Market Reactions due to Environmental Hazards and Unexpected Events

by
Argyro Zisiadou

Department of Economics
School of Economics and Business
University of Thessaly

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Abstract

The purpose of the dissertation is to investigate whether unexpected events are really characterized by randomness. Having those findings as a base, we move forward to the examination of the high-risk areas of each unexpected hazard, in an attempt to provide a priori knowledge for preparedness. Moreover, the main purpose of the research is to examine whether the investors, in an attempt to avoid excess losses, tend to react when those unexpected events occur. Statistical approaches as well as map visualizations, indicate the high-risk areas per hazard category. Such a priori information indicates us the level of potential risk we obtain when we place our capital on those regions. Such a region is the well-known Ring of Fire, which is proven based on our data and analysis, the region where the 80% of earthquakes take place annually. Using C.A.P.M and A.P.T estimations with a combination of diagnostic tests we conduct the best model specifications for each case from which the systematic risk derives. An innovative procedure of the research is to present the under/overestimated systematic risks due to the ignorance of diagnostic tests. Moreover, we present the ex-ante and ex-post systematic risks for 65 events of analysis showing that the risk the investor obtains change when an event with great impact occurs. We observe that volcanic activity has a greater influence on the systematic risk compared to the tsunami and the ground movements. At the same time, we mention the Icelandic case which appears to follow a different path, regarding the betas, compared to other similar cases. The petroleum industry, due to its high profitability, appears to keep its reputation and investors no matter how devastating are the technological accidents that may cause. Regarding the terrorist attacks, we obsere that LDCs lose part of the trustworthiness after a terrorist action. Moreover, ISIL attacks was proven to led to a decrease of the

systematic risk of government bonds. Finally, we examine whether the Abnormal Returns of the bonds and/or stocks are determined by macroeconomic factors. In other words, we prove that in macroeconomic factors, and the economic status of a country, may affect the investors' decisions.

Keywords: Unexpected Events, Environmental Hazards, Terrorism, C.A.P.M approach, A.P.T approach. ARCH specifications, Market Reactions, Systematic Risk, preparedness, high-risk areas, Policy Making, Portfolio Diversification, Hedging Techniques.

Section 1

1. Introduction

Uncertainty is what characterises the world. Every single activity human being do, contains a level of uncertainty. Moreover, the higher the level of uncertainty, the higher the risk that derives from our activities. Regarding the economic and financial activities, as it is well known and accepted, rational investors are by their nature risk averters. This means that they prefer safe investments that will not put their capital into risk. On the other hand, what characterizes markets is uncertainty. The reasoning that high risks lead to high returns and to high profits is what predominates in markets, either capital or stock. Therefore, hedging is the tool that comes to fill the gap between risk adverse investors and markets' uncertainty. In that way, investors can secure themselves for changes in interest rates, exchange rates or even share price changes by using future or option products.

On the circles of the financial sector there is a well-spread knowledge regarding the rational investors' preferences. Investors are usually assumed to be rational, so if we ignore the arbitrage case, they tend to choose more "safe" investments which will allow them to maximize their profits, or in other words minimize potential risk they receive by investing (Merton, 1969; Cohn et al., 1975; Benartzi and Thaler, 1995; Benartzi and Thaler, 1999; Campbell and Cochrane, 1999; Ait-Sahalia and Lo, 2000; Jackwerth, 2000; Rosenberg and Engle, 2002; Brandt and Wang, 2003; Gordon and St-Amour, 2004; Bliss and Panigirtzoglou, 2004; Haigh and List, 2005; Bollerslev et al. 2011; Halkos et al., 2017).

Hedging and portfolio diversification may appear to be efficient in reducing the potential loss of an investment. Great attention has been drawn about the advantages of portfolio diversification (Búgar and Maurer, 2002). Graham and Jennings (1987) have mentioned the ability of transferring the risk of investment through hedging, while

Bond and Thompson (1985) underlying that the size of the optimal hedging ratio is one of the main determinants used by the decision makers apart from cash position of the corporation. Although the potential loss of capital can be reduced using techniques such as hedging and portfolio diversification, there are some cases in which the potential loss cannot be predicted. The act of nature is such a case (Halkos and Zisiadou, 2018a). Nature acts independently, and a common example of that independence is the tectonic plate movement (Halkos and Zisiadou, 2018a). Distinguished sciences such as geology and seismology, do have the techniques to monitor, observe and examine the geophysical events caused by those tectonic plate movements.

However, the question is how they will secure their investments against unexpected events. The main issue in that case is that no one can predict the exact time or place or whether an unexpected event is going to occur or not. Many people assume that some events like weather outbreaks are predictable while there are some cases such as terrorist attacks that are not probably predictable. Among others, Kollias et al. (2011a) using event study and GARCH models explore the influence of the terrorist attacks in Madrid (11th March 2004) and in London (7th July 2005) and the effect of these attacks on equity sectors. They find significant negative abnormal returns only in Spain but with a much quicker market rebound in London compared to the Spanish markets where attackers were not suicide bombers.

Similarly, Kollias et al. (2011b) considered whether market reaction (depending on either targets' type or attacks' perpetrators) to terrorism has been altered diachronically and if market size and its maturity establish reactions. They consider the London and Athens stock exchange capitalization markets and using an event study methodology and conditional volatility models they find empirical evidence that size and maturity together with specific attributes of terrorist incidents are probable determinants of markets' reactions.

Regarding the environmental events, we know that vulnerability is what characterizes the environment and taking into account the human activities that come to strain the current situation, we can think of the less prosperous future we will bequeath to the next generations. Even if we overlook human activities or suppose they do not exist, the nature by itself is not characterized by a static condition, meaning that it changes in a daily base. If we search the word "nature" in any dictionary we will find a great variety of different definitions given by human beings, however, regarding the environmental definition, nature is described as the collection of any existence in the universe we live and is not man-made. Tectonic plate movement is a typical example of those changes. We cannot blame human activities for those movements and at the same time we cannot do anything in order to avoid them. Apart from the tectonic plate movements, there is a great list of natural processes or phenomena that may occur leading to uncountable losses such as life losses, property damage, economic losses and environmental damage. The international literature recognizes those processes with the term "Natural Environmental Hazards".

"Hazard is a dangerous phenomenon, substance, human activity or condition that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage" (UNISDR 2009). Based on the definition of hazard, the occurrence of one hazardous event may cause chain effects to society, economy, health, and the environment. All those categories are topics of high interest nowadays due to the fact that all of them are facing difficult time for different reasons the last decades. The economic crisis, political changes, pollution and its impact on health and climate change are the main factors that influence the categories mentioned above. Environmental hazards come to add more influence to the existing problems. Similar to the definition of hazard is the one that is given for the term disaster. "Disaster is a serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resourse" (UNISDR 2009).

Many people confuse the meaning of "hazard" with the meaning of "risk". Risk is a term that exists in everyone's life not only when an unexpected event occurs but in any decision someone has to make. As Smith mentions in his book (Smith 1996 p.54) the Chinese word *"wei-ji",* which is the word that is used to describe risk, is formed by the words opportunity and danger and it includes the two main aspects of the word risk. Compared to hazard, risk is the probability of occurrence of the under examination event and all the possible drawbacks that this event may have (UNISDR 2009). Okrent (1980) illustrates the term hazard (or cause) as the possible threat of people and their property while risk (or consequence) as the probability of this specific hazard to occur (Islam et al 2013). We can have an environmental hazard such as an earthquake which may not lead to environmental risk if the area of the event is not inhabited (Okrent 1980).

In Smith's book (Smith 1996) when a hazard results to a large number of fatalities such as killed, injured or homeless people as well as huge economic damage then we tend to call it "environmental disaster", however, he mentioned that there is no globally accepted definition. The International Disaster Database[1] gives a definition to disaster as the "situation or event, which overwhelms local capacity, necessitating a request to

[1] Part of the Center for Research in the Epidemiology of Disasters (CRED), which is established by the School of Public Health, Universite Catholique de Louvain

national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction and human suffering. Though often caused by nature, disasters can have human origins" (EM-DAT 2017). Disasters that tend to have human origins are known at the literature review as technological hazards or "man-made" as they will be described thoroughly in the following Section. In most cases those disasters are result of some kind of accident.

