chain with significant market losses. Although these results are sensitive to firm's headquarters not being located in the same state as their operations, their results are interesting and in line with the work of Hertzel, Zhi, Officer & Rodgers (2018). Their study focused on the identified suppliers and customers of 250 bankruptcy filing US firms in the period from 1978 to 2004. They found that distress related to bankruptcy filings of suppliers have significant negative stock price effects on competitors and customers. However, suppliers are most vulnerable to such events, as Pankratz & Schiller (2019) found significant evidence for the termination of contracts in response to climate damage being higher than expected for suppliers. In addition, evidence was found for replacement by other suppliers with less climate risk exposure. Their research was conducted on US supply chain relationships and climate change damage over the period 2000 until 2017. Interesting about this topic is that market integration can also contribute to the economy in times of disaster events. This is confirmed by studies of Todo, Nakajima & Matous (2015) and Carvalho, Nirei, Saito & Tahbas-Salehi (2016), which both conducted a research on the Great East Earthquake in Japan[1]. The first one found that, in the recovery of the event, global supply chains affect recovery negatively due to higher vulnerability to network disruption, and positively through support from trading partners, easier search for new partners and general benefits from agglomeration. The second one analyzed up- and downstream supply chains and the overall macroeconomic impact of the shock on the country's economy. They found that both streams had negative effects on gross output, accounting for a 1.2% percentage point decline in the year following the earthquake. Here, downstream supply chains have the largest negative impact, as they are closest to the final customers, incorporating most value added.

The controversial impact that international integration seems to have on disaster event consequences for companies makes it interesting, from an investor's perspective, to test whether the contributions outweigh the negative impacts. Therefore, H_1 is stated:

H_1: *Global market integration has a positive effect on market returns in countries where disaster events occur.*

Additionally, it is interesting to see if the observed differences in impacts on stock price volatilities, as observed by Bourdeau-Brien & Kryzanowski (2017) on one hand, and Wang & Kutan (2013) on the other hand, can also be explained by market integration levels. If investors believe that markets or economies will not bear as much damage due to international supply chain's benefits, volatility effects of such events should be lower in highly integrated markets. In order to test this, H_2 is stated:

H_2: *Global market integration has a negative effect on abnormal volatility levels in markets where disaster events occur.*

Disaster risk management

In this paper, the importance of managing the disaster risks that were found by studies of Wachter (2013), Berkman, Jacobsen & Lee (2011) and Bordeau-Brien & Kryzanowski (2017), is stressed through the incorporation of market integration as a factor in investment decisions. In previous research, methods to manage this risk have been examined. In an

1 Earthquake that happened on March 11th on the Pacific coast in Tōhoko, Japan, considered as the fourth most powerful earthquake in the world since modern record-keeping began in 1900 (WHO, 2013).

reduce regional risks, Bartram & Dufey (2001), apply international portfolio investment strategies. In this way, an investor reduces regional risks by diversifying a portfolio with stocks in multiple different regions with low correlations. Although the correlation of two countries and the probability of rare disaster events happening are probably unrelated, the probability of the disaster event occurring in the country of an invested stock can be reduced through international diversification.

However, Chesney, Reshetar & Karaman (2011) suggest a different approach. In their study, market reactions of 77 terrorist attacks, four financial crashes and 19 natural disasters in a time period of eleven years in 25 countries are analyzed. They found that certain sectors, such as the aero/defense, pharma/biotech and oil/gas sectors show both positive and negative reactions for all three disaster types, as well as that, in case of extreme event-day return movements, the impacts are not long lasting. In their conclusion, they suggest several diversification strategies. Among them, one is to invest in both groups that react positively, and negatively to terrorism attacks, while the other one includes investing in government bonds and bank industries. However, I have my doubts about the effectiveness of the second strategy, since the disaster events may cause permanent economic effects, to which the financial sector is most sensitive, as found by Baur (2012). In his study, he examined ten sectors in 25 major developed and emerging stock markets and found evidence for large negative co-movements in financial sector stocks across countries in times of economic downturns. These results confirm the doubts about effectiveness of diversification through investing in a banking sector.

A more sophisticated approach to deal with a specific type of disaster risk, namely climate change risks, is suggested in the study of Fang, Seng & Wirjanto (2019). In their work, they discuss the management of climate change risks for equity investments by developing a sustainable portfolio. In their model, the expected effect of climate change on a portfolio is the product of the likelihood and severity of a disaster. In their results, they show that divestment in carbon-intensive sectors is an effective way of reducing climate disaster risks in a portfolio, while also finding evidence of this strategy being employed by a large group of institutional investors. This is in line with the work of Anderson, Bolton & Samama (2016), who developed a multi-factor model for constructing carbon-efficient portfolios through divestiture in the most carbon-intensive holdings. Fang's model is interesting in order to get a perception of disaster risk management regarding climate change risk. Although carbon footprint levels of the entire operating supply chains are used in this model, the impact of the damage caused by climate disaster events on foreign and integrated firms or markets is left uncovered.

Although suggested approaches differ, the importance of managing disaster risks is confirmed by the number of studies conducted on the topic, as well as by the evidence for investors reacting to these risks. Such evidence has been found in multiple research. For example, Narayan & Sriananthakumar (2018) examined the effect of terrorism activities and fear for terrorism on international portfolio investment decisions in eight OECD stock markets from 2001 until 2014. They found that, depending on the business cycle, foreign terrorism risks reduce investments in those countries, and interestingly, also reduce the level of market integration between them. These levels of investments and market integration were based on the stock market correlations between markets, as well as the flight-to-safety hypothesis, as developed by Frijns, Tourani-Rad & Indriawan (2012), which states that the degree of stock market integration in emerging markets in times of political crises decreases as firms and investors flee to safer regions. However, the findings of Narayan and Sriananthakumar say little about investors' portfolio decisions and show no evidence for individual firms or investments fleeing to safer economies.

As the findings of previously mentioned literature on disaster events show, market reactions differ per market. This stresses that investors should not only focus on disaster probabilities, which most existing studies have mainly focused on, but should also look at how sensitive investments are to disaster risks. The tests of hypotheses H_3 and H_4 will provide insights about these sensitivities. In addition, this research distinguishes itself from previous studies by looking further into the role of globalization, and therefore not only assesses the sensitivity of the event country's market, but also of foreign markets. In case of a disaster event in one country, the market reaction of a foreign market may be impacted by the extent in which the market is integrated with the event-country's market. In order to test this for both, market returns and volatility levels, hypotheses H_3 and H_4 are stated.

H_3: *In the occurrence of a disaster event, market integration with the event-country's market negatively affects stock returns in foreign markets.*

H_4: *In the occurrence of a disaster event, market integration with the event-country's market positively affects abnormal volatility levels in foreign markets.*

After testing hypotheses H_1, H_2, H_3 and H_4, more knowledge is obtained about market reactions in markets with respect to their market integration level with the global market, as well as the event-country's market. These results will be interesting for investors, as they can provide profitable investment opportunities if applicable to the world markets. In previous research, conducted by Tavor & Teitler-Regev (2019), it was stated that investors can benefit from superior knowledge about market reactions to disaster events, by short selling an index on natural disaster event days and buying it again two days later, or by short selling on the event day in case of terrorism events. Although they analyzed 344 events happening in different countries, they suggest further research into the topic depending on country characteristics. This research will contribute to their findings as it assesses the market integration as a factor in investment portfolio decisions in response to disaster events. Using the results of the previously mentioned hypotheses, and applying them to other historical disaster events, H_5 tests whether systematically buying and selling on specific trading days with respect to the event date will outperform the world market.

H_5: *Systematically investing and selling on the same specific trading days with respect to disaster event dates will yield higher returns than the world market.*

The literature mentioned above has brought up interesting findings about disaster effects, market integration and risk management. However, papers focusing on differential stock return reactions did not take international market integration into account, while papers that found controversial results on volatility reactions did not suggest any reasons for the differential results found. Also, literature about disaster risk management falls short in taking into account the market correlations factor, as well as in incorporating the contagion consequences of the disasters to correlated markets. In addition, this research is unique in testing possible outperformance of a strategy with respect to the world market by incorporating the knowledge obtained from the results on the market integration tests on historical disaster event returns.

This research will contribute to science by expanding the general understanding of both, globalization impacts (through international market integration) and stock market behavior in occurrence of disaster events, as the event studies will explore possible over- or underreactions, testing the semi-strong form of the EMH. Besides researchers, the results will be relevant for market practitioners too, as they will help in optimally reacting to future disaster events, regarding investment portfolios. Lastly, the results may be useful for policymakers, as the effects of both, globalization and responses to disaster events, on financial markets can be relevant to take into account in their decision processes.

Data and Methodology

Datasources

This paper analyzes terrorist and natural disaster events that took place in 18 different countries over the period 1990 until 2018. Information about the event date, location, characteristics and damage caused by the event are retrieved from the Global Terrorism Database (GTD), which is provided by the National Consortium for the Study of Terrorism and Responses to Terrorism (START). This database includes more than 190,000 terrorist-related attacks worldwide with specific information about each event. START classifies terrorist-related attacks as "The threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation." Information about natural disasters is retrieved from the International Disaster Database (IDD) provided by the Centre of Research on the Epidemiology of Disasters (CRED). This database discloses essential core data on the occurrence and effects of over 22,000 mass disasters in the world that occurred between 1900 and the present day. It is compiled from sources as UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies. The database was created by the World Health Organization (WHO) and the Belgian Government (CRED, 2020). They classify natural disaster events as "Unforeseen and often sudden events that cause great damage, destruction and human suffering, caused by nature". Next, in order to examine financial market behavior following the events, historical daily index stock returns of 23 national indices of stock markets are analyzed. Besides the 18 countries in which the events happened, five extra countries were selected at random in order to increase the dataset and validity of the test results. To assure consistency between the different market returns, the Morgan Stanley Capital International (MSCI) daily market price data of developed and emerging markets are used. MSCI country indexes are calculated using market capitalization of each market converted to USD on each day. In addition, the MSCI All Country World Index (ACWI) is used in order to determine international market integration levels of markets, as well as to serve as the world market benchmark to compare investment strategy's results to. This index represents performance of large- and mid-cap stocks across 23 developed and 26 emerging markets, covering across 3,000 constituents across 11 sectors and approximately 85% of the free float-adjusted market capitalization in each market (MSCI, 2019). This makes it a valid index to use in order to determine global integration levels of markets, as well as an adequate world market benchmark. Furthermore, country specific data, which will be applied in examining factor effects on stock return and volatility performance following disaster events, is retrieved from The World Bank World Development Indicators database, which includes data of indicators on populations, geographies, environments, welfare and economies from 1960 up to 2018 in over 200 countries (Worldbank, 2020). Lastly, factor data, which is used for the calculation of normal market returns (as explained in the analysis technique section) are obtained from the Kenneth R. French Data Library (2020). This database includes monthly data of emerging and developed markets on the 5 factors used in the Fama and French Five Factor Model (Fama & French, 1995). The factors are constructed on a monthly basis from six mimicking portfolios, which are ranked from highly-, to little exposed portfolios, with respect to each factor. Next, the factor data are determined by the return difference between the three highly and three little exposed portfolios, excluding ranges and transaction costs. The five factors in their model are book-to-market, size, operating profitability, and investment.

Sampling selection

In this research, a distinction is made between both terrorism events and natural disasters, as previous research has found that the impact on financial markets, in reaction to both type of events, differs significantly (Tavor & Regev-Teitler, 2019). Events such as financial crises, recessions and aviation disasters are not analyzed due to possible endogenous effects of, and direct effects on, certain stocks and industries. In addition, natural disasters that took a longer period than three days are excluded due to event date uncertainty. The selection of the events is done by taking the 50 major disasters (in terms of damage caused in USD according to the used sources) for both event groups, occurring in countries with available MSCI price data. Next, 25 events from each group are picked at random to assure that countries with most events do not overrepresent the sample. An overview of the analyzed terrorism and natural disasters, with information about the location, type of event, date and damage in USD can be found in the Appendix in Table 1 and Table 2, respectively. In addition, they include identification codes for each event in the first column, which are used to refer to when a specific event is mentioned in the paper.

Analysis technique

In order to analyze the market reactions and recoveries following disaster events, the event dates are determined. In this analysis, the event date (*t*=0) is considered the day on which the event occurred in case it concerns a trading day, and if not, the first trading day that followed. As mentioned earlier, the events are separated into two groups: terrorist and natural disaster events.

In this analysis, hypotheses H_1, H_2, require the determination of an event country's financial market's integration with the global market, while hypotheses H_3 and H_4 require the determination of market integration of a foreign country with the event country's market. What method is most suitable for this determination is an interesting topic itself to study, as several researchers have applied different methods in the past and share different opinions. Akdogan (1997) determined global market integration by calculating the degree in which a domestic market contributes to global systematic and unsystematic risk. Barari (2004) analyzed six Latin American countries between 1988 and 200, and built further on Akdogan's work by using the same method on both, a global and a regional index, to determine global and regional market integration. Since the scope of hypotheses H_3 and H_4 is on international market integration levels, regardless of their geographic location (as the US and Australian markets might be highly correlated at a specific point in time, but not situated in the same geographic region), a different approach is chosen in this study. Here, market integration levels are determined by the average Dynamic Conditional Correlation (DCC) of two markets over the last ten trading days preceding a disaster event. For global market integration, the DCC with the MSCI ACWI is taken. The DCC is calculated using Robert Engle (2002) DCC-GARCH model, which is also widely used as a proxy of market integration, as examples include Joyo and Lefen (2019), Daelemans, Daniels & Nourzad (2018) and Narayan and Sriananthakumar (2018). It is convenient as it allows for market correlations to vary over time, just like market integration does. As found by Büttner & Hayo (2011), financial downturns caused by terrorist attacks tighten correlations of certain stock markets, while they loosen in others. Since most countries in the sample have experienced such events during the studied time span, it is of great importance that time-varying correlations are used in this research. The DCC-GARCH model can be based on both a Gaussian or a multivariate t-distribution. The Gaussian distribution is found to be less efficient in case of heavy-tailed distributions, which suggests the use of the latter distribution in such a case. For this reason, a normality test[1] is applied to all series of stock market returns in the sample. The results (Table 5 in the Appendix) show that all the observed kurtosis of all GARCH models significantly differ from that of a normal distribution, which suggests that the Gaussian distribution is the optimal choice to apply.