An unexpected event category that differs from the previous cases is terrorism. Based on Tilly (2004), terrorism is not a phenomenon similar to all the other we described but it is characterized as strategy due to the fact that most of the times serves political or military interests. Terrorism is not a new phenomenon (Carter et al., 1998). Economic analysis and consequences of terrorism have attracted significant and continuous research interest. Apart from human life losses, the victims of terrorist attacks suffer from fear of brutal violence and immense number of injuries, which may lead to a number of associated indirect costs. These costs are not easily countable and refer to immense amount of resources necessary to protect against terrorism or to the instant harms and losses of property and capital caused by a terrorist attack. Terrorist actions may negatively affect many economic and social activities like among others flows of FDI, tourism, and economic uncertainty and stock markets with reductions in firms' expected profits.

As it is well known and accepted, rational investors are by their nature risk averters. This means that they prefer safe investments that will not put their capital into risk. On the other hand, what characterizes markets is uncertainty. Drakos (2010) investigated whether there is a negative significant return on daily base after a terrorist attack in 22 different countries proving that the event day's return is lower than the expected. That comes in line with Essaddam and Karagianis (2014) who investigated the volatility of the stock prices of the American firms after an attack, with Nikkinen and Vähämaa (2010) also pointing out a significant downward shift. Conversely, Graham and Ramiah (2012) indicated that there is no effect on the market when an attack occurs. The reasoning that high risks lead to high returns and to high profits is what predominates in markets,1 either capital or stock. Therefore, hedging is the tool that comes to fill the gap between risk adverse investors and markets' uncertainty. In that way, investors can secure themselves for changes in interest rates, exchange rates or even share price changes by using future or option products. However, the question is how they will secure their investments against unexpected events. The main issue in that case is that no one can predict the exact time or place or whether an unexpected event is going to occur or not. Many people assume that some events like weather outbreaks are predictable while there are some cases such as terrorist attacks that are not probably predictable.

The purpose of this research is to initially present with details all the different categories of Natural and Technological Environmental Hazards, as well as the case of Terrorism in an attempt to fully understand all terms and their different aspects. Moreover, we will examine hazards and/or disasters that are assumed to be unexpected, such as natural and technological environmental hazard as well as terrorist attacks and conclude whether these events are characterised by randomness, a factor which makes them unexpected. After those findings, we will continue by examining whether the investors, who have placed their capitals on those countries or companies react to each event on a positive or negative way by supporting or by selling their shares respectively.

We firmly believe that our finding can be proved to be useful both to the capital markets' advisors as well as to the governments' and/or corporations' policy makers. More specifically, if the investment advisors known a priori the high-risk areas, if any, of a specific hazard's occurrence and at the same time know the risk tolerance of their clients, they may adjust the portfolio diversification or their hedging techniques in a more accurate way. Regarding the governments' and/or corporations' policy makers, a well-established a priori knowledge of their potential risk will help them structure their policies. For instance, if the governments' advisors know in advance the possibility of occurrence for each disaster, they will have the opportunity to create preparedness plans. In the short-run, a greater amount of financial support in case of a disaster on the annual economic budget, a better staffing of hospitals and rescuing teams, as well as more nursing supplies are some of the measures the government can take beforehand. In the long-run, better building codes regarding the constructions, or more accurate safety plans and better educated citizens may reduce the negative impact of such events.

The dissertation will follow the structure as it is described in this section. Section 2 presents a full terminology review on all categories that will be analysed further on our research, Section 3 includes the literatures review that is attached on the topics of analysis in an attempt to understand what has been done on those fields of research, while Section 5 gives the historical overview of the 65 events that will be examined from a financial point of view, as well as significant events of those categories that have been excluded. Section 6, presents the results that derived from the proposed statistical and econometrical approaches, while at the same time indicate the significance of diagnostic tests that tend to be ignored. Map Visualizations are also included in Section 6. Finally, Section 7 draws conclusion and statements based on the finding of the research. Moreover, further research on the topics is indicated.

Section 2

2. Terminology Review

The environmental hazard is a complicated field of research which contains a great variety of terms and definitions. Hazard can be divided into natural and man-made (also known as anthropogenic or technological), however, there is a difficulty to categorize an event to one of the two categories. Sometimes, the root of the event is difficult to be determined so the humans are not able to decide with certainty whether it is a natural or a man-made hazard (Smith 1996). Another distinction of hazard is between hazard to people, goods, and environment. That distinction is easier to be defined. *Hazard to people* is anything that can cause death, injury, disease, and stress. The *hazard to goods* is anything that can lead to property damage and economic loss. Finally, a *hazard to the environment* is anything that can cause loss of flora and fauna, pollution and loss of amenity (Smith 1996). One more distinction is made between *hazard intensity* and *hazard duration*, giving as hazard intensity the peak deviation beyond the threshold while hazard duration describes the length of time that the threshold is exceeded (Smith 1996).

Using a big dataset which includes all the different events as one category is an inappropriate method to investigate the different aspects both of influences and impacts. For that reason, the EM-DAT has divided all the environmental hazards into 3 main groups, the natural, the technological and the complex, which those three groups are formed by ten subgroups. More specifically, the natural hazards are formed by the biological, the climatological, the geophysical, the hydrological and the meteorological hazards and the extra-terrestrial, the technological hazards, are formed by the industrial, the miscellaneous and the transport hazards, while the complex hazards are a group that is formed by a specific situation called famine. The advantage of separating all different cases into groups, subgroups, types and subtypes is to approach each case from a unique point of view and estimate those factors that can lead to the occurrence or the disaster that this may cause, while at the same time to observe the factors that are influenced as an aftermath. All the different types will be analysed into sub-sections by providing all the relevant terminology. The same flow will be used in the presentation and discussion of the results.

Based on Smith (1996), there is a difficulty on providing a singular definition that may describe all different cases of technological hazards. However, an attempt has been made by UNISDR (2009) which defined the technological hazard as "a hazard originating from technological or industrial conditions, including accidents, dangerous procedures, infrastructure failures or specific human activities, that may cause loss of life, injury, illness or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage" (UNISDR 2009). Smith (1996), additionally mentioned that on the contrary to the natural hazards, the human involvement is highly significant and for that reason a technological hazard can also be called *"man-made"*.

2.1. Biological Hazards

The term of *biological hazard* is described as "the process or phenomenon of organic origin or conveyed by biological vectors, including exposure to pathogenic micro-organisms, toxins, and bioactive substances that may cause loss of life, injury, illness or other health impacts, property damage, loss of livelihood and services, social and economic disruption, or environmental hazards" (UNISDR 2009). The database of CRED divides the biological subgroup into three types of hazard animal accidents, epidemic and insect infestation. The EM-DAT glossary (EM-DAT 2017) provides the definition of *animal accident* as "Human encounters with dangerous or exotic animals in both urban and rural developments"). What is interesting and has to be mentioned in that since 1900 there is only one significant animal accident event which occurred in 2014 in Niger and caused 12 deaths while at the same time affected 5 more people.

As mentioned in Smith (1996 p. 242-244), the World Health Organization defines the *epidemic disease* as "the occurrence of a number of cases of a disease, known or suspected to be of infectious or parasitic origin, that is unusually large or unexpected for the given place and time". The epidemic diseases are divided into bacterial, parasitic and viral diseases. The *bacterial disease* is the "unusual increase in the number of incidents caused by the exposure to bacteria either through skin contact, ingestion or inhalation (EM-DAT 2017). Some of the most well-known bacterial disease are cholera, tuberculosis, measles, whooping cough, tetanus and diphtheria (Smith, 1996, p. 245). The *parasitic disease* is the "exposure to a parasite - an organism living on or in a host – causes an unusual increase in the number of incidents" (EM-DAT 2017). Some of the most known parasitic diseases are malaria, chagas disease, giardiasis and trichinellosis and may occur due to the consumption of contaminated water or food, or the contact with insects, animals (zoonotic) and pets (EM-DAT 2017).

The third type of biological hazards is the insect infestation, which based on the CRED database is divided into grasshopper events and locust events. According to EM-DAT glossary (EM-DAT 2017), *insect infestation* is the "pervasive influx and development of insects or parasites affecting humans, animals, crops and materials". Seaman et al. (1984) suggest that insect infestation tend to appear after the occurrence of another natural hazard. For that reason, they outline six main factors which may lead to such disease to outbreak. These six factors that can lead to a disaster-related disease can be a) the existence of the disease in the population even before the natural event, b) the ecological change that is caused from a disaster, c) the migration (movement) of the population, d) the damage (demolition) of the public utilities, e) the disruption of disease control programs and f) altered individual resistance to disease. What is also mentioned is the more than one factors may occur at the same time.