In this paper, market returns are examined. Equation (*1.1*) shows that the return of stock market *i* on day *t* is the logarithm of today's market price, divided by the preceding trading day's market price. The analysis of logarithmic returns instead of prices allows to examine compound returns and reduces heteroskedasticity in the data (Brooks, 2019).

$$R_{i,t} = \ln\left(P_{i,t}/P_{i,t-1}\right) \qquad 1.1$$

The first step in calculating the DCCs is to compute the univariate conditional variances of each timeseries $h_{i,t}$, for *i* at *t*, using the GARCH method (*1.2* and *1.3*), based on the lowest Akaike Information Criterion (AIC)[2]. The lengths of the resulting GARCH models can be found in the second row of Table 5 in the Appendix. In equation (*1.2*), market *i*'s return, $R_{i,t}$ at *t* is calculated using a time-series analysis, where *a* represents the constant, $\mathring{R}_{i,t}$ the continuously compounded returns of *i* at *t*, and $\varepsilon_{i,t}$, the error term, which is normally distributed with variance $h_{i,t}$. In equation (*1.3*), $h_{i,t}$ is retrieved from w_i, the constant of the GARCH model, while $\alpha_{i,x}$ represents *i*'s non-negative ARCH coefficient at lag *x,* and $\beta_{i,y}$ the non-negative GARCH coefficient at time *t* at lag *y*.

$$R_{i,t} = \alpha + \beta \mathring{R}_{i,t} + \varepsilon_{i,t}, \varepsilon_{i,t} \sim N(0, h_{i,t}) \qquad 1.2$$

$$h_{i,t} = w_i + \sum_{x=1}^{X_i} \alpha_{i,x} \varepsilon_{i,t-x}^2 + \sum_{y=1}^{Y_i} \beta_{i,y} h_{i,t-y}, for\ i = 1,2, \ldots., k \qquad 1.3$$

Having obtained the conditional variances, the conditional variance matrix, D_t (*1.4*) is computed using the conditional standard deviations ($\sqrt{h_{i,t}}$). Next, the time-varying correlation matrix, R_t (*1.7*) is computed. Equation (*1.5*) shows that the square roots of the unconditional correlations ($q_{i,j}$) between markets *i* and *j* make up matrix Q_t^* at time *t*. Next, equation (1.6) uses a GARCH (1,1) approach to determine Q_t, with ARCH coefficient ϑ, GARCH coefficient δ, and the unconditional covariance ($\bar{Q}$) of the standardized residuals

1 Tests whether the distribution contains significant skewness and kurtosis. Here, the null hypotheses statee that observed skewness and kurtosis are equal to that of a normal distribution (Jarque & Bera, 1980).
2 The AIC is an estimator is an estimator of out-of-sample prediction error and indicates the relative quality of a prediction model, such as the GARCH model.

($\sigma_{i,t}$ for all t's, where $\sigma_{i,t} = r_{i,t}/\sqrt{h_{i,t}}$). Having obtained both D_t and R_t in equations (*1.4*) and (*1.5*), the DCC can be calculated using equation (1.8).

$$D_t = \begin{bmatrix} \sqrt{h_{11,t}} & .. & 0 \\ .. & .. & .. \\ 0 & .. & \sqrt{h_{kk,t}} \end{bmatrix} \quad 1.4$$

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & .. & 0 \\ .. & .. & .. \\ 0 & .. & \sqrt{q_{kk}} \end{bmatrix} \quad 1.5$$

$$Q_t = (1 - \vartheta - \delta) * \bar{Q} + \vartheta r_{t-1} - 1r'_{t-1} + \delta Q_{t-1} \quad 1.6$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad 1.7$$

$$DCC = D_t * R_t * D_t \quad 1.8$$

For hypotheses H_1 and H_2, markets are subdivided into 'little', 'medium', and 'highly' globally integrated groups, depending on their average DCC with the MSCI ACWI over the ten pre-event trading days. When the resulting average DCC is below 0.2, they are placed in the 'little' group, when between 0.2 and 0.4, they belong to the 'medium' group, while all larger values are placed into the 'highly' group. For hypotheses H_3 and H_4, the average DCC of a foreign market with the event country's market over the ten pre-event trading days is used to classify countries into 'little', 'medium', and 'highly' integrated markets. Again, the same thresholds are used (below 0.2, between 0.2 and 0.4 and higher) for the subdivision. The reason for choosing for three different categories instead of two is that countries with DCCs close to each other should not be placed into opposite groups, while the choice of the average DCC over the ten pre-event trading days is to control for one day outliers, and not to be influenced by the unforeseen event.

In order to test hypotheses H_1 up to H_4, MacKinlay's event study methodology (1997) is applied. This method examines market reactions through the determination of abnormal returns, which are defined as the observed returns on day *t* minus the normal returns (*2.1*). Normal returns are computed using a historical control period (*T1*, *T2*), for which (t=-200, t=-10) is chosen, since multi-country analysis estimation windows need to be sufficient to control for unusual market movements (Park, 2004). There are three most commonly used models to compute normal returns, namely the constant mean model (*2.2*), the Fama and French 5-factor model (1995) (*2.3*), and the Market Model (MM) (*2.4*). In order to find out what model is most suitable for this event study, all three models are applied to each event, and used to predict returns in the prediction period (t= -9 up to t=-5) for each event-country's market. Next, the adjusted R squared[3], an F-test of overall significance[4], and the RSME[5] of all three models are computed and compared. The results can be found in Table 6 and Table 7 in the appendix and show that the MM performs best in forecasting, especially for terrorism events, while the 5-factor model performs poorly. Therefore, the MM was chosen.

3 The proportion of the variance in the dependent variable that is predictable from the independent variable.
4 A statistical test that compares the fit of the model with a regression without independent variables and tests whether the currently chosen independent variables in the regression are significant overall or not.
5 The standard deviation of the prediction errors. This is a measure of well the prediction predicted the observed values.

Following MacKinlay's methodology, abnormal returns ($ar_{i,t}$) are computed as in equation (*2.1*), where $\bar{R}_{i,t}$ represents the normal return, computed using the MM and market return $R_{mi,t}$ at time *t*. In the equations (*2.1*) up to (*2.5*), μ_i represents the mean of returns over the control period of market *i,* and $\zeta_{i,t}$ its error term at *t*. Equation (*2.3*) contains data retrieved from the aforementioned Kenneth F. French library[1]. Here, $R_m - R_f$ represents market *i*'s return in excess of the one-month Treasury bill rate, *SMB* (Small Minus Big) the average return on the three small portfolios minus the average return on the three big portfolios, *HML* (High Minus Low) the average return on the two value portfolios minus the average return on the two growth portfolios, *RMW* (Robust Minus Low) the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, and the *CMA* (Conservative Minus Aggressive) the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios. In this same equation, β, γ, δ, λ and ϖ represent each factor's coefficient, respectively. In the other equations, $R_{m,i}$, represents the market index return (MSCI ACWI) at *t*, $\overline{ar_i}$, the average abnormal return of i. and s_i^2, the standard deviation of $ar_{i,t}$.

$$ar_{i,t} = R_{i,t} - \bar{R}_{i,t} \quad 2.1$$

$$\bar{R}_{i,t} = \mu_i + \zeta_{i,t} \quad 2.2$$

$$\bar{R}_{i,t} = a + \beta(R_m - R_f) + \gamma SMB + \delta HML + \lambda RMW + \varpi CMA + \zeta_{i,t} \quad 2.3$$

$$\bar{R}_{i,t} = a + \beta R_{mi,t} + \zeta_{i,t} \quad 2.4$$

$$\overline{ar_i} = \frac{1}{T_2 - T_1 + 1} \sum_{i=T_1}^{T_2} ar_{i,t} \quad 2.5$$

Although the normality tests (Table 5 in the Appendix) rejected the significance of kurtosis, skewness was not rejected in most cases. For this reason, Standardized Abnormal Returns (SAR) are computed for the 23 markets (*N*), using Patell's approach (1976) (equations (*2.6*), (*2.7*) and (*2.8*)). Next, the Cumulated Standard Abnormal Returns (CSARs) for multiple periods (*K,L)* are computed in line with the same methodology, shown in equation (*3.0*), to assess both the initial price reaction and recovery periods. In order to test for significance, equation (*2.9*) and (*3.1*) compute the corresponding t statistics of SAR and $CSAR_{KL}$ respectively.

$$s_i^2 = \frac{1}{T_2 - T_1} \sum_{i=T_1}^{T_2} (ar_{i,t} - \overline{ar_i})^2 \quad 2.6$$

$$sar_{i,t} = \frac{ar_{i,t}}{s_i} \quad 2.7$$

$$SAR_t = \frac{1}{N} \sum_{i=1}^{N} sar_{i,t} \quad 2.8$$

[1] In this library, monthly factor values for both developed and emerging countries are provided, which are calculated by the differences in stock performance of different factor mimicking portfolios.

$T_{SAR} = \frac{SAR_t}{1/\sqrt{N}}$ *2.9*

$CSAR_{KL} = \sum_{K=1}^{L}(\frac{1}{N}\sum_{i=1}^{N} sar_{i,t})$ *3.0*

$T_{CSAR} = \frac{CSAR_{KL}}{\sqrt{(L-K+1)}/N} \frac{\sqrt{T_2-T_1-3}}{\sqrt{T_2-T_1-1}}$ *3.1*

In order to examine the risk that the studied events imply on the capital markets in the sample, Beaver's method (1968) is used. Here, the Abnormal Volatility of Abnormal Returns at time *t* ($AVAR_t$) is calculated according to equations (*3.2*) and (*3.3*), using no new input.

$avar_{i,t} = \frac{ar_{i,t}^2}{s_i{}^2}$ *3.2*

$AVAR_t = \frac{1}{N}\sum_{i=1}^{N} avar_{i,t}$ *3.3*

$AVAR_t$ indicates the effect of the event on market volatility. It takes value one in case there is no effect. This means that the abnormal percentage change in volatility on any *t* of the event window (*L,K*) is given by (*AVAR* - 1). Similar to the *SAR* and the *CSAR*s, the *AVAR* differs per *t* and therefore, the Cumulative Abnormal Volatility of Abnormal Returns (*CAVAR*) is computed in equation (*3.3*). *CAVAR* takes value (*L*-*K*+1) in case of no effect, and is larger in case of abnormal market volatility.

$CAVAR_{KL} = \sum_{t=K}^{L}(AVAR_t)$*-(L-K+1)* *3.3*

In order to test the significance of these abnormal volatilities, null hypotheses (*1.A*) and (*1.B*) are tested. Under null hypothesis (*1.A*), $AVAR_t$ is a variance of *N* independent *N*(0,1) random variables, and follows a Chi-Squared distribution, with (*N*-1) degrees of freedom. Under null hypothesis (1.B), a Chi-Squared distribution is assumed with (*N*-1)*(*L*-*K*+1) degrees of freedom.

$H_0: AVAR_t = 1$ *1.A*

$H_0: CAVAR_{KL} = L - K + 1$ *1.B*

SAR_t and $AVAR_t$ are calculated for days t=0 up to t=100. Following the most significant results, the $CSAR_{KL}$ for (0,2), (0,5), (0,10) are calculated for assessing the short run market behavior, while (0,30), (0,50), (10,50) and (10,100) are used to assess long run price behavior. For volatilities, the intervals (0,1), (0,3), (0,5) and (0,10) are analyzed. In addition, CAVAR(-4,-1) is calculated as a robustness check for the results. Since this study assumes that the sample events happened unexpectedly, on average, no abnormal volatility should be found on the days preceding the events.

The results on SAR_t, $CSAR_{KL}$, $AVAR_t$ and $CAVAR_{KL}$ are displayed in both a table and a graph to provide a clear overview, with the abnormal volatility levels displayed next to benchmark dashed line that indicates the values of $CAVAR_{KL}$ in case of no abnormal volatility.

In order to test the effect that market integration has on these market reactions, the above mentioned $CSAR_{KL}$ and $CAVAR_{KL}$ intervals are regressed on the average 10 pre-event date DCC, using Huber-White robust standard errors (White, 1980) in order to control for heteroskedasticity. Equations (*3.4*) and (*3.5*) show the regression applied to test H_1 and H_2

for terrorism events, equations (*3.6*) and (*3.7*) for natural events, while equations (*3.8*) and (*3.9*) show the regressions applied to test H_3, H_4 for both groups.

$$CSAR_{KL} = \theta + \beta_1 * MI_{i,t} +* \beta_2 * GDP_{i,c} + \beta_3 * M_{i,c} + \beta_3 * FDI_{i,c} + \beta_4 * D_{i,e} + \beta_5 * MilExp_{i,c} + \beta_5 * \sum_{c=1990}^{2018} Y_{i,c} + \partial_{i,t} \quad 3.4$$

$$CAVAR_{KL} = \theta + \beta_1 * MI_{i,t} +* \beta_2 * GDP_{i,c} + \beta_3 * M_{i,c} + \beta_3 * FDI_{i,c} + \beta_4 * D_{i,e} + \beta_5 * MilExp_{i,c} + \beta_5 * \sum_{c=1990}^{2018} Y_{i,c} + \partial_{i,t} \quad 3.5$$

$$CSAR_{KL} = \theta + \beta_1 * MI_{i,t} +* \beta_2 * GDP_{i,c} + \beta_3 * M_{i,c} + \beta_3 * FDI_{i,c} + \beta_4 * D_{i,e} + \beta_5 * \sum_{c=1990}^{2018} Y_{i,c} + \partial_{i,t} \quad 3.6$$

$$CAVAR_{KL} = \theta + \beta_1 * MI_{i,t} +* \beta_2 * GDP_{i,c} + \beta_3 * M_{i,c} + \beta_3 * FDI_{i,c} + \beta_4 * D_{i,e} + \beta_5 * \sum_{c=1990}^{2018} Y_{i,c} + \partial_{i,t} \quad 3.7$$

$$CSAR_{KL} = \theta + \beta_1 * MI_{i,t} +* \beta_2 * GDP_{i,c} + \beta_3 * M_{i,c} + \beta_3 * FDI_{i,c} + \beta_4 * \sum_{c=1990}^{2018} Y_{i,c} + \partial_{i,t} \quad 3.8$$

$$CAVAR_{KL} = \theta + \beta_1 * MI_{i,t} +* \beta_2 * GDP_{i,c} + \beta_3 * M_{i,c} + \beta_3 * FDI_{i,c} + \beta_4 * \sum_{c=1990}^{2018} Y_{i,c} + \partial_{i,t} \quad 3.9$$

These equations show how $CSAR_{KL}$ and $CAVAR_{KL}$ are regressed on constant θ and the degree of international market integration ($MI_{i,t}$), which is measured as market *i*'s DCC at *t* with the ACWI for equations (*3.4*), (*3.5*), (*3.6*) and (*3.7*), and with the event country in equations (*3.8*) and (*3.9*). In order to control for effects that previous literature has found, for country i in event year *c*, $GDP_{i,c}$ controls for relative wealth effects (Karolyi, 2006, Foo & Witkowska, 2017) as it indicates GDP per capita, $M_{i,c}$ controls for market capitalization (Kollias, 2011), $D_{i,e}$ controls for the direct physical damage caused by event *e* in the event country, while $FDI_{i,c}$ controls for foreign direct investment (Harrigan & Martin, 2002), which is indicated as a percentage of national GDP, with a criterion of a minimum of ten percent of ownership of foreign voting stock (Worldbank, 2020). The variable $MilExp_{i,c}$ controls for being a confronting area (Tavor, 2011), as it indicates the country's military expenses as a percentage of government expenses in year *c*. Binary variable $Y_{i,c}$ controls for year effects, as it takes a value of one for the event year and value of zero otherwise, and lastly, $\partial_{i,t}$ represents the residual of the equation. All variables are measured in USD in the event year, *c*. A consequence of the inclusion of these variables is that when data concerning a variable is not available, the observation is dropped from the dataset. This is the reason why the sample sizes of terrorism and natural disasters in equations (*3.6*) up to (*3.9*) differ (402 and 503, respectively).

Based on the results of the statistical tests on H_1, H_2, H_3 and H_4, H_5 will be tested by conducting a number of investment strategies on historical data returns following disaster events. The sample used here exist out of nine natural disaster events that happened in the period from 1990 to 2018, and are picked at random from the same database as the sample used for the first four hypotheses, which were first excluded from the database in otder to avoid data snooping issues. An overview of the events can be found in Table 3 in the Appendix. Here, the strategies will exist of systematic post-event date investment actions, based on the variables that seem significant in causing the observed abnormal returns in either event-, or non-event countries. The observed returns will then be compared to the MSCI ACWI returns in the same periods to measure outperformance. Outperformance of any disaster-event-based strategy will test the relevance and robustness of the results on the previously stated hypotheses. Therefore, the results of H_5, as well as all previously stated hypotheses will help deriving a conclusion about the stated research question. In addition, the results could be used as a suggestion for future investment decisions in times of disaster events.

Descriptive statistics

Table 1 shows the descriptive statistics of the variables of equations (3.4) and (3.5) for terrorism disaster event markets. Market integration, measured as the DCC, ranges from 0.02 to 0.80 in the sample. This wide range provides the opportunity to analyze little- and highly integrated markets. The large standard deviation (245 million USD) and range (from 6.4 to 2700 million USD) of damage levels indicate that damage degrees differ to a large extent between the first and 25th event in the sample. This stresses the importance of controlling for this effect on stock returns and volatilities in the regression analyses. The average market capitalization is 4050 billion USD, while the average GDP per capita is 20631.76 USD. Both variables show large standard deviations (7.44 billion and 17484.65 USD, respectively), which stress the large market differences within the sample. The average foreign direct investment of these countries was 1.85 percent of national GDP, while the average military expenses were 8.8 percent of total government expenses, with a standard deviation of 3.62%, indicating that some countries in the sample have more military activity than others, as some were situated in confronting areas, while others were not. The correlations in columns 7 up to 12 show low correlations between most variables. However, because of the high correlation of 0.78 between GDP and M, possible multicollinearity issues will have to be taken into account in the results analyses.

Table 1. Descriptive statistics and correlations for variables in the terrorism disaster event countries analysis at t=0.

	Descriptive Statistics					**Correlations**					
Variable	**Obs.**	**Mean**	**St. Dev**	**Min**	**Max**	**MI**	**GDP**	**M**	**FDI**	**D**	**MilExp**
MI	25	0.45	0.28	0.02	0.80	1.00					
GDP	25	20631.76	17484.65	832.80	55047.73	0.77	1.00				
M	25	4050.00	7440.00	1.33	26300.00	0.50	0.78	1.00			
FDI	25	1.85	0.57	1.02	3.14	0.29	-0.12	-0.21	1.00		
D	25	245.00	645.00	6.40	2700.00	0.10	0.00	-0.13	0.08	1.00	
MilExp	25	8.80	3.62	1.93	15.64	-0.46	-0.15	0.24	-0.48	-0.02	1.00

Similar to the terrorism disaster event countries, the natural disaster event countries sample, as shown in Table 2, shows large ranges from 0.12 to 0.87 for market integration levels and 0.5 to 210 million USD in physical damage levels. Market capitalization levels differ widely across times and markets in the sample, as the maximum value (32100 billion USD) is much larger than that of the terrorism event country sample, but the average (987 billion USD) and minimum (44.1 billion USD) are lower. This can mainly be explained by the wide variety of years and countries in this sample, as the US market prior to the 2018 natural disasters (Nat3 and Nat5) and the Turkish market prior to its 1999 disaster (Nat 13) are expected to show very different sizes. The average GDP per capita and FDI levels are higher in this sample in comparison to Table 1, just like its maximum values. A possible explanation for this may be that the USA makes up eleven out of the twenty-five event countries in this sample, as many severe natural disasters have occurred there in the past thirty years and drive up the sample's statistics. Furthermore, the minimum FDI is negative, which can be explained for three reasons according to OECD (2020): One is disinvestment in assets, the second reason is repaid loans to investors by foreign affiliates, and the third may be negative reinvested earnings or dividends paid exceeding the recorded income of the period. Column 9 shows again, a high correlation between market capitalization and GDP per capita, while other correlations shown in the table show no indications for multicollinearity issues.

Table 2. Descriptive statistics and correlations for variables in the natural disaster event countries analysis at t=0.

	Descriptive Statistics					Correlations				
Variable	Obs.	Mean	St. Dev	Min	Max	MI	GDP	M	FDI	D
MI	25	0.52	0.21	0.12	0.87	1.00				
GDP	25	33607.86	19471.70	1573.88	59957.73	0.38	1.00			
M	25	987.00	10400.00	44.10	32100.00	0.49	0.80	1.00		
FDI	25	2.29	2.38	-0.01	9.90	0.19	-0.33	-0.24	1.00	
D	25	44.70	50.40	0.50	210.00	-0.12	0.26	0.14	-0.25	1.00

In the non-event country sample for terrorism events, Table 3 shows that the average DCC to the event countries is 0.31, but ranges from a negative 0.02 (considered as uncorrelated to the event country) and positive 0.80 (a very high correlation). The large ranges for GDP per capita (463.95 to 86605.52 USD), market capitalization (1.68 to 7320 billion USD) and FDI (-3.81 to 86.59 percent) are justified by the fact that this sample consists of 23 different countries at 25 different moments in time for both developed and undeveloped countries. The averages are 21748.32 USD for GDP, 839 billion USD for market capitalization, and 3.64 percent for FDI, while the standard deviations are larger than the means for both market capitalization and FDI, and slightly lower than its average for GDP per capita. Furthermore, columns 7 up to 10 show no highly correlated variables.

Table 3. Descriptive statistics for non-event countries at the time of a terrorism disaster event at time t=0 and the correlations between variables.

	Descriptive Statistics					Correlations			
Variable	Obs.	Mean	St. Dev	Min	Max	MI	M	GDP	FDI
MI	25	0.31	0.25	-0.02	0.94	1.00			
M	25	839.00	1150.00	1.68	7320.00	0.024	1		
GDP	25	21748.32	17717.00	463.95	86605.52	0.296	0.41	1.00	
FDI	25	3.64	7.89	-3.81	86.59	0.022	-0.02	0.22	1.00

The results in Table 4 for the non-event countries at time of natural disasters in the sample show results that are very similar to those of Table 3, with an average market integration level of 0.36 and a standard deviation of 0.23. Meanwhile, the average market capitalization is 898 billion USD, and ranges from small markets (1.07 billion USD) to large ones (8710 billion USD). Also, the GDP and FDI averages (22405.58 USD and 3.76 percent), as well as the standard deviations (20154.87 USD and 5.6 percent) are similar. Again, no high correlations between variables are shown.

Table 4. Descriptive statistics for non-event countries at the time of a natural disaster event at time t=0.

	Descriptive Statistics					Correlations			
Variable	Obs.	Mean	St. Dev	Min	Max	MI	GDP	M	FDI
MI	503	0.36	0.23	-0.08	0.93	1.00			
GDP	503	22405.58	20154.87	627.77	88415.61	0.44	1.00		
M	503	898.00	1270.00	1.07	8710.00	0.12	0.27	1.00	
FDI	503	3.76	5.60	-2.76	36.73	0.21	0.25	-0.12	1.00

Results and discussion

In this section, the results for hypothesis tests on H_1, H_2, H_3 and H_4 are displayed in tables and figures. In each one of these, the results are displayed separately for the "little", "medium", and "highly" integrated markets (with respect to the global market for the first two hypotheses, and to the event country's market for the latter two), based on the thresholds 0.2 and 0.4 of average DCCs on the ten pre-event trading days (as described in the methodology section). For tables 5, 7, 9 and 11, the first 13 rows show abnormal return results (using equations (*2.8*) and (*3.0*)), while row 14 until 23 show abnormal volatility results (using equations (*3.2*) and (*3.3*)). Row 24 in each of these tables show the results of each group's CAVAR on the four trading days prior to the event date, and serves as a robustness test of the results, in line with the methodology explained earlier. Figures 1, 3, 5 and 7 display the CSAR levels at different intervals, while figures 2, 4, 6 and 8 do so for CAVAR, including the (-4,-1) robustness check. In order to detect abnormal volatility levels in these figures, a dashed line is included as a benchmark, which indicates the value of CAVAR at each interval in case of no abnormal volatility (equation (*3.3*)). In tables 6, 8, 10 and 12, columns 2 until 8 display the regression results of CSAR, while columns 9 until 12 do so for the CAVAR regressions, both on multiple intervals. For the test results of hypothesis H_5, a table with historical average returns is displayed in Table 13.

Event countries

The CSAR results of event country's markets in response to terrorism events in Figure 1 and Table 5 show lower initial levels for medium-, and highly globally integrated markets, while the "little" group shows high returns in the long run. It is important here to take into account the small size of each subgroup, letting the impressing large price run-up of the little globally integrated Sri Lanka MSCI in 2001 influence the overall group by great extent (Terr4). This confirms that little can be concluded about each of the sub-group's results. Moreover, no significant results are obtained with the exception for the (10, 100) interval for the little integrated group, although a good overview of initial negative reactions and positive returns in the long run for all groups can be observed. Looking at the effect of market integration, Table 6 shows that no effect on any CSAR interval was found. Although positive in the short run (intervals (0,2), (0,5) and (0,10)), the association is negative for the intervals (0,30), (0,50) and (10,50), while positive again for (10,100). Therefore, no evidence for inefficient markets are found. In addition, GDP, FDI and military expenses show negative coefficients on all intervals, with significant results on the (0,10) interval for GDP and FDI, negatively impacting stock returns after terrorism events. These findings are in line with the results of previous research (Karolyi, 2006, Harrigan & Martin, 2002). However, on other intervals for GDP and FDI, as well as on all intervals for military expenses, coefficients are insignificant. Market capitalization shows slightly positive coefficients for all intervals, being significant for the (0,10) interval, which is in line with the findings of Kollias, Manou, Papadamou & Stagiannis (2011). Besides, damage shows no significant effects on abnormal returns, while the significance and signs of year effects differ per year and interval.

In contrast with earlier expectations, Table 5 and Figure 2 show no abnormal volatility levels during the first ten post-event trading days. In the figure, only the "medium" and "highly" integrated lines slightly surpass the dashed normal volatility line, however the results in the table show that these results were not significant, besides trading day four in the "medium" group. The robustness check on interval (-4,-1) confirms the robustness of the results, as its volatility levels are far from abnormal. The regression results in Table 6 show positive, but insignificant coefficients for market integration on all intervals. Market capitalization on the other hand, reduces volatility on the five days following a terrorism event. This is in line with its dampening effect on negative return reactions on the ten post-event trading day interval, observed in column 4, as it seems to contribute to market stability during post terrorism disaster event trading days. Furthermore, GDP, military expenses and FDI show negative, insignificant coefficients, while some years did seem to have significant effects on abnormal volatility levels.

Table 5. Abnormal return- and volatility results in terrorism disaster event countries.

	Little	Medium	Highly	All
Obs.	6	5	14	25
SAR0	-0.18	-0.41	-0.25	-0.27
SAR1	0.15	0.00	-0.07	0.00
SAR2	0.05	0.09	-0.16	-0.06
SAR3	0.23	-0.59	0.08	-0.02
SAR4	-0.01	-0.49	-0.13	-0.17
SAR5	0.14	0.69	-0.27	0.02
CSAR(0,2)	0.02	-0.33	-0.48	-0.33
CSAR(0,5)	0.37	-0.72	-0.80	-0.50
CSAR(0,10)	-0.69	-0.14	0.16	-0.10
CSAR(0,30)	0.44	1.46	0.56	0.78
CSAR(0,50)	0.00	1.16	0.53	0.53
CSAR(10,50)	2.43	1.51	-0.32	0.44
CSAR(10,100)	12.62 ***	1.19	-1.75	0.68
AVAR0	0.43	0.93	0.33	0.48
AVAR1	0.06	0.23	1.36	0.82
AVAR2	0.41	1.04	1.42	1.10
AVAR3	0.15	1.28	0.72	0.70
AVAR4	0.09	2.32 *	0.74	0.90
AVAR5	0.13	0.59	0.82	0.61
CAVAR(0,1)	0.49	1.16	1.69	1.30
CAVAR(0,3)	1.06	3.48	3.84	3.10
CAVAR(0,5)	1.28	6.39	5.40	4.61
CAVAR(0,10)	5.51	10.13	8.45	8.08
CAVAR(-4,-1)	1.33	1.71	2.38	2.00

*Note. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.*

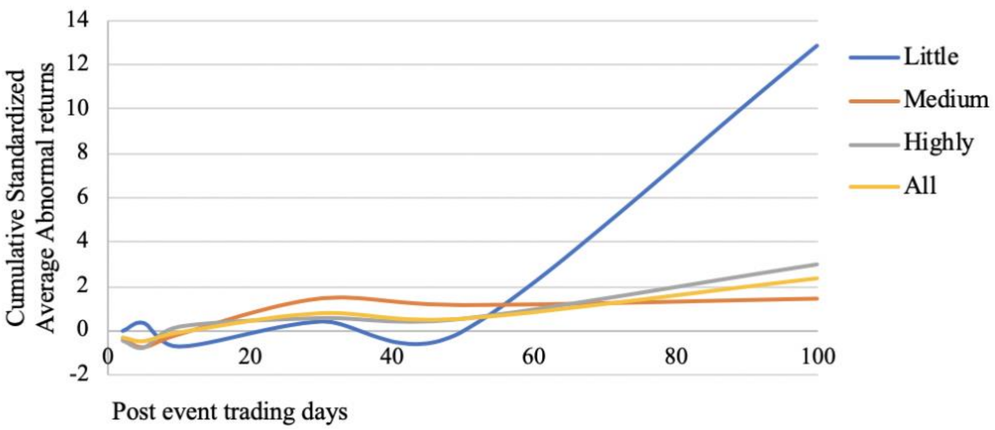

Figure 1. Levels of CSAR per number of post trading days for terrorism disaster event countries.