Large-scale disasters can be caused by biological hazards especially in the LDCs due to the lack of program controls. The immune system condition can be worsening due to malnutrition, lack of hygiene, restricted access to health care facilities and low-construction level of housing. Especially for the epidemics, the population subgroups which are more vulnerable are the very young ones, the elder and the disadvantaged whose immune system is eager compared to the other subgroups of the population (Smith 1996 p.244). Due to the significant drawbacks of the epidemics, in 1993 the World Health Organization (WHO) reorganized and renamed the Division of Emergency Relief Operations (ERO) into Division of Emergency Humanitarian Action (EHA) in an attempt to strengthen the sharp response to emergencies (Smith 1996 p. 245).

2.2. Climatological Hazards

The term *climatological hazard* is described as "a hazard caused by long-lived, meso-to-macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variability" (EM-DAT 2017). The database of CRED divides the climatological subgroup into two types of hazard: drought and wildfire. The complication of the environmental hazards appears once more even in the categorization of the hazard subtypes. Based on Smith (1996), the drought is part of the hydrological hazards[2], while wildfire is part of the biophysical hazards[3].

The EM-DAT glossary (EM-DAT 2017) provides the definition of *drought* as "an extended period of unusually low precipitation that produces a shortage of water for people, animals and plants". Because of the slow development that may last sometimes over years, droughts appear to be so different from other environmental hazards (EM-DAT 2017; Smith 1996 p.286). Moreover, drought is not a place concentrated hazards such as tectonic geophysical hazards which are tectonically or topographically concentrated. Drought can take place in any region of the globe (Smith 1996 p. 286). Moreover, drought can lead to different impacts depending on the region of occurrence. Although in the MDCs, there is no deaths connected to drought occurrence, in the case of the LDCs a drought event can lead to lack of water and food supplies which creates a strong bondage to drought and famine. Based on Wilhite and Glantz (1985), it is not appropriate to establish a global definition of drought events but each definition should be regionally concentrated.

The definition of EM-DAT glossary (EM-DAT 2017) concerning the *wildfires* introducing it as "any uncontrolled and non-prescribed combustion or burning of plants in a natural setting such as a forest, grassland, brush land or tundra, which consumes the natural fuels and spreads based on environmental conditions". As described by Smith (1996), the most dangerous scenery (condition) for a wildfire to established is an area which after a period of active vegetation, has faced a long period of drought and recorded high temperatures, commonly during the same annum. These sceneries are common in Mediterranean areas where during summer, and after a productive winter-

[2] Will be analyzed in a following sub-section.

[3] Based on Smith (1996), biophysical hazards include extreme temperatures, epidemics and wildfires.

spring period, drought is a common condition and the existing climate condition allows high temperatures to be recorded. Due to the fact that wildfires tend to occur to rural areas, it has been observed that there is always ecosystem damage attached to those events (Smith 1996). Knowing that, fuel and weather are the two main elements which can light up a fire, and having already described the weather conditions above, it is important to mention that the type and the quantity of fuel can affect both the intensity and the spread rate of the fire (Smith 1996). The most dangerous period of a wildfire with the most fatalities and losses, both life loss and economic loss, is encountered during the first few hour of the fire (Cheney 1979).

2.3. *Geophysical Hazards*

The term *geophysical hazard* is described as “a hazard originating from solid earth.” (EM-DAT 2017). As it is mentioned in the EM-DAT glossary (EM-DAT 2017), the term geophysical hazard is sometimes substituted by the term geological hazard. This has been proven by the UNISDR (2009) which mentions that the geological hazard is a “geological process or phenomenon that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage”. What is also commented by the UNISDR (2009) is that under the term of geological hazard we can include *earthquakes, volcanic activities* and *mass movements*. The database of CRED divides the geophysical subgroup into three types of hazard: earthquake, mass movement and volcanic activity.

According to the EM-DAT glossary (EM-DAT 2017) earthquake is a “sudden movement of a block of the Earth’s crust along a geological fault and associated ground shaking”. As *ground shaking* is recognized any “surface displacement of earthen materials due to ground shaking triggered by earthquakes or volcanic eruptions” (EM-

DAT 2017). Although the natural environmental hazards tend to be recognized as random events may occur, the literature provides evidence for the non-randomness of these tectonic events. More specifically, Bolt (1988) mentioned that as far as randomness of earthquakes is concerned, there is a regional distribution due to the fact that more that 65 percent of all large earthquakes have been observed in an area around the Pacific Ocean which is recognized as the "*Ring of Fire*". The fact that more that fifteen lithospheric plates exist which constantly move across the globe, increase the earthquake, as well as volcanic activity, occurrence across the tectonic margins (Smith 1996).

Regarding the losses counted due to earthquakes, it is important to mention that different factors, such as topography, frequency of occurrence, high population density, construction techniques and lifestyle, can influence the level of losses (Smith 1996). Another factor that may have a significant impact on the causalities is the time of the occurrence. The time of the event cannot influence the structural damage that may be caused, however, it can significantly influence fatalities, mentioning that during night hours fatalities are higher due to the fact that "victims" tend to sleep at those times.

When examining an earthquake, the main two measures that scientist take into consideration are *earthquake's magnitude* and *intensity*. Earthquake magnitude is described as the energy produced by the seismic waves and it is measured by a well-known scale, the Richter Scale, while earthquake intensity is the ground-shaking measure that is connected to the hazard impact and it uses the Modified Mercalli Scale for measurement purposes (Smith 1996). What is also important to have in mind is that the magnitude is not the only cause of fatalities due to the fact that there are other conditions which may influence the number of fatalities such as the *hypocentre*, which is the point of rupture, and the *epicentre*, which is the source point of the earthquake, additional to the factors that have already been mentioned (Smith 1996).

The CRED database divides the earthquakes into the following two subtypes, ground movements and tsunamis. On the other hand, Smith (1996), presented the subtype of tsunami as a secondary earthquake hazard. In other words, he assumed that a tsunami event is actually an earthquake-related hazard, and it is not recognized as a hazard by itself. In an attempt to describe the meaning of the word tsunami, we should once again refer to the Asian vocabulary and more specifically to the Japanese language which is the "mother" of the word tsunami. Therefore, the word tsunami derives from the words "tsu" which in Japanese meaning "port or harbour" and "nami" meaning "wave or sea". The EM-DAT glossary (EM-DAT 2017) comes to agree on the definition calling tsunamis "waves in the port" and describing them as "a series of waves (with long wavelengths when traveling across the deep ocean) that are generated by a displacement of massive amounts of water through underwater earthquakes, volcanic eruptions or landslides.

Tsunami waves travel at very high speed across the ocean but as they begin to reach shallow water they slow down and the wave grows steeper". The reason why Smith (1996) recognizes tsunamis as an earthquake-related event, and it is similar to the EM-DAT term, is the fact that the main root of a tsunami is a tectonic movement of the seabed, also known as submarine earthquake, which is similar to a ground movement resulting to a wave, a disastrous wave when the discussion comes to tsunamis, breaking into the port and causing uncountable fatalities and damages.

Another type of geophysical hazard is the volcanic activity and for some scientists is a derivative of earthquakes. Based on the terminology given by the EM-DAT glossary (EM-DAT 2017), the volcanic activity is "a type of volcanic event near an opening/vent in the Earth's surface including volcanic eruptions of lava, ash, hot vapour, gas, and pyroclastic material". The common element between earthquakes and volcanoes is the fact that both of them appear to be distributed on the top of the tectonic plates (Smith 1996). In other words, the volcanic activities are highly correlated to the tectonic plate movements as in the case of the earthquakes. As Smith (1996) mentions, there are almost five hundred active volcanoes around the globe from which about the 80% are under the category of the subduction volcanoes. Volcanoes are categorized in three different types. The first and most dangerous category is the *subduction volcano* which took its name from the subduction zone where one tectonic plate is moving beneath another. That fact creates the most explosive volcano which historically has led to the most significant explosions. Known volcanoes of that category are the Fujiyama in Japan, the Mt Vesuvius in Italy, the Mt Hood in Oregon and the Mayon in Philippines (Smith 1996).