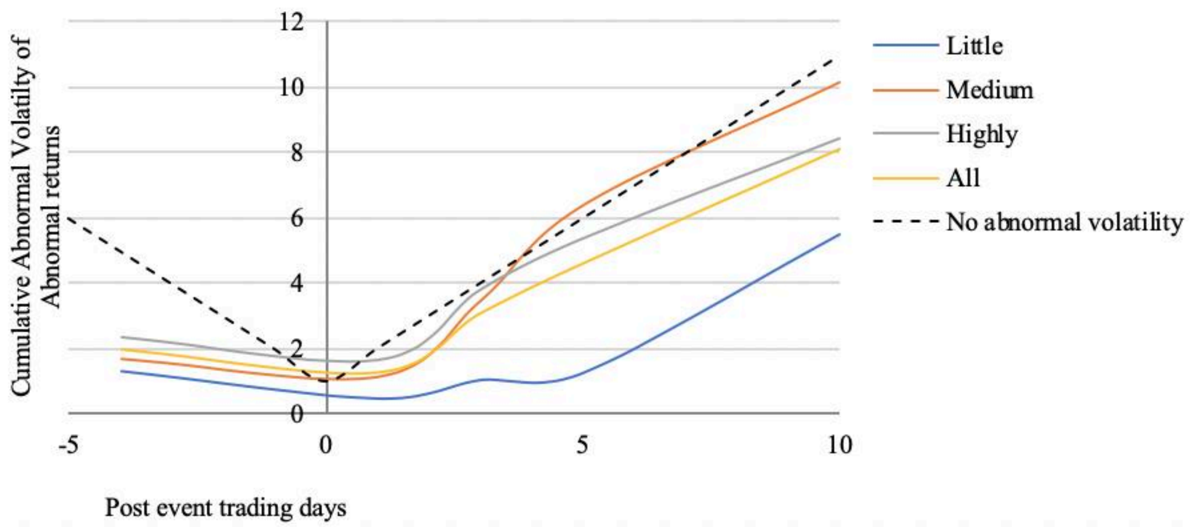

Figure 2. Levels of CAVAR per number of post trading days for terrorism disaster event countries compared to normal volatility levels.

Table 6. Results for CSARs and CAVARs in terrorism disaster event countries regressed on intervals market integration, GDP, market capitalization, foreign direct investment, damage and the event year.

	CSAR							CAVAR			
Variable	(0,2)	(0,5)	(0,10)	(0,30)	(0,50)	(10,50)	(10,100)	(0,1)	(0,3)	(0,5)	(0,10)
MI	4.83	1.71	2.50	-2.33	-3.84	-15.36	5.51	1.32	7.52	9.90	10.67
	(1.00)	(4.48)	(0.67)	(3.29)	(12.69)	(15.89)	(15.66)	(1.76)	(1.92)	(1.24)	(3.07)
GDP	0.00	0.00	-0.00*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M	0.00	0.00	0.00*	0.00	0.00	0.00	0.00	0.00	0.00	-0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FDI	-2.25	-3.16	-5.33*	-6.68	-10.51	0.15	-33.58	-0.86	-4.54	-5.99	-6.17
	(0.59)	(2.64)	(0.4)	(1.94)	(7.5)	(9.39)	(9.25)	(1.04)	(1.14)	(0.73)	(1.81)
D	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MilExp	-0.13	-0.28	-0.52	-1.10	-1.39	-0.65	-2.88	-0.05	-0.30	-0.39	-0.42
	(0.07)	(0.32)	(0.05)	(0.23)	(0.9)	(1.12)	(1.1)	(0.12)	(0.14)	(0.09)	(0.22)
1992	-0.06	-4.47	-3.61	-6.31	-5.28	-0.31	7.28	0.15	1.26	-0.53	-0.78
	(0.72)	(3.23)	(0.48)	(2.37)	(9.15)	(11.46)	(11.29)	(1.27)	(1.39)	(0.89)	(2.21)
1996	-1.06	-5.25	-2.94	-8.53	-9.85	-5.95	18.43	0.83	2.50	0.97	0.96
	(1.6)	(7.13)	(1.07)	(5.24)	(20.23)	(25.33)	(24.96)	(2.8)	(3.07)	(1.97)	(4.89)
2001	-3.28	-10.38	-16.67*	-21.15	-20.79	25.57	67.67	2.14	0.35	-2.71	-3.62
	(1.07)	(4.77)	(0.71)	(3.51)	(13.53)	(16.94)	(16.7)	(1.87)	(2.05)	(1.32)	(3.27)
2003	-7.16*	-10.35	-8.91*	-15.85	-23.63	-9.09	-9.38	2.17	14.59*	12.18*	12.64
	(0.48)	(2.14)	(0.32)	(1.57)	(6.07)	(7.6)	(7.49)	(0.84)	(0.92)	(0.59)	(1.47)
2004	-6.28	-9.61	-6.33	-8.33	-9.46	-4.41	21.07	3.52	20.39	19.50*	20.52
	(0.84)	(3.75)	(0.56)	(2.76)	(10.64)	(13.32)	(13.13)	(1.47)	(1.61)	(1.04)	(2.57)
2006	-2.33	-10.31	-13.30*	-11.98	-18.63	-10.39	-13.10	0.29	-0.19	-2.51	-3.00
	(1.26)	(5.62)	(0.84)	(4.13)	(15.93)	(19.95)	(19.66)	(2.21)	(2.41)	(1.55)	(3.85)
2007	-1.96	-8.36	-7.70	-14.61	-12.37	-4.28	17.62	0.55	1.50	-0.33	-0.82
	(1.35)	(6.03)	(0.9)	(4.43)	(17.09)	(21.4)	(21.09)	(2.37)	(2.59)	(1.66)	(4.13)
2008	-1.67	-1.38	1.36	2.15	2.65	-6.24	47.34	2.49	18.08	17.87*	18.84
	(0.99)	(4.43)	(0.66)	(3.25)	(12.55)	(15.71)	(15.48)	(1.74)	(1.9)	(1.22)	(3.04)
2013	-2.40	-9.67	-11.69*	-19.38	-21.43	2.67	-10.30	0.63	-0.19	-2.95	-3.69
	(1.09)	(4.87)	(0.73)	(3.58)	(13.81)	(17.29)	(17.04)	(1.91)	(2.09)	(1.34)	(3.34)
2014	-13.48*	-20.56	-13.53*	-17.77	-27.42	-11.51	11.76	13.96	40.49*	39.59*	44.71*
	(0.82)	(3.67)	(0.55)	(2.69)	(10.4)	(13.02)	(12.83)	(1.44)	(1.58)	(1.01)	(2.52)
2016	-1.82	-6.45	-7.13	-10.13	-11.08	-0.02	-7.36	1.12	-1.51	-3.37	-3.05
	(0.86)	(3.84)	(0.57)	(2.82)	(10.88)	(13.62)	(13.42)	(1.51)	(1.65)	(1.06)	(2.63)
Constant	7.71	18.57	25.89*	41.96	53.54	8.80	86.94	1.74	11.45	17.30	18.73
	(1.63)	(7.26)	(1.09)	(5.33)	(20.58)	(25.76)	(25.38)	(2.85)	(3.12)	(2)	(4.98)
Observations	19	19	19	19	19	19	19	19	19	19	19

*Note. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.*

For natural disaster events, Table 7 and Figure 3 show largest abnormal return results for medium globally integrated markets in the long run, while highly integrated markets are faced with negative returns on all intervals. Little integrated markets start with negative returns, which increase rapidly in the long run. SARs are significantly negative for the highly integrated group on the second post-event trading day, while positively significant on the fourth trading day following the event. The relatively large sample size of this group lets it influence the overall results of all event-countries, as can be observed by the similar results in the fourth and fifth columns of the table. However, the regression results shown in Table 8 indicate that, after controlling for GDP, market capitalization, FDI and damage, market integration affects market returns positively on the (0,10) and (0,30) intervals. The coefficients are positive, but insignificant on shorter and longer intervals. Among the other variables, none have significant effects on the CSARs. Except for the (0,2) interval, GDP seems to be positively associated with returns on all intervals, while market capitalization and foreign direct investment are positively associated with returns on all intervals. Damage shows negative, but insignificant coefficients, while year effects differ per year and CSAR interval again.

For abnormal volatilities, significant levels are obtained on the second, third and fourth post-event date trading days for all event countries (Table 7). Again, this seems to be mainly driven by the highly integrated group, which shows significant results for CAVAR intervals (0,3), (0,5) and (0,10). Figure 4 shows how clearly highly integrated markets experience higher abnormal volatility levels than the others. Again, the robustness-check shows no abnormal volatilities during the pre-event days. Strikingly however, the regression results show a negative association between market integration and abnormal volatility levels, after controlling for the other variables (Table 8). Here, GDP shows positive associations with abnormal volatility for the intervals until (0,5), while being negative on the (0,10) interval. Market capitalization shows negative coefficients for the first few days and positive ones afterwards, while FDI has initial positive coefficients, but is followed by negative ones. Lastly, the binary variables for event-years show little significance.

Table 7. Abnormal return- and volatility results in terrorism disaster event countries.

	Little	Medium	Highly	All
Obs.	2	7	16	25
SAR0	-0.64	-0.25	-0.07	-0.16
SAR1	-0.29	-0.12	0.24	0.13
SAR2	-0.09	-0.40	-0.55 **	-0.38 *
SAR3	-0.39	0.18	-0.36	-0.09
SAR4	0.32	0.00	0.68 ***	0.60 ***
SAR5	0.44	-0.06	-0.38	-0.03
CSAR(0,2)	-1.03	-0.77	-0.38	-0.54
CSAR(0,5)	-0.66	-0.65	-0.45	-0.52
CSAR(0,10)	-0.89	0.17	-0.20	-0.15
CSAR(0,30)	-1.36	1.16	-0.82	-0.31
CSAR(0,50)	-1.08	1.95	-2.19	-0.94
CSAR(10,50)	1.10	2.93	-1.83	-0.27
CSAR(10,100)	3.40	4.38	-1.29	0.68
AVAR0	1.11	0.31	0.71	0.61
AVAR1	1.06	0.19	0.94	0.75
AVAR2	0.25	0.61	3.41 ***	2.36 ***
AVAR3	0.16	0.39	5.03 ***	3.33 ***
AVAR4	0.22	0.13	2.89 ***	1.98 ***
AVAR5	0.93	0.57	1.00	1.03
CAVAR(0,1)	2.17	0.50	1.65	1.37
CAVAR(0,3)	2.43	1.11	5.05 *	3.74
CAVAR(0,5)	2.59	1.50	10.08 ***	7.08 *
CAVAR(0,10)	2.81	1.63	12.97 *	8.98
CAVAR(-4,-1)	1.34	3.44	2.50	2.67

*Note. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.*

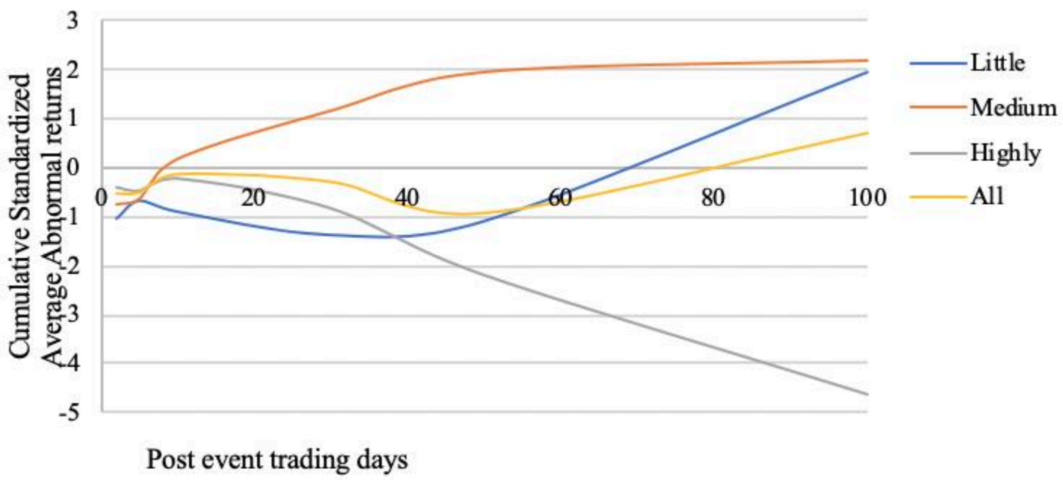

Figure 3. Levels of CSAR per number of post trading days for natural disaster event countries.

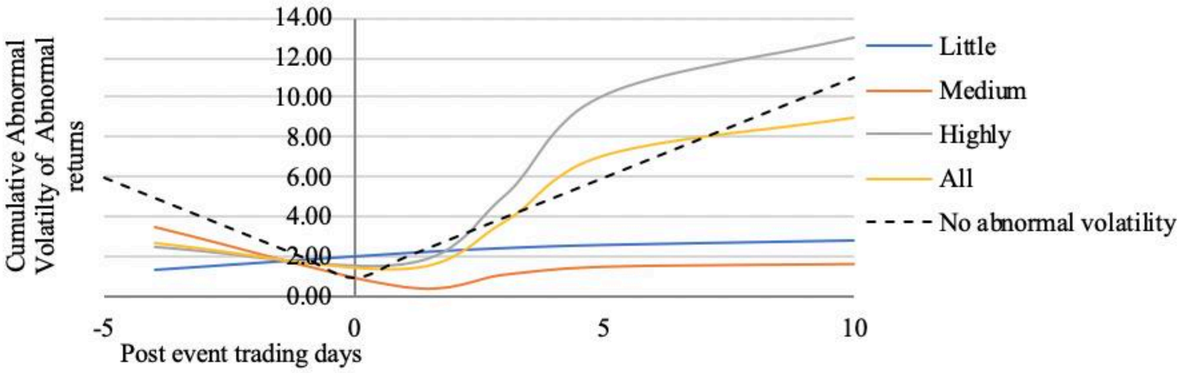

Figure 4. Levels of CAVAR per number of post trading days for natural disaster event countries compared to no abnormal volatility levels.