The second category is the *rift volcano* and compared to the first category is the case in which the two tectonic plates tend to diverge. The volcanoes that belong to this category tend to be less explosive compared to the other two categories. The last category is the *hot spot* which are located to the middle of a tectonic plate where the crust of the surface presents a weakness that allows molten material emerge from the earth's interior. The most known case of hot spots is the Hawaiian Islands complex that has been created due to such volcanic eruptions (Smith 1996). The type of volcanic activity hazard can be divided into two main subtypes: the ash fall and the lava flow. Based on EM-DAT glossary (EM-DAT 2017), the *ash fall* is a "fine (less than 4mm in diameter) unconsolidated volcanic debris blown into the atmosphere during an eruption; can remain airbone for long periods of time and travel considerable distance from the source", while on the other hand the *lava flow* is "the ejected magma that moves as a liquid mass downslope from a volcano during an eruption".

The last type of geophysical hazards is the *mass movement*. The short definition provided by the EM-DAT glossary (EM-DAT 2017) describes the mass movement as "any type of downslope movement of earth materials". Smith (1996) adds more description to that definition by mentioning that the downslope movement contains large volumes of materials which may be hazardous when the terrain of occurrence is mountainous. The CRED database divides the mass movement type of hazards into four subtypes: the avalanche, the landslide, the rockfall and the subsidence. Based on the EM-DAT definitions (EM-DAT 2017) the word *avalanche* describes "a large mass of loosened earth material, snow or ice that slides, flows or falls rapidly down a mountainside under the force of gravity".

There can be either snow avalanche or debris avalanche. The *snow avalanche* has an expected definition meaning that is a mass downslope of snow and ice. The not so common term that has been used is the debris avalanche which can be either *cold debris avalanche* or *hot debris avalanche* being an unstable slope suddenly collapsing and results from volcanic activity leading to instability and collapse respectively. Once again, the connection between two or more events can be clear emphasizing even more the complexity of the environmental hazards. The term *landslide* is defined as "any kind of moderate to rapid soil movement including lahar, mudslide, debris flow. A landslide is the movement of soil or rock controlled by gravity and the speed of the movement usually ranges between slow and rapid, but not very slow. It can be superficial or deep, but the materials have to make up a mass that is a portion of the slope or the slope itself. The movement has to be downward and outward with a free face" (EM-DAT 2017).

Although the EM-DAT glossary does not provide an official term for *rockfall*, Smith in his book (1996) explains the rockfalls as "movements of debris (mainly rock) largely through the air" (Smith 1996 p. 186). That hazard subtype is the simplest and most common type of all movements that have already been described and it occurs on steep faces. The last but not least subtype of geophysical hazards is the subsidence. The existing definition for that hazard is that the "*subsidence* refers to the sinking of the ground due to groundwater removal, mining, dissolution of limestone, extraction of natural gas, and earthquakes" (EM-DAT 2017).

What is important to mention, once again, is that the environmental hazards cannot be easily classified, which is one of the reasons which makes this field of research a very difficult and demanding research area. More specifically, the type of mass movement that has been described with details on the geophysical hazards (with the four subtypes included) also appears on the hydrological hazards under the term of landslides (including once again the same four subtypes and with any other addition on them). The terminology used is exactly the same, and it classifies those four event categories (avalanche, landslide, rockfall, subsidence) also under the hydrological hazards.

That allows the researchers to analyze the events from different point of view. This unclear classification is one more evidence of the complexity of nature. Because of not knowing, or to be more specific because of not being absolutely sure of, the origin and the main route of cause of an event, we cannot classify it under one absolute category, therefore, we give flexibility to the researcher or analyst to place an event to a specific category after examining all the aspects that caused each specific occurrence.

2.4. Hydrological Hazards

The term *hydrological hazard* is described as "a hazard caused by the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater" (EM-DAT 2017). The CRED Database separates the term hydrological from the term meteorological, however, the UNISDR (2009) recognizes all those phenomena under the same classification which is called *hydrometeorological hazards* (which will be described later on). Being focused on the database of CRED, the hydrological hazards are divided into two types of hazards: floods and landslides. As it has already been mentioned in the previous subsection of geophysical hazards, the type of *landslide* is exactly the same type as mass movement and it includes the avalanche, the landslide, the rockfall and the subsidence, so the repetition will be avoided.

The EM-DAT glossary (EM-DAT 2017) provides the definition of *flood* as "a general term for the overflow of water from the stream channel onto normally dry land in the floodplain (riverine flooding), higher-than-normal levels along the coast and in lakes or reservoirs (coastal flooding) as well as ponding of water at or near the point where the rain fell (flash floods)". Smith (1996) mentioned that this specific environmental hazard is one of the most common, if not the most common, and at the same time can have both advantages as well as drawbacks.

The database of CRED divides the floods into three subtypes: *coastal flood, flash flood and riverine flood*, whose definitions have already been mentioned in the definition of flood. Based on Smith (1996), the river floods can be caused by atmospheric hazards such as rainfalls, snowmelts and ice jams, by tectonic hazards such as landslides and by technological hazards such as dam failures, while the coastal floods can be caused by atmospheric hazards such as storm surges and tectonic hazards such as tsunamis.

Since we had already explained the landslides, we will move forward to the meteorological hazards. In the beginning of this subsection we mentioned that UNISDR (2009) recognizes the hydrological hazards and meteorological hazards as a common category called *hydrometeorological hazards* which as describes as "process or phenomenon of atmospheric, hydrological or oceanographic nature that may cause loss of life, injury, or other health impact, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage" (UNISDR 2009). However, due to the fact that we are using the datasets from the CRED database, we should follow their categorization and we will analyze the hydrological and meteorological hazards separately.

2.5. <u>Meteorological Hazards</u>

Moving forward, the term *meteorological hazard* is described as "events caused by short-lived/small to mesoscale atmospheric processes (in the spectrum from minutes to days)" (EM-DAT 2017). The CRED database divides the meteorological hazards into three subtypes: the extreme temperature, the fog and the storms. The complication of the environmental hazards appears once more even in the categorization of the hazard subtypes. Based on Smith (1996), the severe storms are part of the atmospheric hazards[4], while extreme temperature is part of the biophysical hazards. What is more, the subtype of fog is not mentioned at all by Smith (1996).

Extreme temperature includes the cold wave, the heat wave and the extreme winter conditions. *Cold Wave* is "a period of abnormally cold weather. Typically, a cold wave lasts two or more days and may be aggravated by high winds. The exact

[4] The term meteorological hazard does not exist in Smith's classification.

temperature criteria for what constitutes a cold wave vary by location" (EM-DAT 2017). *Heat Wave* is "a period of abnormally hot and/or unusually humid weather. Typically, a heat wave last two or more days. The exact temperature criteria for what constitutes a heat wave vary by location" (EM-DAT 2017). *Extreme winter conditions* are defined as "damage caused by snow and ice. Winter damage refers to damage to building, infrastructure, traffic (esp. navigation) inflicted by snow and ice in form of snow pressure, freezing rain, frozen waterways etc." (EM-DAT 2017).

Fog is defined as "water droplets that are suspended in the air near the Earth's surface. Fog is simply a cloud that is in contact with the ground" (EM-DAT 2017). What is interesting and deserves to be mentioned in that since 1900 there is only one significant fog event which occurred in 1952 in United Kingdom and caused 4,000 deaths.

Storm includes the convective storm, the extra-tropical storm and the tropical cyclone. *Convective storm* is "a type of meteorological hazard generated by the heating of air and the availability of moist and unstable air masses. Convective storms range from localized thunderstorms (with heavy rain and/or hail, lightning, high winds, tornadoes) to mesoscale, multi-days events" (EM-DAT 2017). *Extra-tropical storm* is "a type of low-pressure cyclonic system in the middle and high latitudes (also called mid-latitude cyclone) that primarily gets its energy from the horizontal temperature contrasts (fronts) in the atmosphere. When associated with cold fronts, extratropical cyclones may be particularly damaging (e.g. European winter/windstorm, Nor'easter)" (EM-DAT 2017). *Tropical Cyclones* are defined as "storms of marine origin and they create coastal hazards because most of the systems decay rapidly over land areas" (Smith 1996 p. 211).