Table 6. Results for CSARs and CAVARs in natural disaster event countries regressed on intervals market integration, GDP, market capitalization, foreign direct investment, damage. and the event year.

	CSAR							CAVAR			
	(0,2)	(0,5)	(0,10)	(0,30)	(0,50)	(10,50)	(10,100)	(0,1)	(0,3)	(0,5)	(0,10)
MI	6.13	6.14	12.56*	26.69*	16.78	13.31	18.37	-0.36	-6.51	-11.45	-16.74
	(4.55)	(6.25)	(4.48)	(10.34)	(17.05)	(16.66)	(20.32)	(2.98)	(22.82)	(54.56)	(75.09)
GDP	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FDI	0.10	0.48	1.01	1.31	1.74	1.32	2.52	0.62	0.05	-1.16	-1.98
	(0.46)	(0.63)	(0.45)	(0.91)	(1.59)	(1.7)	(2.49)	(0.32)	(1.95)	(4.54)	(6.17)
D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2004	-0.01	3.09	8.33	10.17	14.13	12.39	22.24	6.45	0.73	-10.34	-18.80
	(4.5)	(6.17)	(4.12)	(7.5)	(12.95)	(14.15)	(20.2)	(2.79)	(18.45)	(42.81)	(57.97)
2005	-0.67	1.96	5.74	6.51	9.60	12.35	19.87	7.12*	14.67	23.94	27.49
	(4.76)	(6.85)	(5.6)	(10.37)	(15.46)	(15)	(20.94)	(2.74)	(21.19)	(49.49)	(67.41)
2008	3.57	6.84	11.73*	20.37*	24.88	26.56	26.36	5.93	-2.65	-14.71	-25.19
	(4.21)	(5.55)	(3.46)	(7.21)	(13.29)	(14.58)	(20.9)	(2.82)	(19.14)	(44.93)	(60.93)
2010	-3.32	-0.41	0.22	-0.62	1.88	7.85	15.33	5.961*	3.98	-3.44	-9.02
	(2.8)	(3.83)	(2.55)	(4.33)	(7.57)	(8.54)	(14.29)	(1.68)	(12.17)	(28.33)	(38.38)
2011	4.90	8.77	15.29*	27.70	29.78	26.93	33.93	5.35	-8.57	-30.64	-46.77
	(5.85)	(8.05)	(5.3)	(11.47)	(19.56)	(20.15)	(27.04)	(3.75)	(27.29)	(64.57)	(88.36)
2012	-0.12	3.41	5.59	2.85	8.29	8.82	18.79	4.69	-2.27	-16.34	-25.93
	(3.91)	(5.51)	(3.84)	(6.39)	(9.99)	(10.62)	(17.82)	(2.05)	(17.61)	(41.24)	(56.18)
2014	2.03	4.53	17.83**	32.07*	31.88	30.19	42.67	6.24	-1.27	-13.82	-24.06
	(5.53)	(7.1)	(4.18)	(9.4)	(18.12)	(20.17)	(28.58)	(3.91)	(24.66)	(57.73)	(78.11)
2016	2.19	5.07	9.45	17.22	22.54	22.90	35.15	4.92	-1.83	-14.55	-23.78
	(4.36)	(6.03)	(4.35)	(9.19)	(15.91)	(16.61)	(22.93)	(3.09)	(18.66)	(43.6)	(59.35)
2017	0.54	3.93	5.55	0.24	2.20	3.56	11.96	5.59	-1.98	-16.48	-26.91
	(4.37)	(6.13)	(4.33)	(7.4)	(11.59)	(12.12)	(19.65)	(2.32)	(20.24)	(47.58)	(64.89)
Constant	-3.57	-7.66	-17.63*	-30.12	-29.39	-28.39	-42.25	-6.96	1.39	15.09	26.57
	(6.8)	(8.73)	(5.25)	(12.23)	(23.26)	(25.52)	(35.04)	(4.91)	(30.24)	(70.86)	(95.97)
Observations	20	20	20	20	20	20	19	20	20	20	20

*Note. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

According to these results, we indeed find that, in line with Tavor & Teitler-Regev's results (2019), market reactions to natural and terrorism disasters events differ significantly. Also, the influence of global market integration levels on these market reactions in event countries differs between both groups. Interestingly, the sign of market integration's association with market returns in the long run is negative for terrorism events, while positive for natural ones. Based on the regression results in Table 4 and Table 6, market integration was not found to affect returns following terrorism disaster events, while dampening the negative price reactions in the first ten to thirty trading days after natural disaster events. Therefore, hypothesis H_1: "*Global market integration has a positive effect on market returns in countries where disaster events occur"* is accepted for natural disaster events, but rejected for terrorism events.

Regarding hypothesis H_2: "*Global market integration has a negative effect on abnormal volatility levels in markets where disaster events occur"*, Table 4 indeed showed a negative association with volatility levels in terrorism event country's markets, but did not find significant effects. Table 6 showed that, for natural disaster events, no signs of market integration's contribution to market stability in the after-event days were observed at all and therefore, the hypothesis is rejected for both disaster event types.

Correlated countries

Table 9 and Figure 5 show larger initial negative results for countries with medium and high integration levels with terrorism disaster event countries than the "little" group. The highly correlated group shows a significant negative price reaction on the event date, while also showing negative CSARs until 5 trading days after the event. As can clearly be seen in the same table and figure, highly correlated markets perform really well in the 100 post-event trading days. Here, the medium and highly integrated markets show significant positive CSAR results for the intervals to (0,30), (0,50), (10,50) and (0,100). In Table 10, however, after controlling for GDP, market capitalization, FDI and year effects, the impact of market integration is insignificant. The results in column 2, 3, 4 and 5 show a negative correlation for the interval until (0,5), while positive in longer runs. The coefficients of market capitalization, GDP, and FDI seem negligible on either interval, while some year effects are significant.

Moving on to the volatility results of these countries, abnormal volatility was only significant on the event date in medium groups, while it stayed low to no abnormal results for most of the post-event trading days (Table 9 and Figure 6). Again, the pre-event trading days show similar and non-abnormal volatility levels, which confirms robustness of the results. Regarding the regression results in Table 10, market integration shows negative, but insignificant coefficients for all intervals. Meanwhile, GDP seems to have small ambiguous effects, as its coefficient is slightly positive and significant on the 5-day interval, while slightly negative and significant on the 10-day interval. Market capitalization's coefficients are close to zero here, while FDI shows a small negative association for the intervals up until 5 trading days after the event date, followed by a negligible one. Here, multiple year effects are found, which are negative in most cases and especially present on the large post-event intervals.

Table 9. Abnormal return- and volatility results in non-event countries at times of terrorism disaster events.

	Little	**Medium**	**Highly**
Obs.	268	146	94
SAR0	0.02	-0.05	-0.23 **
SAR1	0.08	0.00	-0.11
SAR2	0.06	0.09	0.09
SAR3	0.01	-0.09	-0.07
SAR4	0.05	0.03	0.00
SAR5	0.08	-0.06	0.05
CSAR(0,2)	0.15	0.02	-0.28
CSAR(0,5)	0.26 *	-0.18	-0.44 *
CSAR(0,10)	0.46 **	0.40	-0.02
CSAR(0,30)	0.07	1.49 ***	1.09 *
CSAR(0,50)	-0.14	2.01 ***	1.48 **
CSAR(10,50)	-0.67 *	1.68 ***	1.67 **
CSAR(10,100)	-0.06	2.27 ***	2.34 **
AVAR0	0.71	1.16 *	0.82
AVAR1	0.86	1.00	1.12
AVAR2	0.73	1.15	0.91
AVAR3	0.64	0.99	0.63
AVAR4	0.81	0.82	0.44
AVAR5	0.65	0.75	1.15
CAVAR(0,1)	1.58	2.17	1.95
CAVAR(0,3)	2.31	3.31	2.84
CAVAR(0,5)	2.94	4.29	3.44
CAVAR(0,10)	3.73	5.09	3.85
CAVAR(-4,-1)	3.50	2.80	2.83

*Note. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

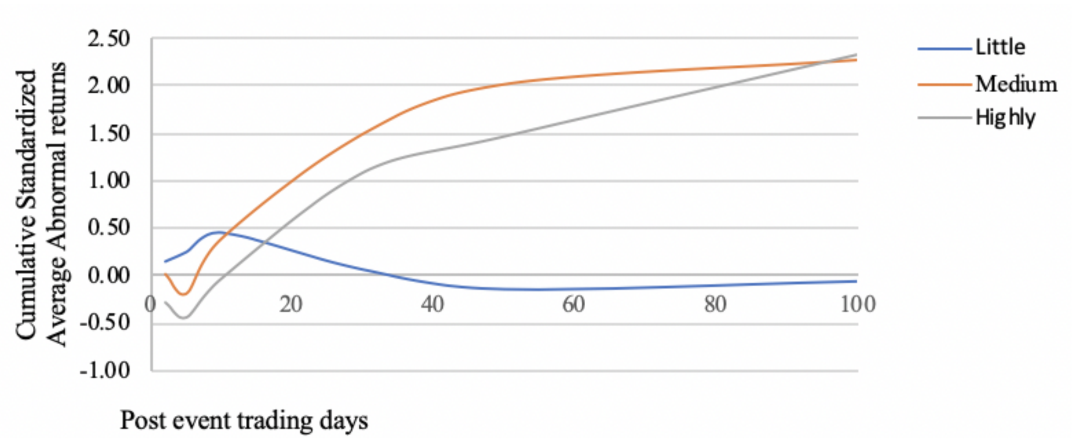

Figure 5. Levels of CSAR per number of post trading days for non-event countries after terrorism disaster events.

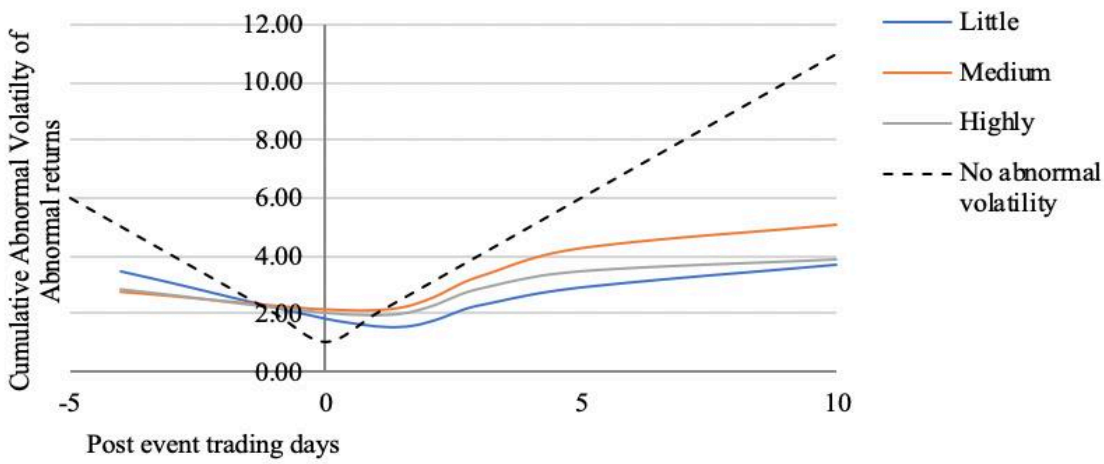

Figure 6. Levels of CAVAR per number of post trading days for non- event countries after terrorism disaster events compared to no abnormal volatility levels.

Table 10. Results for CSARs and CAVARs markets at times of foreign terrorism disaster events regressed on market integration, GDP, market capitalization, foreign direct investment, and the event year.

	CSAR							CAVAR			
	(0,2)	(0,5)	(0,10)	(0,30)	(0,50)	(10,50)	-10,100	(0,1)	(0,3)	(0,5)	(0,10)
MI	-0.20	-0.31	0.39	0.90	1.71	1.33	5.41	-0.29	-0.63	-1.02	-1.43
	(0.51)	(0.68)	(0.88)	(1.37)	(1.98)	(1.98)	(2.76)	(0.71)	(0.89)	(1.07)	(1.17)
GDP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00*	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FDI	-0.01	-0.02	0.00	-0.01	0.00	-0.02	-0.04	-0.01	-0.02	-0.02	0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)	(0.02)
1992	-0.47	0.23	0.38	-0.95	-2.98	-4.32	-7.218*	2.39	2.27	3.03	2.86
	(0.63)	(0.75)	(1.12)	(2.01)	(2.77)	(2.4)	(3.34)	(1.57)	(2.08)	(2.29)	(2.55)
1994	-1.48	-0.86	-2.08	-7.53**	-11.83**	-14.26***	-15.78***	-0.45	-1.07	0.11	-0.19
	(0.81)	(0.92)	(1.43)	(2.28)	(3.86)	(3.8)	(4.34)	(0.88)	(1.45)	(1.95)	(2.32)
1995	-0.08	0.90	1.43	1.64	-0.46	0.42	-2.50	0.08	-0.34	0.12	-0.02
	(0.77)	(0.92)	(1.25)	(2.16)	(2.9)	(2.66)	(3.5)	(0.71)	(1.2)	(1.24)	(1.61)
1996	-0.58	-0.46	-0.06	-4.87*	-6.85*	-8.68***	-10.41**	-0.70	-1.48	-1.62	-1.36
	(0.64)	(0.78)	(1.22)	(2.17)	(2.78)	(2.32)	(3.33)	(0.67)	(1.15)	(1.13)	(1.54)
1998	-0.39	-0.19	0.28	-0.63	-4.24	-4.15	-4.73	-0.47	-0.20	0.14	-0.22
	(0.79)	(0.83)	(1.3)	(2.2)	(2.67)	(2.63)	(3.58)	(0.67)	(1.29)	(1.25)	(1.63)
2001	-1.733*	-1.06	-1.51	-4.03	-12.58***	-11.93***	-10.49**	0.57	-0.57	-0.45	-0.73
	(0.77)	(0.89)	(1.23)	(2.07)	(2.99)	(2.48)	(3.51)	(0.87)	(1.26)	(1.29)	(1.67)
2002	-0.42	-1.19	-0.91	-4.66*	-6.83*	-6.76**	-12.35***	-0.74	-1.89	-1.78	-1.38
	(0.66)	(0.82)	(1.18)	(2.04)	(2.7)	(2.21)	(3.3)	(0.83)	(1.25)	(1.24)	(1.73)
2003	-0.44	-0.43	0.17	-3.59	-4.91	-6.29**	-8.65*	-0.58	-0.86	-0.62	-0.75
	(0.66)	(0.75)	(1.09)	(2)	(2.82)	(2.36)	(3.79)	(0.67)	(1.16)	(1.15)	(1.57)
2004	-1.53*	-1.56*	-1.99	-4.88*	-8.92***	-8.06***	-12.32***	-0.16	-0.42	-0.30	-0.55
	(0.64)	(0.75)	(1.11)	(1.9)	(2.62)	(2.2)	(2.98)	(0.63)	(1.16)	(1.13)	(1.53)
2006	-0.52	-0.33	-0.59	-3.15	-7.07**	-7.05**	-8.00*	-1.520*	-2.19	-2.37	-3.227*
	(0.66)	(0.79)	(1.2)	(2.01)	(2.68)	(2.44)	(3.29)	(0.69)	(1.26)	(1.26)	(1.63)
2007	-1.19	-0.75	-0.41	-6.51**	-9.13***	-9.13***	-13.00***	0.44	-0.32	0.05	-0.29
	(0.64)	(0.79)	(1.18)	(2)	(2.6)	(2.18)	(3.28)	(0.85)	(1.25)	(1.25)	(1.61)
2008	-1.20	-1.03	-2.58*	-6.71***	-10.06***	-9.63***	-16.22***	0.26	0.00	0.21	0.11
	(0.66)	(0.78)	(1.29)	(1.95)	(2.58)	(2.21)	(3.09)	(0.72)	(1.21)	(1.19)	(1.61)
2013	-0.11	-0.17	-0.29	-5.17**	-9.23***	-9.640***	-10.34***	-0.85	-1.57	-1.72	-2.40
	(0.64)	(0.74)	(1.08)	(1.89)	(2.52)	(2.16)	(3.07)	(0.67)	(1.14)	(1.12)	(1.51)
2014	-2.50***	-4.40***	-3.53**	-8.62***	-10.93***	-8.41**	-11.78**	4.04*	5.35**	7.99**	8.28**
	(0.72)	(1.01)	(1.22)	(2.29)	(2.98)	(2.71)	(3.85)	(1.62)	(1.88)	(2.49)	(2.79)
2016	-0.56	-0.72	0.28	-3.21	-5.00	-5.229*	-7.312*	-0.51	-0.43	-0.47	-0.94
	(0.66)	(0.82)	(1.12)	(2.08)	(2.69)	(2.46)	(3.46)	(0.67)	(1.2)	(1.16)	(1.57)
Constant	0.79	0.82	1.23	4.44*	7.07**	6.55**	7.77**	2.02**	3.64**	4.44***	5.32***
	(0.64)	(0.76)	(1.1)	(1.97)	(2.58)	(2.08)	(2.95)	(0.7)	(1.19)	(1.19)	(1.6)
Observations	358	358	358	358	358	358	358	358	358	358	358

*Note. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

For foreign market reactions to natural disaster events, the results concerning abnormal returns are shown in Table 11 and Figure 7 below. These results show that initial price reactions are negative on all intervals for markets with little correlations to event countries. Their CSAR results are significant on intervals (0,5), (0,50) and (10,50). The higher the correlation with the event country's market, the more positive the results. Abnormal positive returns are found on the second and fourth post-event trading day, as well as for CSAR on intervals (0,10), (0,30), (0,50) and (10,50) for highly correlated markets. The lines in the figure show a clear difference in CARs between the sub-groups, where the "highly" line stays much higher than the other lines on all intervals with a small reduction between 30 and 50 trading days after the event date. In line with these results, Table 12 shows evidence for a positive effect of market integration on CSAR intervals (0,30), (0,50) and (10,50). Among the control variables, GDP and FDI show negative associations with post-event stock performance in foreign countries. Market capitalization, on the other hand, seems to be an important factor here, as significant positive effects are found for CSAR on the intervals (0,30), (0,50) and (10,50). Again, certain years show significant effects, with varying magnitudes and signs. Based on these results, it seems that foreign markets benefit from the recovery of a natural disaster event in a market that they are highly correlated with, with market capitalization being a determinant of this benefit.

Figure 8, as well as the volatility rows in Table 11, shows that abnormal volatility levels are barely observed after the event date, without any significant results. Meanwhile, Table 12 does show significant results. Here, in contrast with the expectations, market integration negatively affects CAVAR on the intervals (0,3) and (0,5). Meanwhile, GDP seems positively correlated with volatility levels for the first few days following an event, while it is associated with lower abnormal volatility levels after that. The opposite is true for market capitalization, which shows no significant results here. Furthermore, FDI shows negative associations on all intervals.

Table 11. Abnormal return- and volatility results in non-event countries at times of natural disaster events.

	Little	**Medium**	**Highly**
Obs.	216	198	127
SAR0	-0.05	-0.10	0.10
SAR1	-0.02	-0.02	0.22 **
SAR2	-0.06	0.07	-0.06
SAR3	0.00	0.02	0.06
SAR4	-0.07	-0.06	0.16 *
SAR5	-0.06	0.04	-0.11
CSAR(0,2)	-0.16	-0.07	0.23
CSAR(0,5)	-0.34 **	-0.13	0.25
CSAR(0,10)	0.02	0.11	0.74 **
CSAR(0,30)	0.03	0.34	1.69 ***
CSAR(0,50)	-1.23 **	0.06	1.50 **
CSAR(10,50)	-0.95 **	0.07	1.44 **
CSAR(10,100)	-0.19	1.00	0.73
AVAR0	0.73	0.97	0.55
AVAR1	0.81	0.59	0.51
AVAR2	0.92	0.63	0.63
AVAR3	0.86	0.90	0.83
AVAR4	1.11	1.01	0.76
AVAR5	1.12	0.75	0.94
CAVAR(0,1)	1.54	1.55	1.06
CAVAR(0,3)	2.46	2.18	1.68
CAVAR(0,5)	3.30	3.07	2.49
CAVAR(0,10)	4.40	4.07	3.23
CAVAR(-4,-1)	2.40	1.89	2.05

Note. Standard errors in parentheses. $^{*} p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$.

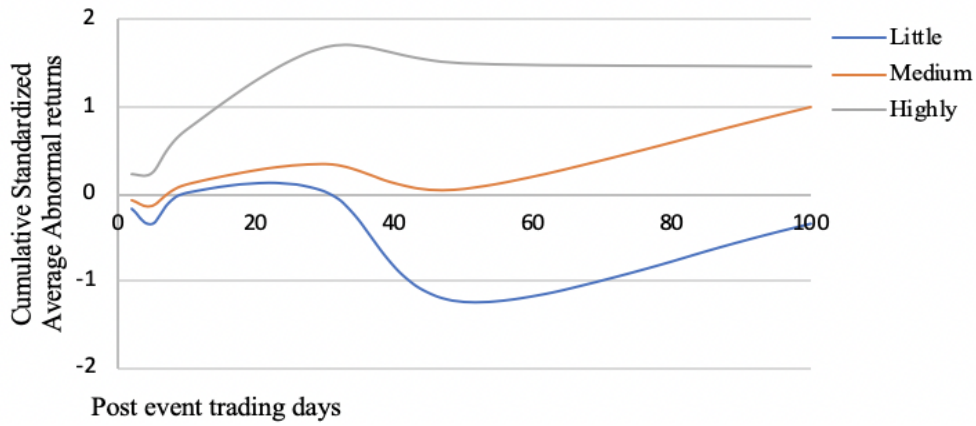

Figure 7. Cumulative Standardized Average Abnormal Returns per number of post trading days for non-event countries at times of natural disaster events.

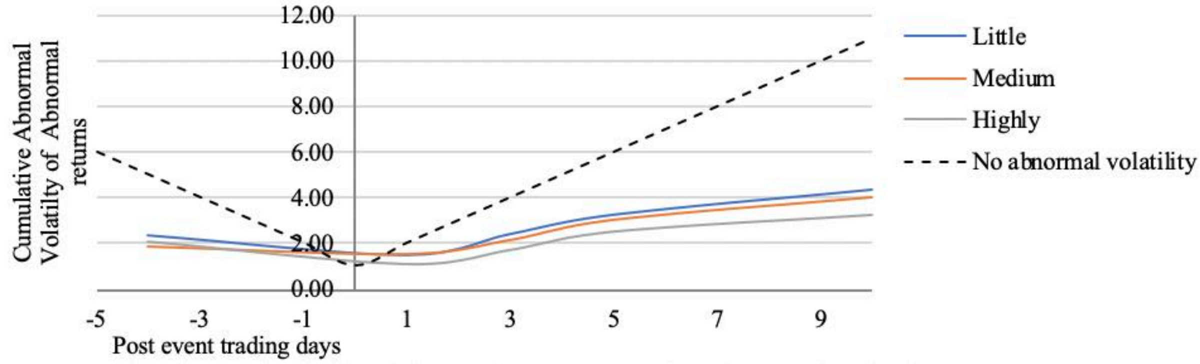

Figure 8. Cumulative Abnormal Volatility of Abnormal Returns per number of post trading days for non-event countries at times of natural disaster events.

Table 12. Results for CSARs and CAVARs markets at times of foreign natural disaster events regressed on market integration, GDP, market capitalization, foreign direct investment, and the event year.

	CSAR							CAVAR			
	(0,2)	(0,5)	(0,10)	(0,30)	(0,50)	(10,50)	(10,100)	(0,1)	(0,3)	(0,5)	(0,10)
MI	0.54	0.46	1.39	3.470*	4.968*	5.028*	2.34	-0.28	-1.869**	-1.675*	-1.93
	(0.4)	(0.55)	(0.76)	(1.68)	(1.98)	(2.07)	(2.64)	(0.7)	(0.7)	(0.79)	(1.14)
GDP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M	0.00	0.00	0.00**	0.00**	0.00**	0.00*	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FDI	0.00	0.00	0.01	0.00	0.00	-0.02	0.00	-0.03	-0.02	-0.01	-0.02
	(0.01)	(0.02)	(0.02)	(0.04)	(0.05)	(0.06)	(0.06)	(0.02)	(0.01)	(0.02)	(0.02)
1994	0.99	-0.30	-0.33	-11.53***	-21.03***	-22.76***	-34.40***	-0.05	-0.02	0.40	0.74
	(0.67)	(0.95)	(0.94)	(2.11)	(2.64)	(3)	(4.49)	(0.78)	(1.33)	(1.33)	(1.33)
1999	-0.01	-1.50	-2.593**	-4.181*	-6.747**	-3.47	-6.40	0.77	-0.95	-0.53	-0.95
	(0.63)	(0.92)	(0.8)	(1.8)	(2.12)	(2.31)	(3.58)	(0.82)	(1.44)	(1.52)	(1.54)
2000	-0.51	-1.22	-2.25**	-3.91	-10.11***	-8.48**	-9.91*	1.25	-0.04	0.27	0.22
	(0.61)	(0.91)	(0.83)	(2.17)	(2.37)	(2.59)	(4.18)	(0.94)	(1.47)	(1.48)	(1.58)
2004	-0.42	-1.38	-2.67***	-3.66*	-7.03***	-5.82**	-8.07**	0.20	-0.55	-0.50	-0.92
	(0.56)	(0.8)	(0.59)	(1.52)	(1.82)	(1.98)	(3.06)	(0.64)	(1.29)	(1.28)	(1.28)
2005	0.09	-1.21	-2.29***	-3.34*	-8.39***	-6.51**	-8.97**	0.26	1.30	2.09	3.899*
	(0.59)	(0.86)	(0.64)	(1.65)	(2.01)	(2.13)	(3.2)	(0.65)	(1.32)	(1.33)	(1.55)
2008	1.03	0.69	1.73	5.470*	1.82	4.41	0.39	1.19	0.35	2.09	2.88
	(0.6)	(0.89)	(0.97)	(2.31)	(2.71)	(2.88)	(3.84)	(0.93)	(1.36)	(1.46)	(1.56)
2010	0.06	-0.78	-2.25***	-2.70	-6.21***	-5.14*	-7.64*	-0.43	-0.74	-1.21	-1.64
	(0.58)	(0.82)	(0.63)	(1.55)	(1.85)	(2)	(3.12)	(0.66)	(1.31)	(1.3)	(1.29)
2011	-0.21	-1.09	-1.75**	-1.84	-6.65**	-5.12*	-12.39***	-0.22	-0.05	0.16	-0.12
	(0.64)	(0.89)	(0.68)	(1.74)	(2.11)	(2.21)	(3.37)	(0.7)	(1.41)	(1.42)	(1.47)
2012	-0.25	-1.09	-2.26***	-3.83*	-6.46***	-5.31**	-9.15**	0.79	-0.61	-0.79	-1.34
	(0.56)	(0.8)	(0.58)	(1.49)	(1.76)	(1.97)	(3.12)	(0.67)	(1.28)	(1.27)	(1.26)
2014	0.46	-0.88	-1.25	-2.49	-6.68**	-5.25*	-7.52*	0.26	-1.22	-1.49	-2.02
	(0.64)	(0.89)	(0.7)	(1.75)	(2.25)	(2.38)	(3.67)	(0.83)	(1.38)	(1.39)	(1.42)
2016	0.28	-0.79	-2.79***	-3.84*	-8.13***	-7.57**	-10.57**	-0.36	-1.75	-2.04	-2.768*
	(0.63)	(0.91)	(0.76)	(1.79)	(2.35)	(2.34)	(3.39)	(0.79)	(1.36)	(1.35)	(1.36)
2017	-0.15	-1.67	-3.10***	-5.69**	-10.57***	-9.22***	-13.76***	-0.92	-0.63	-0.58	-0.31
	(0.6)	(0.86)	(0.72)	(1.74)	(2.11)	(2.19)	(3.29)	(0.68)	(1.33)	(1.34)	(1.42)
Constant	-0.16	0.75	1.79**	2.48	5.59**	4.06	9.114**	1.04	3.07*	3.60**	4.76***
	(0.59)	(0.84)	(0.63)	(1.67)	(2)	(2.11)	(3.27)	(0.64)	(1.37)	(1.36)	(1.32)
Observations	503	503	503	503	503	503	503	503	503	503	503

*Note. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

In testing hypothesis H_3: "*In the occurrence of a disaster event, market integration with the event-country's market negatively affects stock returns in foreign markets*", Table 9 did show that, in case of a terrorism disaster event, highly correlated markets are negatively affected on a 5-trading day post-event interval. However, Table 10 and Table 12 showed no significant effect for market integration driving negative effects on stock markets in the days following either type of disaster event. Therefore, the hypothesis is rejected. However, interestingly, for both disaster types, in the long run, markets that are highly integrated to event country's markets show positive abnormal returns in the long run. Table 12 even showed that for natural disaster events, market integration and capitalization seem important factors in driving these returns.