2.6. *Extra-terrestrial Hazards*

The last and not so common natural environmental hazard is the extra-terrestrial hazard. Based on EM-DAT glossary (EM-DAT 2017), the *extra-terrestrial hazard* is "a hazard caused by asteroids, meteoroids and comets as they pass near-earth, enter the Earth's atmosphere, and/or strike the Earths, and by changes in interplanetary conditions that effect the Earth's magnetosphere, ionosphere, and thermosphere". What is interesting and deserves to be mentioned in that since 1900 there is only one significant extra-terrestrial event which occurred in 2013 in Russian Federation from which 1,491 people were injured, 300,000 people were affected and the total economic damage was 33,000,000 USD. This event was classified under the type of *impact*.

2.7. *Industrial Hazards*

The term of *industrial accident* is described as "disaster type term used in EM-DAT to describe technological accidents of an industrial nature/involving industrial buildings (e.g factories)" (EM-DAT 2017). The database of CRED divides the industrial subgroup into nine subtypes of hazard chemical spill, collapse, explosion, fire, gas leak, oil spill, poisoning, radiation and other. The EM-DAT glossary (EM-DAT 2017) provides the definition of *chemical spill* as "accident release occurring during the production, transportation, or handling of hazardous chemical substances".

The *collapse* is the "accident involving the collapse of building or structure. Can either involve industrial structures or domestic/non-industrial structures" (EM-DAT 2017). The case of industrial structures is included and analyzed on the industrial hazard sections while the domestic collapse refers to the miscellaneous hazards which will be analyzed later on.

The *explosion* is the "explosions involving buildings or structures. Can either involve industrial structures" (EM-DAT 2017). This is one more subtype that can either be found on industrial or miscellaneous hazard. The fourth subtype of industrial hazard is the fire, which based on the CRED database can be either an industrial fire or a miscellaneous fire. Neither the EM-DAT (2017) nor the UNISDR (2009) give an explanation on the term fire probably due to the assumption of being a well-known definition. The next subtypes of analysis are the gas leak and the oil spill that appear only on the industrial hazard sections. Similarly, to the fire subtype, there is no given explanation for the gas leak accidents assuming that it is widely known. Moving forward, the analysis contains two more hazard subtypes, the poisoning and the radiation.

The EM-DAT (2017) describes *poisoning* as "poisoning of atmosphere or water courses due to industrial sources", while *radiation* is the disturbance of radio. *Radio disturbance* is "triggered by x-ray emissions from the Sun hitting the Earth's atmosphere and causing disturbances in the ionosphere such as jamming of high and/or low frequency radio signals. This affects satellite radio communication and Global Positioning System (GPS)" (EM-DAT 2017). Last subtype of analysis is a subtype called *other* and although there is no explanation given for that subtype, we can assume that it includes any other industrial accident that cannot be categorized under the already mentioned subtypes. Based on Smith (1996), in the case of industrial accidents, "risk is usually defined as the probability of death or injury per person per number of hours exposed" (Smith 1996 p. 316), who defines industrial hazards as "manufacturing, power production, storage and transport of hazardous materials" (Smith, 1996 p.316).

2.8. Miscellaneous Hazards

The term *miscellaneous hazard or accident* (as it is also mentioned) is described as a "disaster type term used in EM-DAT to describe technological accidents of a non-industrial or transport nature (e.g houses)" (EM-DAT 2017). Smith (1996) did not use the term miscellaneous, instead he called them *large-scale structures* including public building, bridges, dams (Smith 1996 p. 316). The database of CRED divides the miscellaneous subgroup into four subtypes of hazard: *collapse, explosion, fire and other*. All subtypes have already been defined in the previous subsection, however, it is important to mention once again that on miscellaneous accidents, non-industrial accidents are included. Moreover, the miscellaneous hazard list does not include any transport accident which is analyzed separately both by Smith (1996) and EM-DAT (2017). Based on Smith (1996), in the case of large-scale structure accidents, "risk is usually defined as the probability of death or injury per kilometer travelled" (Smith 1996 p. 316).

2.9. Transport Hazards

The term *transport hazard* is described as a "disaster type term used in EM-DAT to describe technological transport accidents involving mechanized models of transport. It comprises of four disaster subsets: accidents involving aeroplanes, helicopters, airships and balloons "Transport: Air"; accidents involving sailing boats, ferries, cruise ships, other boats "Transport: Boat"; accidents involving trains "Transport: Rail"; and accidents involving motor vehicles on roads and tracks "Transport: Road"." (EM-DAT 2017). Based on Smith (1996), in the case of large-scale structure accidents, "risk is usually defined as the probability of failure during the life-time of the structure" (Smith 1996 p. 316).

There is an additional type of hazard that appears in the literature which strengthens the doctrine of this topic's complexity. This theory has been named *"na-tech"* and was initially mentioned by Showalter and Myers (1994) who mentioned that a natural hazard may, under certain circumstances, lead to the release of dangerous materials such as chemicals, radiological and/or oil materials or spills which will therefore lead to a technological disaster. However, due to the difficulty of recognizing such events, the CRED database does not provide information and/or datasets of those events. For that reason, natural hazards (Halkos and Zisiadou 2018a) and technological hazards are reported and examined separately.

2.10. Complex Hazards

Moving forward, there is the last type of hazards provided by CRED database which is not categorized either on natural or technological hazards. There is recognized as a separate type of hazard called *complex hazard* and consists the rare case of famine. More specifically, the *complex hazard* is described by EM-DAT (2017) as "major famine situation for which the drought was not the main causal factor" while *famine* is defined as "catastrophic food shortage affecting large numbers of people due to climatic, environmental and socio-economic reasons" (EM-DAT 2017). Smith (1996) referred to the famine events occurred by natural hazards and especially drought. In those cases, famine was the impact of an existed natural environmental disaster and not an individual hazard. CRED database provides information of individual famine disasters which were not led by drought, giving 14 events over the last 117 years which will be analyzed later on this paper.

2.11. Terrorism

As it has already been mentioned in Section 1, Terrorism is described as a form of strategy due to the fact that serves political or military interests (Tilly, 2004). Based on Tilly's paper (2004), the State Department after the great terrorist attack of September 11, 2001, mentioned that terrorism is a threat that has no limits, neither geographical nor ethical, that apart from causing fatalities and injuries to the citizens, threatens the democracy and its institutions. Terror is a word used to express the extreme levels of fear. A term for terrorism is given by Kydd and Walter (2006) by mentioning that "We define terrorism as the use of violence against civilians by nonstate actors to attain political goals" (Kydd and Walter, 2006, pp. 52).

Institute for Economics and Peace, which reports useful statistics about terrorist attacks while also conducting the Global Terrorism Index, four (4) major terrorist groups exist nowadays at the terrorist scenery. The first is the Islamic State of Iraq and the Levant (ISIL), which is also known as ISIS and is based on Iraq and Syria. That terrorist group is responsible for 1,132 attacks which caused 9,132 fatalities and 7,723 injuries (Institute for Economics and Peace, 2017). On the same report, it is mentioned that there was a connection between ISIL and Al-Qaida, however a rupture was caused due to aggressive attacks against Shia Muslims.

Al-Qaida and Affiliates, on the other hand, is the second major terrorist group reported by Institute of Economics and Peace (2017), which is responsible for 359 events, which caused 1,349 fatalities and 3,170 injuries. The formation of Al-Qaida is timed in 1988 by Usama bin Laden and Abdullah Azzam and its greatest attacks was the September 11, 2001 (Institute for Economics and Peace, 2017). Six years after the formations of Al-Qaida, another well-known terrorist group was formed under the name of Taliban, which is located in Afghanistan and Pakistan and is responsible for 848 events worldwide. Those events caused 3,583 fatalities and 3,550 injuries (Institute for Economics and Peace, 2017).

Last but not least is the terrorist group "Boko Haram" which is also known as Group of People of Sunnah for Preaching and Jihad, and as Islamic State West Africa Province, and is placed in Nigeria. The forth group is responsible for 192 events which caused 1,079 fatalities and 1,119 injuries (Institute for Economics and Peace, 2017). What is important to mention is that more terrorist groups exist on the globe, however, those are the four major mentions by the Institute of Economics and Peace.

Section 3

3. Historical Overview

The greatest technological, and more specifically nuclear, disaster in history that shocked the globe was the one that took place in Chernobyl. It was in 1986, that an explosion in Unit 4 of the nuclear power station in Chernobyl occurred creating the worst nuclear accident of all times (Smith and Beresford, 2005). For the first time, an industrial and more specifically nuclear accidents receives a rank of Level 7 in INES scale and it is the only event with the highest possible ranking. That changes in 2011 (11.03.2011) with the nuclear accident on Daiichi Nuclear Power Plant, which will be analysed later on.

The history thought has faced more nuclear disasters with the most known examples the Hiroshima and Nagasaki cases. It was August 1945 during the World War II was for two days the US military bombed with 2 different nuclear bombs, the first in Hiroshima by Enola Gay dropping the "Little Boy" as it was named and the second in Nagasaki by Bockscar dropping the "Fat Boy", in Japan destroying the cities and their surroundings. However, those two events were excluded from our analysis due to the fact that two place during war period where normality does not characterizes humans' activities and decision. Moreover, during war every kind of man-made disaster may be expected.

3.1. Na-tech Events

The survey sample contains 25 events, including 12 earthquakes, 9 volcanic eruptions, and just 4 industrial disasters. A significant number of industrial disasters has been excluded due to the fact that the most corporations are not publicly listed, thus there are no stock prices available for the market reaction estimation. Moreover, regarding the geophysical disasters, the 2006 Indonesia earthquake has been excluded from the research after observing anomalies on its behaviour, and more specifically, negative systematic risk.

The first event of the analysis (*Event 1*) is the Denali earthquake in Alaska, USA on 3 November 2002 (Dunham and Archuleta, 2004; Eberhart et al. 2003; Jibson et al. 2006; Freed et al. 2006), with a M_w= 7.9 and a maximum intensity IX. This earthquake caused an estimated total damage of $ 20-56 millions and 1 injury, while it triggered several landslides with the major of them causing a collision of 30 million m^3 of rocks and ice (Eberhart et al. 2003). The 2004 Indian Ocean earthquake, which took place in Thailand on 26 December 2004 (*Event 2*), with a M_w= 9.1-9.3 and a maximum intensity IX, caused an estimated total damage of $ 15 billion, and 227,838 fatalities. The tsunami created after the ground movement reached a 51-meters wave. According to Telford and Cosgrave (2007), the most interesting evidence from the earthquake occurred over the Burma and Indian Plate joint, was the immediate funding response across the globe.

Wang and Liu (2006), characterized this geophysical event as one of the most devastating over the last 100 years. Moreover, they mentioned that the initial magnitude estimation was 9.0 which afterwards was updated to 9.1-9.3 while the waves created by the earthquake travelled at the speed of 700Km/h. In 2005 in Pakistan, the Kashmir earthquake took place on 8 October 2005 (*Event 3*) giving a M_w= 7.6 and a maximum intensity of VII. The casualties of that disaster were 28 million displaced citizens, an estimation of 86,000-87,351 fatalities and 69,00-75,266 injuries citizens (Avouac et al. 2006). According to Kamp et al. (2008), the Kashmir earthquake triggered a sever landslides, however, the majority of the fatalities were caused due to inappropriate design of buildings and poor quality of construction materials. The aftermath of natural disasters regarding losses can be reduced by respecting and following the construction building codes (Priest, 1996).

Based on Liu-Zeng et al. (2009), the 2008 Sichuan earthquake (12.05.2008) in China (*Event 4*) was a geophysical disaster with a M_w= 8.0 which devastated the western rim of Sichuan basin. The maximum intensity of that earthquake was XI and the estimated total damage was $150 billion, while the fatalities were 87,587, 374,643 citizens were injured and 18,392 are missing. One of the most known and disastrous geophysical events of the new millennium is the tsunamigenic[5] earthquake in Tohoku, Japan on 11 March 2011 (*Event 5*) which led to the greatest nuclear accident of the latest years, after the case of Chernobyl, at the Fukushima Daiichi Nuclear Power Plant. The M_w=9.0-9.1 with a maximum intensity IX earthquake created waves up to 40.5 meters as well as landslides. The estimated total damage is $360 billion. The industrial case of Daiichi disaster is described further in detail as Event 25. Moving forward, on 22 February 2011 in Christchurch in New Zealand, a M_w=7.2 earthquake, which also led to a tsunami and landslides, caused 115 fatalities and 1,500-2,000 injuries. The maximum intensity of this event (*Event* 6) was IX. Bradley and Cubrinovski (2011) explained that since New Zealand is located on the joint of the Pacific and Australian plates, two active tectonic plates with lateral sedimentations.

Less than 8 years after the devastating Indian Ocean earthquake in 2004, another M_w=8.6 earthquake struck on 11 April 2012 the Indian Ocean, however, that time the affected country was Indonesia (*Event 7*). Pollitz et al. (2012), mentioned that this earthquake, with a maximum intensity VII, 10 fatalities and 12 injured citizens, was by

[5] Based on Kanamori (1972), all earthquakes that can create tsunamis can be classified as tsunamigenic earthquakes

far the largest strike-slip event. 2012 Indian Ocean earthquake was a tsunami associated event, as most of the cases examined in this paper, showing that natural events, or even disasters, are not individual incidents; nature interacts. The Illapel case was a M_w=8.3 earthquake which affected two countries when on 19 September 2015 shook both Chile and Argentina with maximum intensity IX and created a tsunami. The aftermath of this earthquake was 15 fatalities and 6 missing citizens in Chile, while one 1 fatality and minor injured citizens in Argentina (*Event 8*). Ruiz et al. (2016) mentioned that since the earthquake of Malue in 2010, there is an extensive post seismic distortion. Based on Heidarzadeh et al. (2016), the Illapel case raised a lot of attention and has been observed by the Pacific Tsunami Warning Center and the Japan Meteorological Agency. The tsunami, which has been created by the earthquake in South America and affected Chile and Argentina, reached the coastlines of Japan, Hawaii, New Zealand, Vanuatu and Australia.

It was on 25 October 2010, when Indonesia faced all three cases of geophysical disasters (*Event 9*). The Mentawai earthquake in Sumatra was a M_w=7.8 earthquake, which led to a tsunami as well, caused 408 fatalities and 303 missing citizens. As Newman et al. (2011) mentioned, the Mentawai earthquake is characterized as a rare slow-source tsunami earthquake. At the same day, in the region near Java in Indonesia, one of the most active and hazardous volcanoes globally, Mount Merapi, erupted (Jousset et al. 2012). This volcanic eruption caused a chaotic situation regarding the air traffic to a point that 2,000 flights have been canceled. In the end of 2011, and more specifically on 23 December 2011, New Zealand came through another earthquake event (*Event 10*).

As Bannister and Gledhill (2012) described, two ground movements took place in Christchurch 10Km and 15Km east from the city center respectively, only 10 months after the first earthquake of the same year. On 21 July 2014, a lake tsunami occurred in Iceland and more specifically in Aksja, caused by a volcanic activity (*Event 11*). Gylfadottir et al. (2017) emphasize the unique phenomenon of a tsunami into the lake due to the rockslide that has been released from the inner Askja caldera. The last earthquake included in the sample of analysis in the one that took place in Kaikoura (New Zealand) on 14 November 2016 (*Event 12*). Once again, it was the joint of the Pacific and Australian plates, two active tectonic plates with lateral sedimentations that created the Mw=7.8 earthquake event with a maximum intensity IX which afterwards led to a tsunami causing 2 fatalities and 57 injured citizens (Hollingsworth et al. 2017).

Moving forward, the next events included to the analysis are related to the volcanic activity since 2000. On 7 August 2008, Kasatochi volcano (*Event 13*) in USA erupted unexpectedly. Based on Waythomas et al. (2010), this specific volcano had no significant eruptions since then, however, the eruption of 2008 received a level 4 rating on the VEI scale. Almost a year later, another eruption received a level 4 rating. On 11 June 2009, in Russia the Sarychev Peak erupted (*Event 14*). As Urai and Ishizuka (2011) mentioned, the Sarychev Peak is not monitored with ground-based instruments, however the great eruption of 2009, that lasted almost 8 days was captured by satellites. Iceland is very famous regarding the volcanic activities. On 20 March 2010 and for 39 days (*Event 15*), a level 4 volcanic eruption tool place in Eyjafjallajokull (Gudmundsson et al. 2012). Moreover, the next year, another level 4 eruption occurred in Iceland. Specifically, on 22 May 2011 (*Event 16*), it was the most active volcano in Iceland, Grimsvotn, that is located beneath the Vatnajokull ice sheet (Sigmarsson et al. 2013).