Moving on to hypothesis H_4: "*In the occurrence of a disaster event, market integration with the event-country's market positively affects abnormal volatility levels in foreign markets*", Table 10 and Table 12 showed that market integration does not seem to increase abnormal volatility levels in markets that are correlated to countries in which either disaster type occurred. Therefore, this hypothesis is rejected for both event types as well. Striking and unexplained for foreign countries at times of natural disaster events remain the negative effects that were found for market integration on CAVAR intervals (0,3) and (0,5), just like the initial negative price reactions being mainly found in little integrated markets.

Investment strategies

Following the positive significant CSAR long run results (intervals up to 30 and fifty trading days after the event) for markets that were integrated to natural disaster event countries, as well as the positive effects that market integration and market capitalization had on these results, trading strategies that involve systematic investment activity following other historical natural disaster events were tested. The first column in Table 5 shows each strategy's systematic buying and selling moments with respect to a natural disaster's event date in a foreign country. The strategy is the same for each of the applied ones in Table 5, with different systematic activity days. The strategies involve, as a natural disaster event happens, the practitioner to invest systematically in an equally weighted portfolio, existing of all MSCI indices that have a market capitalization of over 700 billion USD in that year, and an average DCC of more than 0.5 over the ten trading days prior to the event. Strategy one and three include the fifth post-event date trading day as the investing moment, while strategies two and four invest on the tenth trading day after the event took place. For selling the indices, the first two strategies systematically choose trading day 30, while the last two include selling on trading day number 50. As mentioned earlier in the "Data sampling" section, the overview of the events can be found in Table 3 in the Appendix, while the index prices of all indices invested in, as well as the ACWI on the same dates can be found in Table 4 (Appendix). Table 13 (below) shows the average return of each strategy in column two, and the average return of the MSCI ACWI over the same time periods in column three. As can be observed, strategies one and two outperform the benchmark, while strategy three and four show negative returns. This is in line with the results in Figure 7, which showed a slight decrease in CSARs for the highly integrated group between t=30 and onwards. Relatively, strategy two outperforms the ACWI by more than 200 percent, while the first strategy's outperformance is over 100 percent. Following these outperformances, hypothesis H_5:*"Systematically investing and selling on the same specific trading days with respect to disaster event dates will yield higher returns than the world market"* is accepted. However, in interpreting these results, it is important to take into account that transaction costs were not included in the calculation of returns here.

Table 13. Average returns of each developed investment strategy based on this paper's findings compared to the average MSCI ACWI returns over the same time periods.

Buying and selling moment	**Strategy's average return**	**ACWI's average return**
1. (5,30)	0.019	0.007
2. (10,30)	0.004	0.001
3. (5,50)	-0.003	0.011
4. (10,50)	-0.012	0.007

Conclusion

International market integration can have an impact on companies and financial markets in the period following disaster events. In this research, this was illustrated by an example in which firm's operational activity heavily depended on both national and international government policies regarding the economic lockdowns that followed from the 2020 COVID-19 pandemic. Subsequently, the question that this research tries to answer is: *How does global market integration impact financial markets' reactions to disaster events?* In order to find an answer, a sample of 25 terrorism disaster events, as well as a sample of 25 natural disaster events that happened between 1990 and 2018, in multiple countries were analyzed, together with market returns in 23 different countries. The first hypothesis that this study stated was whether global market integration has a positive effect on market returns following a disaster event in the event country. Using event study methodologies to obtain abnormal returns, and regressing these results on multiple variables, this hypothesis was rejected for terrorism, but not for natural disaster events, which was found to drive negative returns on the second trading day after the event. For the second hypothesis, which tested whether global market integration has a negative effect on abnormal volatility levels in event countries following disaster events, the same event studies methods and regression analysis techniques were used. The results showed that terrorism disaster events are not followed by abnormal volatility levels, while natural ones, in line with the findings of Bourdeau-Brien & Kryzanowsky (2017), drive abnormal market volatility up to five trading days after the event date. However, no evidence for market integration affecting these abnormal volatilities were found. Therefore, the second hypothesis was rejected for both event types. Next, the focus of this study moved to markets in non-event countries following disaster events. Hypothesis three tested whether market integration with an event country's market negatively impacts market returns. Using the same methodology as for hypothesis one, but on the analysis of 22 foreign markets, it was found that in the occurrence of terrorism disaster events, highly correlated markets (with an average DCC of over 0.4 in the ten trading days prior to the event date) experience abnormal negative returns on the event date, as well as up to five trading days after the event date. However, from the regression results followed that market integration does not drive these market reactions. Since for natural disaster events no negative market reactions were found at all, the hypothesis was rejected. However, evidence was found that highly correlated markets benefit in the long run from event country's recovery. For terrorism disaster events this goes for 30 up to 100 post-event trading days, while for natural disasters this is for the 30 trading days that follow the event date. For the latter event type was found that market integration, as well as market capitalization drive these returns. In analyzing the volatility effects of disaster events in non-event countries, hypothesis four tested whether market integration with an event country's market drives abnormal volatility levels in stock markets. It was rejected for both event types since none of the regression results showed evidence for market integration effects on any interval. Strikingly, however, is that market integration seems to have a dampening impact on volatility levels on the first five post-event trading days in those markets. Lastly, hypothesis five tested whether, with the obtained results, a profitable investment strategy could be elaborated by trading on specific trading days with respect to disaster events. This hypothesis was accepted, as it was found that when an investor invests systematically on the tenth post-event trading day in MSCI markets with a market capitalization of over 700 billion USD in the event year, and a higher than 0.5 average DCC with the event country's market on the ten trading days prior to the event date, followed by selling them twenty trading days later, the world market is outperformed by over 200 percent. To conclude, following the results of these hypotheses tests, an answer to the research question is that market integration with a natural disaster event country's market impacts financial markets positively up to thirty trading days following the event date and that investors can achieve outperformance by incorporating these results in their investment strategies in the occurrence of natural disaster events.

Furthermore, the results in this paper confirm some earlier findings on terrorism disaster event countries, as evidence was found for market capitalization positively affecting returns on a ten trading day post-event interval, which was also found by Kollias, Manou, Papadamou & Stagiannis (2011). On this same interval it was also found that GDP and FDI negatively affect abnormal returns, in line with earlier findings of Karolyi (2006), and Harrigan & Martin (2002), respectively. Besides, the results showed evidence for market capitalization having a dampening effect on volatility up to five trading days after terrorism disaster events in the event country. In addition, the findings of Kollias, Manou, Papadamou & Stagiannis (2011) about market capitalization positively affecting returns in event countries in the aftermath of a terrorist disaster event, were found for a ten trading day post-event interval. Also, the results in this study showed that GDP and FDI negatively affect abnormal returns in terrorism event countries on the same interval, which is in line with earlier findings of Karolyi (2006), and Harrigan & Martin (2002), respectively. Besides, it was found that market capitalization has a volatility dampening effect up to five trading days after terrorism events, while for foreign countries, only evidence for effects of GDP on volatility has been found. Here, GDP has a positive effect on a five trading day interval, while having a negative effect on a ten trading day interval after the occurrence date.

Regarding the findings of this paper, the investment strategy results seem robust to data snooping, as the strategy was applied to different disaster events than the event study was based on. However, the findings on a dampening effect of market integration on abnormal volatility levels in these same markets in the post-event trading days remain unexplained and demand further investigation, as well as the negative initial price reactions to terrorism events observed in little correlated markets. Furthermore, the results in this study are based on the assumption that disaster events happened unpredictively, although in the real world some natural disaster events could have been forecasted with the use of technology, and increasing terrorism tensions can affect country correlations prior to terrorism events. Another limitation of the findings discussed above is the causality assumption, where it was assumed that the observed abnormal returns and volatilities in foreign countries were caused by the event country, without taking into account possible feedback loops on the event country. Table 8 and Table 9 in the Appendix disclose results of the Granger causality test[1] computed on the event country's market with respect to highly integrated markets (with an average DCC above 0.4 on the ten trading preceding a disaster event). The results show that reverse causality issues differ per event, with no evidence for overall unidirectional Granger causality of event countries towards highly integrate markets. A last limitation of this research is that, Patell's approach (1976) does not take into account event induced volatilities in calculating standard errors. According to Boehmer, Musumeci, and Poulsen (1991) the abnormal return tests may be mis-specified as a consequence.

Due to current global tendencies, research on the role of market integration on financial markets is a highly relevant topic. Therefore, more research is encouraged. Taking into account the limitations of this research, future studies on the same topic using different

[1] Statistical test that tests whether one time-series contains enough information to predict another time-series. It is used to test whether there is unidirectional-, bidirectional- or no causality between two series.

techniques could be interesting to see if similar or more results will be found. Different techniques could include a different method to calculate market integration, analyzing Granger- and reverse causality in contagion effects of disaster events, as well as using different standard errors, which would control for induced volatility. Besides, the scope of this study included national stock markets only, while studies on industry and individual firms could reveal information about systemic and idiosyncratic volatility, respectively. Furthermore, the results showed indications of possible overreactions in markets where natural disaster event occurred. More findings on such investor's behavior following disaster events could be found by studies on abnormal trading volumes using the method explained in the work of Landsman, Maydew and Thornock (2012).

Appendix

Table 1. Overview of terrorism disaster events in the analyzed in the sample.

Event Identification Code	Country	Main Affected Regions	Event Date	Disaster type	Damage (in millions of USD)
Terr1	UK	London	10/04/1992	Bombing/Explosion	2700
Terr2	UK	Manchester	15/06/1996	Bombing/Explosion	1079.12
Terr3	US	Oklahoma City	19/07/1995	Bombing/Explosion	652
Terr4	Sri Lanka	Katunayake	24/07/2001	Bombing/Explosion	350
Terr5	UK	London	09/02/1996	Bombing/Explosion	155
Terr6	US	Los Angeles	07/12/2014	Facility/Infrastructure Attack	100
Terr7	Turkey	Sanliurfa	17/02/2016	Bombing/Explosion	100
Terr8	Colombia	Riohacha	15/02/2002	Bombing/Explosion	73
Terr9	UK	Belfast	27/01/1991	Facility/Infrastructure Attack	50
Terr10	India	Srinagar	19/12/1994	Bombing/Explosion	30
Terr11	Colombia	Palmacara	21/09/1996	Unknown	29.5
Terr12	Sri Lanka	Saliyapura	22/10/2007	Bombing/Explosion	28.7
Terr13	US	Vail	19/10/1998	Facility/Infrastructure Attack	24
Terr14	Indonesia	Tasikmalaya	26/12/1996	Armed Assault	21
Terr15	Netherlands	Arnhem	02/02/1992	Insurgency/Guerilla Action	20
Terr16	US	San Diego	01/08/2003	Facility/Infrastructure Attack	20
Terr17	UK	Manchester	03/12/1992	Bombing/Explosion	15
Terr18	US	Indian Head	09/12/2004	Facility/Infrastructure Attack	13
Terr19	Sri Lanka	Mullaitiuvu	23/12/2006	Hijacking	10
Terr20	Sri Lanka	Mawlai	06/10/2013	Facility/Infrastructure Attack	8.03
Terr21	Switzerland	Zurich	16/04/1991	Facility/Infrastructure Attack	8
Terr22	US	Woodinville	03/03/2008	Facility/Infrastructure Attack	7
Terr23	Spain	Madrid	11/03/2004	Bombing/Explosion	6.6
Terr24	India	Shillong	07/10/2013	Facility/Infrastructure Attack	6.46
Terr25	Mexico	Queretaro	10/07/2007	Bombing/Explosion	6.4

Table 2. Overview of natural disaster events in the analyzed in the sample.

Event Identification Code	Country	Main Affected Regions	Event Date	Disaster type	Damage (in millions of USD)
Nat1	Japan	Nagano provinces	11/03/2011	Earthquake	210
Nat2	USA	Southern and Eastern states	23/08/2005	Tropical cyclone	125
Nat3	USA	Eastern Texas	17/08/2017	Tropical cyclone	95
Nat4	China	Wenchuan Xian, Aba Xian areas	12/05/2008	Earthquake	85
Nat5	USA	Southern and Eastern states	30/08/2017	Tropical cyclone	57
Nat6	USA	Northern, Eastern states	22/10/2012	Tropical cyclone	50
Nat7	Thailand	Samut Sakhon provinces	31/07/2011	Riverine flood	40
Nat8	USA	California	17/01/1994	Earthquake	30
Nat9	USA	Southern states	01/09/2008	Tropical cyclone	30
Nat10	Chile	Central Chile	27/02/2010	Earthquake	30
Nat11	Japan	Niigata province	23/10/2004	Earthquake	28
Nat12	USA	Florida, Louisiana, Bahamas	24/10/1992	Tropical cyclone	26.5
Nat13	Turkey	Izmit, Kocaeli, Yalova	17/08/1999	Earthquake	20
Nat14	USA	Oklahoma Province	12/05/2010	Convective Storm	20
Nat15	Japan	Miyazaki provinces	14/04/2016	Earthquake	20
Nat16	USA	Southern and Eastern states	16/09/2004	Tropical cyclone	18
Nat17	India	Jammu and Kashmir provinces	03/09/2014	Flood	16
Nat18	Italy	Mirandola towns, Sant'Agostino area	20/05/2012	Earthquake	16
Nat19	New Zealand	Christchurch city	22/02/2011	Earthquake	16
Nat20	Taiwan	Taiwan	21/09/1999	Earthquake	15.8
Nat21	Mexico	Puebla, Morelos, Mexico city	19/09/2017	Earthquake	15
Nat22	UK	England province	09/10/2000	Flood	14.3
Nat23	Mexico	Quintana Roo province	21/10/2005	Tropical cyclone	14.1
Nat24	USA	Louisiana, Texas, Mississippi provinces	24/09/2005	Tropical cyclone	5.9
Nat25	USA	Southern and Eastern states	13/08/2004	Tropical cyclone	5

Table 3. Overview of natural disaster events to which the investment strategies are applied.

Country	Main Affected Regions	Event Date	Disaster type	Damage (in millions of USD)
China	Guangdong, Guangxi, Guizhou,	22/06/2017	Flood	96
UK	England Province	22/10/2000	Flood	67
Japan	Okayama	08/02/2014	Storm	95
Canada	Southern Alberta province	20/06/2013	Flood	85
Italy	Rieti and Ascoli Piceno provinces	24/08/2016	Earthquake	57
Indonesia	Sumatera Utara provinces	26/12/2004	Earthquake	50
France	Unknown	27/12/2004	Storm	40
India	Karnataka provinces	28/07/2006	Flood	30
US	Southern states	01/05/1998	Extreme temperature	30

Table 4. MSCI indices included in the investment strategy's portfolio, as well as the benchmark's index (MSCI ACWI).