Scollo et al. (2014) and Viccaro et al. (2015) examined the Etna eruption on 05 March 2013 (*Event 17*) which received a level 3 rate in VEI scale. In a period of two years, Etna in Italy produced 38 basaltic lava fountains. The volcanic activity started after 8 months of rest as Viccaro et al (2015) mentioned. Kato et al. (2015) analyzed the Mount Ontake, Japan, volcanic eruption on 27 September 2014 (*Event 18)*, that caused the deaths of 57 climbers. The number of fatalities increases since 6 more missing climbers assumed to be dead. Kaneko et al. (2016) characterized this eruption as a small eruption with a short period, since it received a level 3 rate, it has not been examined thoroughly, thus the causes remain unknown.

The volcanic eruption of Kelud, Indonesia on 13 February 2014 (*Event 19*), raised a lot of attention as it was characterized as the most powerful eruption of the decade (Caudron et al. 2015). A historic eruption was the one of Calbuco, Chile on 22 April 2015 (*Event 20*) since it hasn't any recorded eruption the last 43 years (Van Eaton et al. 2016). Due to eruption, volcanic ash was dispersed in Chile, Argentina and Uruguay. Ivy et al. (2017) observed the change on the ozone hole caused by that eruption. The last volcanic eruption included in the sample is that of Sinabung (*Event 21*) on 22 May 2016. Sinulingga and Siregar (2017) mentioned that Sinabung is one of the 130 volcanoes in Indonesia, and it lies on the Ring of Fire, which is a high-risk area concerning earthquakes.

The final category of the events included in the sample are related to the industrial accidents. Only 4 events could be included to the analysis due to the fact that the rest of the corporations, which caused industrial disasters, are not publicly listed. Three of those events are oil spills while the last event of the analysis is the greatest nuclear disaster of the latest years, and one of the two greatest disasters in history. *Event 22* is the Prudhoe Bay oil spill caused by BP on 2 March 2006. Based on Kurtz (2010) this specific oil spill was the largest pipeline incident in the history of the operating system. The reputation of BP suffered from this incident and four years after the first oil spill of the new millennium, a new oil spill, but this time in the Gulf of Mexico, occurred and aggravated the existing situation. On 20 April 2010, the Deepwater Horizon (*Event 23*), caused 11 fatalities and 17 injuries, as well as an environmental disaster due to the 2.1 million gallons of dispresants on the surface and wellhead of the Gulf of Mexico (Kujawinski et al. 2011). Three years later, on 29 March 2013, the Mayflower oil spill (*Event 24*) caused by Exxon Mobil, released more than 5,000 barrels of crude oil. Based on Droitsch (2014), 1.36 million gallons of crude oil have been proven very difficult to clean up.

Last but not least is the nuclear disaster of the Fukushima Daiichi Nuclear Power Plant. On 11 March 2011, after the Tohoku earthquake and tsunami that reached the coast of Japan. Due to the earthquake 11 nuclear power plant stopped their operations. The cooling system of Fukushima's power plant also stopped operating, causing the mot catastrophic nuclear accident after the one in Chernobyl. Initially, Fukushima Daiichi disaster received a level 5 rate on INES scale, but after the reassessment of the situation, Fukushima disaster received a level 7 rate. Till that day, only Chernobyl had a level 7 rate (Norio et al.2011).

3.2. Terrorist Attacks

It was September 11, 2001 when Al-Qaida attacked to USA causing 2996 life losses, numerous injuries and huge economic losses (Event 1) (Galea et al., 2002). This terrorist attack was the biggest events of the new Millennium, till the most recent events that took places over the last 5 years in Europe and USA. What is also important to mention is that still encounters the most life losses compared to all the other events that will be analysed in this research. A year later, in September 10, 2002 another great terrorist attack took place in India which caused 130 fatalities and 150 injuries to citizens (Event 2)[6].

For the next two years, the terrorist attacks were not so disastrous causing less life losses, which is the first factor that lead us to include an event in our analysis. In February 7, 2004 in Philippines a terrorist attack caused 116 life losses, while the injuries were not reported (Event 3). A month after that attack, Europe and more specifically Spain faces a huge terrorist attack in March 11, 2004 leading to 191 fatalities while the number of injured citizens reached the 2,050 people (Event 4). Compared to the 911 attack in USA, which was an airplane attack, the one occurred in Spain was a train bombing however those two events had a lot of similarities as López-Rousseau (2005) mentioned.

One and a half year later, Russian Federation faced the fear of terrorism in September 13, 2005 encountering 138 and 115 fatalities and injuries respectively (Event 5). It was almost 2,5 years after that event when an Asian country, and more specifically Israel was attacked leading to only 9 fatalities and 11 injured citizens (Event 6). However, Western Asia is proved to be one on the most suffered regions regarding terrorism and this event raised some attention. In the same year, another Asian country, and more specifically India in November 26, 2008 faced once again a terrorist attack (Event 7) with more life losses and injuries 173 and 327 respectively, compared to previous event (Event 2).

The last decade of our analysis starts with a terrorist event in France in July 14, 2010 with fewer affected citizens compared to previous events mentioned. The fatalities

[6] Most events were detected through the Global Terrorism Database which gives the exact date and time of the events, as well as other important information. Some cases were supported by literature as will be mentioned.

equal to 87 and the injuries to 434 citizens (Event 8). A year after that attack, Europe is shocked again from a new event in Norway this time in July 11, 2011 which encountered 77 life losses and 319 injuries (Event 9). The next great event in once again in Asia and more specifically in Pakistan in January 10, 2013 with 126 and 270 fatalities and injuries respectively (Event 10). Till that time, terrorist actions are now as frequent as it appeared to be the last five years of the analysis.

Boston (USA) in April 15, 2013 encounters 5 life losses and 264 injuries from the 11th Event that we will include in our analysis. The affected citizens were dramatically less compared to the 911 event. Philippines, 9 years after the previous event we will analyse, faced terrorism once again in September 9, 2013 with 220 and 254 fatalities and injuries respectively (Event 12).

Nigeria on the other hand, was not so lucky, compared to Philippines with the low frequency events. More specifically, in 2014 Nigeria suffered from 5 terrorist attacks, starting with February 15 (Event 13) with 106 fatalities and not recorded injuries, moving to March 15 (Event 14) with 212 fatalities, and May 5 (Event 15) with 300 life losses and at the same month (May 20) with 118 fatalities and 56 injuries, which is an event that will not be analysed due to the fact that the estimation period is overlapping with the previous event and it will be analysed further on. The last Nigerian event of 2014 was in July 19 (Event 17) which encountered 100 fatalities.

Event 16 on the other hand took place in Europe, and specifically in Belgium in May 25, 2014 which reported on 4 life losses, a value significantly low compared to the events that we mentioned so far. The last event of 2014 was in Pakistan in December 16, with the fatalities and injuries reaching the 144 and 114 respectively (Event 18). The so suffered Nigeria is facing terrorism even in 2015 with 3 events in January 3 (Event 19), July 1 (Event 22), and September 20 (Event 23). The fatalities for those events are 2,000, 145 and 145 respectively, making event 19 on Januray 3, 2015 the second most disastrous event after 911.

Event 20 took place in France in January 7, 2015, and is the known Charlie Hebdo shooting which caused the loss of 12 lives while 11 people were injured. That event raised a lot of media attention and it was assumed to be the beginning of those attacks followed which took place on the European Continent and shocked the globe. Kenya in April 2, 2014 saw 151 of its citizens losing their lives while 79 more getting injuries due to a terrorist attack (Event 21). Turkey is now included in our sample due to the event that occurred in October 10, 2015 causing 102 fatalities and 508 injuries (Event 24). Less than a month after this attack, and more specifically in October 31, Egypt encounters 224 life losses due to another terrorist action (Event 25)

It was November 13, 2015 when France lived the dramatic night of Bataclan (Event 26) which lead to 137 fatalities and 368 injured citizens and spread the panic to the whole Europe for the next target. ISIL announced that was triggering that attack, and as it is proven more were about to follow. One month after that event, San Benardino (USA) faced the Islamic terrorism in December 2, 2015 encountering 16 fatalities and 24 injuries (Event 27). The next three months were assumed to be peaceful, till March 22, 2016 when Belgium became for the first time ISIL's target causing 35 and 304 fatalities and injuries respectively (Event 28). Six months after the previous attack in USA, Orlando this time is coming across to the terrorist actions in June 12, 2016, causing 50 deaths including the perpetrator and 53 injuries (Event 29).