Event Country	China	UK			Japan	Canada	
Date	22/06/2017	22/10/2000			09/02/2014	20/06/2013	
Market	ACWI	Switzerland	Canada	ACWI	ACWI	Spain	ACWI
Post-event trading day							
1	1925.015	975.13	1370.7	1264.392	1634.467	675.498	1421.185
2	1927.486	973.422	1249.466	1240.826	1637.705	661.614	1400.976
3	1917.568	978.582	1238.761	1238.106	1643.195	666.142	1412.534
4	1931.725	981.519	1217.987	1253.725	1650.117	686.11	1425.513
5	1919.594	990.605	1210.212	1261.502	1653.554	686.248	1436.029
6	1916.426	993.089	1266.285	1282.138	1660.544	679.304	1433.548
7	1920.582	991.239	1258.959	1288.208	1655.044	691.611	1444.335
8	1918.895	1005.35	1259.754	1293.265	1656.015	690.13	1444.856
9	1920.325	1002.45	1274.341	1295.781	1659.85	679.714	1440.585
10	1909.008	1010.771	1272.519	1300.045	1668.31	702.072	1448.222
30	1968.716	1004.246	1172.763	1216.204	1645.968	755.605	1524.915
50	1959.743	1016.999	1156.394	1221.253	1672.396	745.143	1481.113
60	1983.418	985.219	1134.831	1210.638	1689.773	790.415	1532.928
100	2042.364	1248.747	2076.058	2103.448	1743.415	962.183	2103.448

Event Country	Italy							Indonesia	
Date	24/08/2016							26/12/2004	
Market	USA	Netherlands	Switzerland	Spain	Canada	France	ACWI	France	ACWI
Post-event trading day									
1	2069.879	1357.267	1077.284	793.447	1846.19	1563.948	1727.296	1258.857	1167.715
2	2066.646	1365.379	1080.89	799.396	1848.505	1574.91	1726.081	1259.775	1165.808
3	2077.356	1365.382	1082.701	795.756	1854.987	1569.389	1725.57	1260.185	1169.977
4	2073.234	1376.293	1089.098	802.685	1857.909	1579.7	1723.645	1258.253	1169.341
5	2068.568	1375.265	1085.126	807.095	1846.774	1574.265	1719.524	1269.326	1161.535
6	2069.006	1376.41	1078.256	810.932	1855.838	1576.469	1723.548	1270.578	1148.835
7	2078.044	1404.98	1097.563	824.459	1868.196	1611.048	1734.6	1259.341	1142.252
8	2078.044	1402.794	1099.727	828.566	1868.196	1611.275	1737.39	1268.032	1142.085
9	2084.326	1393.94	1098.919	822.99	1867.323	1606.777	1745.893	1275.089	1139.906
10	2084.191	1397.066	1101.072	834.057	1866.726	1615.735	1747.474	1275.759	1144.147
30	2059.704	1387.779	1085.5	812.729	1857.822	1590.158	1721.139	1313.273	1156.229
50	1998.403	1345.753	1023.887	830.212	1859.356	1574.134	1672.826	1354.446	1192.304
60	2072.819	1357.402	1048.246	808.338	1885.523	1601.018	1698.414	1328.943	1162.078
100	2544.576	1642.672	1248.747	962.183	2076.058	1910.805	2103.448	1910.805	2103.448

Event Country	France						India	USA	
Date	27/12/2004						28/07/2006	01/05/1998	
Market	Canada	Italy	Spain	Switzerland	USA	ACWI	ACWI	France	ACWI
Post-event trading day									
1	1527.906	765.323	971.756	892.094	1065.61	1149.392	1327.233	1265.52	1091.459
2	1531.311	776.105	985.29	892.156	1065.883	1157.366	1318.658	1256.719	1086.309
3	1529.095	778.974	993.145	891.427	1069.548	1155.596	1330.664	1257.037	1079.249
4	1548.771	794.115	1019.118	897.223	1084.448	1170.459	1327.09	1244.601	1068.105
5	1547.751	799.067	1024.538	897.477	1084.404	1174.701	1335.694	1244.601	1075.916
6	1541.309	797.976	1017.054	899.123	1086.329	1174.11	1324.404	1277.851	1081.083
7	1545.451	807.988	1028.317	900.086	1091.441	1180.315	1324.232	1270.768	1080.511
8	1548.163	804.859	1020.392	897.294	1095.762	1182.688	1326.959	1280.935	1081.57
9	1553.729	805.061	1022.735	895.553	1095.682	1187.374	1322.277	1280.706	1079.46
10	1552.625	798.033	1011.161	893.881	1095.795	1181.99	1318.503	1273.275	1074.181
30	1570.373	829.897	1053.892	908.179	1139.357	1229.345	1344.475	1291.611	1047.663
50	1543.786	749.589	954.499	851.554	1102.422	1153.481	1383.806	1348.352	1105.211
60	1491.593	680.201	856.185	815.188	1020.978	1064.014	1409.579	1337.061	1103.391
100	2076.058	740.397	962.183	1248.747	2544.576	2103.448	2103.448	1910.805	2103.448

Table 5. Results of the normality tests of each country's stock return's GARCH models.

	UK	**US**	**SriLanka**	**Turkey**	**Colombia**	**India**	**Indonesia**	**Netherlands**
	GARCH(1,1)	GARCH(1,2)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,2)	GARCH(1,1)
P-Value for Skewness test	***	***	***	0.7193	0	0	0.0718	0
P-Value for Kurtosis test	***	***	***	***	***	***	***	***

	UK	**US**	**SriLanka**	**Turkey**	**Colombia**	**India**	**Indonesia**	**Netherlands**
	GARCH(1,1)	GARCH(1,2)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,2)	GARCH(1,1)
Skewness test	***	***	***		***	***	*	***
Kurtosis test	***	***	***	***	***	***	***	***
	Switzerland	**Spain**	**Mexico**	**Japan**	**China**	**Thailand**	**Chile**	**Italy**
	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,2)	GARCH(1,2)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
Skewness test	***	***	***	***		***	***	***
Kurtosis test	***	***	***	***	***	***	***	***

	New Zealand	**Taiwan**	**South Africa**	**Peru**	**Canada**	**France**	**Myanmar**	**Greece**
	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
Skewness test	***		***	***	***	***	**	***
Kurtosis test	***	***	***	***	***	***	***	***

*Note. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 6. Model comparisons for terrorism disaster events

	Terr1			Terr2			Terr3		
	Constant	Market	5-Factor	Constant	Market	5-Factor	Constant	Market	5-Factor
R^2		0.28	0.92		0.54	0.92		0.22	0.95
F-test		0.00	0.06		0.00	0.06		0.00	0.03
RMSE	0.01286	0.00726	0.00864	0.00602	0.00326	0.00978	0.00272	0.00376	0.00353

	Terr4			Terr5			Terr6		
	Constant	Market	5-Factor	Constant	Market	5-Factor	Constant	Market	5-Factor
R^2		0.69	0.66		0.31	0.94		0.54	0.66
F-test		0.00	0.17		0.00	0.03		0.00	0.08
RMSE	0.00743	0.01364	0.01405	0.00666	0.00395	0.01718	0.00819	0.00166	0.01708

	Terr7			Terr8			Terr9		
	Constant	Market	5-Factor	Constant	Market	5-Factor	Constant	Market	5-Factor
R^2		0.92	0.39		0.17	0.31		0.39	0.06
F-test		0.00	0.31		0.01	0.13		0.00	0.10
RMSE	0.01550	0.01107	0.03520	0.03019	0.01302	0.02135	0.00677	0.00776	0.01485

	Terr10			Terr11			Terr12		
	Constant	Market	5-Factor	Constant	Market	5-Factor	Constant	Market	5-Factor
R^2		0.80	0.17		0.04	0.07		0.00	0.23
F-test		0.00	0.74		0.02	0.76		0.41	0.09
RMSE	0.00456	0.00665	0.00978	0.00581	0.00575	0.01249	0.01890	0.00584	0.04703

	Terr13			Terr14			Terr15		
	Constant	Market	5-Factor	Constant	Market	5-Factor	Constant	Market	5-Factor
R^2		0.51	0.15		0.09	0.19		0.16	0.30
F-test		0.00	0.28		0.00	0.21		0.00	0.13
RMSE	0.00990	0.01294	0.01544	0.01456	0.00868	0.01037	0.01379	0.00541	0.01678

	Terr16			Terr17			Terr18		
	Constant	Market	5-Factor	Constant	Market	5-Factor	Constant	Market	5-Factor
R^2		0.51	0.02		0.27	0.06		0.39	0.21
F-test		0.00	0.94		0.00	0.78		0.00	0.10
RMSE	0.00111	0.00644	0.01853	0.00634	0.00346	0.01045	0.01185	0.00388	0.02718

	Terr19			Terr20			Terr21		
	Constant	Market	5-Factor	Constant	Market	5-Factor	Constant	Market	5-Factor
R^2		0.42	0.29		0.43	0.07		0.43	0.03
F-test		0.00	0.08		0.00	0.82		0.00	0.98
RMSE	0.00828	0.00375	0.01702	0.01301	0.00365	0.02655	0.00612	0.01150	0.01173

	Terr22			Terr23			Terr24		
	Constant	Market	5-Factor	Constant	Market	5-Factor	Constant	Market	5-Factor
R^2		0.63	0.07		0.36	0.04		0.17	0.33
F-test		0.00	0.61		0.00	0.79		0.00	0.01
RMSE	0.00575	0.01118	0.01134	0.00770	0.00296	0.01701	0.01435	0.00184	0.02956

	Terr25		
	Constant	Market	5-Factor
R^2		0.47	0.21
F-test		0.00	0.04
RMSE	0.01020	0.00652	0.02485

Table 7. Table 2. Model comparisons for terrorism disaster events

	Nat1			Nat2			Nat3		
	Constant	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**
R^2		0.43	0.34		0.24	0.17		0.30	0.26
F-test		0.00	0.00		0.00	0.04		0.00	0.10
RMSE	0.01257	0.01294	0.03748	0.00231	0.00350	0.01330	0.00717	0.00432	0.04754

	Nat4			Nat5			Nat6		
	Constant	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**
R^2		0.46	0.02		0.33	0.26		0.23	0.15
F-test		0.00	0.87		0.00	0.10		0.00	0.14
RMSE	0.01057	0.01166	0.02203	0.00584	0.00315	0.00600	0.00590	0.00390	0.00796

	Nat7			Nat8			Nat9		
	Constant	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**
R^2		0.09	0.35		0.11	0.09		0.60	0.15
F-test		0.00	0.00		0.00	0.30		0.00	0.14
RMSE	0.00541	0.00683	0.01170	0.00746	0.00749	0.00410	0.01620	0.00939	0.01405

	Nat10			Nat11			Nat12		
	Constant	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**
R^2		0.31	0.23		0.17	0.10		0.25	0.07
F-test		0.00	0.00		0.00	0.41		0.00	0.87
RMSE	0.00826	0.00548	0.00831	0.00405	0.00648	0.01935	0.00814	0.00805	0.00972

	Nat13			Nat14			Nat15		
	Constant	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**
R^2		0.34	0.18		0.53	0.33		0.18	0.13
F-test		0.00	0.29		0.00	0.00		0.00	0.63
RMSE	0.01196	0.01176	0.07851	0.00615	0.00369	0.01965	0.01577	0.01604	0.06419

	Nat16			Nat17			Nat18		
	Constant	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**
R^2		0.32	0.15		0.08	0.30		0.70	0.25
F-test		0.00	0.04		0.00	0.00		0.00	0.05
RMSE	0.00392	0.00492	0.00891	0.00392	0.00449	0.02720	0.01599	0.00808	0.02203

	Nat19			Nat20			Nat21		
	Constant	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**
R^2		0.03	0.14		0.28	0.12		0.15	0.05
F-test		0.01	0.40		0.00	0.16		0.02	0.63
RMSE	0.00655	0.00637	0.01170	0.01153	0.01178	0.01749	0.00413	0.01023	0.00971

	Nat22			Nat23			Nat24		
	Constant	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**	**Constant**	**Market**	**5-Factor**
R^2		0.73	0.14		0.33	0.16		0.23	0.14
F-test		0.00	0.54		0.00	0.22		0.00	0.09
RMSE	0.01193	0.00509	0.02720	0.00724	0.01096	0.03863	0.00470	0.00425	0.00971

	Nat25		
	Constant	**Market**	**5-Factor**
R^2		0.33	0.09
F-test		0.00	0.32
RMSE	0.00746	0.00630	0.03863

Table 8. Results on Granger Causality tests for terrorism disaster events on foreign markets.

Event		Reverse causality	Granger causality
Terr1	50	Netherlands*	Canada*
	100	Netherlands*	Canada*
Terr3	50		Switzerland* Chile***
	100	-	-
Terr5	50	Canada***	
	100		Canada*
Terr6	50	South Africa**	UK*** Netherlands*** Spain*** Sout Africa** Chile**
	100	South Africa***	UK*** Netherlands*** South Africa*** Spain*** Myanmar**
Terr9	50		Canada*
	100		Canada*** Switzerland***
Terr13	50		Netherlands**
	100	Canada*** Peru*** South Africa*** Switzerlan* UK***	Italy** Netherlands*
Terr15	50	USA*	
	100	USA* France**	
Terr16	50	South Africa** Netherlands* UK*	France** Canada***
	100	Netherlands* UK*	Canada*
Terr17	50		Canada*
	100		Canada**
Terr18	50	South Africa* UK**	Italy** Netherlands** Canada**
	100	France* South Africa** UK***	
Terr21	50	UK**	
	100		Switzerland**
Terr22	50	South Africa* Chile*** UK**	UK*
	100	Peru* Chile*** Switzerland** UK***	

*Note. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table 9. Results on Granger Causality tests for natural disaster events on foreign markets.

Event	Reverse causality	Granger causality
Nat2		Switzerland**
Nat3		Netherlands** South Africa** Canada**
Nat4	Indonesia* Taiwan**	Taiwan**
Nat5	Switzerland**	Canada*
Nat6	UK*** Netherlands*** Switzerland*** South Africa*** France*** Canada* Chile***	South Africa* Switzerland*** France** Peru**
Nat9	South Africa*** Chile***	Netherlands*** Italy** South Africa*** Spain*** Chile***
Nat10	Switzerland* France*** USA*	Italy**
Nat12	Chile*	France** Chile***
Nat16	France**	Netherlands*
Nat18	Spain** Switzerland*	
Nat24	South Africa*** France* Canada**	Canada**
Nat25	Canada**	South Africa**

*Note. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

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