The Jo Cox murder in June 16, 2016 was a domestic terrorism action that was not connected to the ISIL, however, in deed shocked the media due to the fact that Jo Cox was elected on the Parliament (Event 30). No other fatalities or injuries were recorded to that event. One day after that event, Nigeria, once again faced the terrorist actions in

June 17, 2016, an event that caused 156 fatalities and 10 injuries (Event 31). Nine months after the Belgium's attack, Germany and more specifically Berlin in December 19, 2016 was the next ISIL's target causing 12 life losses and 56 injuries (Event 32). Event 33, is the terrorist attack that took place in Turkey in January 1, 2017 causing 36 and 709 fatalities and injuries respectively. The responsibility for this attack was raised by the ISIL similarly to the most events of that period.

In 2017, United Kingdom faced 3 great terrorist attacks. The first was on March 22, in Westminster encountering 6 life losses and 49 injuries (Event 34), the second was two months later, on May 22, 2017 in Manchester encountering 23 fatalities and 800 injured citizens (Event35) and the third one was on September 15, 2017 in Parsons Green causing only 30 injuries and no fatalities (Event 37). All three attacks were connected to the Islamic extremism while for the last one the responsibility was raised by ISIL. Event 36 is a terrorist action occurred in Spain on August 17, 2017 causing 16 fatalities and 152 injuries.

Europe continues to suffer from terrorism with France and more specifically Marseille being the next target in October 1, 2017 with 3 fatalities including the perpetrator. ISIL raised the responsibility for this event as well (Event 38). Two weeks after this attack, New York (USA) on October 31, 2017 was the target of ISIL causing 3 life losses and 12 injuries, spreading more panic around the globe regarding the ISIL actions (Event 39). The last terrorist attack of our analysis in the one that took place in Egypt on November 24, 2017 causing 309 fatalities and 128 injuries (Event 40).

Since that day, more terrorist actions occurred around the globe, however, the sample of our analysis included events till 2017 due to the fact that the official database of terrorism "Global Terrorism Database" has updated the datasets till December 31, 2017. Having that in mind, and not having official records for the following years, we decided not to include terrorist attacks for the years 2018-2019. The main reason for including na-tech events till the end of 2016 relies on the same aspect. The official database which reports all environmental hazards has updated it datasets it December 31, 2016.

Section 4

4. Literature Review

Among those studying or working in the financial sector there is a well-spread knowledge regarding the rational investor's preferences. Regardless of the business sector that will choose to invest, investors' main goal is to maximize their profits. For that reason, they are characterized in literature as "risk averters" (Merton, 1969; Benartzi and Thaler, 1999; Campbell and Cochrane, 1999; Ait-Sahalia and Lo, 2000; Jackwerth, 2000; Rosenberg and Engle, 2002; Brandt and Wang, 2003; Gordon and St-Amour, 2004; Bliss and Panigirtzoglou, 2004; Bollerslev et al. 2011; Halkos et al., 2017). Investors have usually been assumed to be rational, so if we ignore the arbitrage case, they tend to choose more "safe" investments which will allow them to maximize their profits, or in other words minimize the potential risk they receive by investing (Cohn et al., 1975; Benartzi and Thaler, 1995; Haigh and List, 2005).

Hedging and portfolio diversification may appear to be efficient in reducing the potential loss of an investment. Great attention has been drawn about the advantages of portfolio diversification (Búgar and Maurer, 2002). Graham and Jennings (1987) have mentioned the ability of transferring the risk of investment through hedging, while Bond and Thompson (1985) underlying that the size of the optimal hedging ratio is one of the main determinants used by the decision makers apart from the cash position of the corporation. Based on available information, such as credit rating, the stability of the corporation or government, whether we are working with stocks or bonds, as well as the investors' preferences, the diversification of the portfolio and the assurance of the investor's capital may be achieved. When considering investments of individuals, hedging alternatives and portfolio diversification will be proposed by investment advisors regarding the level of risk each investor is prone to receive. However, if we focus on the corporation investments then, as mentioned by Stulz (1984), the hedging policy is decided by the manager, thus the shareholders are not part of those decisions. For that reason, the manager of a firm should be able to know and predict the possible risk threats a firm is facing. In that way, the most appropriate hedging policy will be adopted to protect their capital and ensure the liquidity and the reputation of each corporation.

What we should always bear in mind is that any hedging policy we may follow comes with a cost. As Stulz (1984) mentioned, generally we have as base that the manager of a corporation can adopt a hedging strategy without a cost, and in that case the shareholders will probably not care about the manager's actions. However, hedging cost does exist and we should mention that, shareholders may not be able to cancel the manager's hedging plans regarding costly decisions, they may bring up obstacles to these decisions. In such cases, if the manager cannot hedge in a straightforward way, he or she will use more indirect hedging techniques, that the shareholders will not be able to detect, in an attempt to run project that have a positive net present value (Stulz, 1984). Thus, if the hedging cost for common risk sources create such conflicts in a corporation, we can perceive the possibility of hedging against an unexpected situation which will have higher hedging cost and obviously probability of non-occurrence.

The first researcher who extended the Markovitz theoretical idea of the modern portfolio selection was Grubel (1968). We can use options or future derivatives concerning our predictions regarding the value of exchange rates for instance. Based on Mello and Parsons (2000), futures markets provide the most liquid and convenient instruments for managing risk. One disadvantage that is mentioned is the fact that it is often impossible to simultaneously hedge cash flows and values due to the fact that the future contracts are marked to markets. Corporations can hedge predictable risks using many alternative contracts such as Futures, Forwards and Swaps. However, there are some cases which cannot be predicted. The act of nature is such a case (Halkos and Zisiadou, 2018a).

Nature acts independently, and a common example of that independence is the tectonic plate movement (Halkos and Zisiadou, 2018a). Distinguished sciences such as geology and seismology, do have the techniques to monitor, observe and examine the geophysical events caused by those tectonic plate movements. However, even those specialized sciences cannot predict the occurrence, and more specifically the exact place, epicenter and intensity of an upcoming event. Thus, those actions which cannot be predicted may cause significant losses, both economic and life-related. Regarding the economic losses, they can be due to many factors such as the partial or total destruction of homes or business premises that will lead to reduced, if not zero, productivity. In an attempt to reduce the risk deriving from unexpected disasters both individuals and corporations tend to use insurance against the most common hazards such as earthquakes, floods, hurricanes etc. In that way, they avoid large losses by transferring the risk to the insurance companies. For several years, there has been a discussion in the insurance industry of the need for additional capital sources to participate in insuring the financial risk posed by natural catastrophes (O' Brien, 1997). As it is obvious, those unexpected disastrous phenomena cause losses both direct and indirect that influence individuals, corporations and even governments.

Regarding the country that may be affected by such a situation, reduced productivity can cause drastic decline in GDP, affect the country's borrowing capacity and reliability, which tends to be depicted in its credit rating. As we have already mentioned, the credit rating of a country or corporation is one of the most common rates that mirror the potential risk the investor is about to perceive by investing on this specific bond or stock. In the case of businesses, reduced productivity may affect investors' perceptions causing fluctuations in the share price or even volatility in its broad of directors. Although disasters are associated with risk, investors tend to have a different perspective regarding the source of the disaster. More specifically, if a country is facing a natural disaster, where no one can be blamed for, the foreign investors who may hold this country's bonds will continue to trust the country due to the "innocence" of the country.

On the other hand, when a firm causes a technological disaster, such as a nuclear power plant explosion, the investors, if this corporation is publicly traded, will "punish" the firm by selling its shares at any price to avoid a bigger loss. In such cases, the corporation may lose its trustworthiness. Nevertheless, in some cases, the possible technological disaster is not a firm's fault. These cases tend to be called "na-tech" by the literature, a term that actually pictures the source of the disaster. Sometimes, one natural disaster, caused by a tectonic plate movement, can lead to another natural or even technological disaster. For instance, a ground movement may lead to another earthquake[7] at the seabed, known as tsunami, or an earthquake, in general, may cause a disfunction of a factory installation which may therefore cause an industrial disaster. A characteristic example is the case of Fukushima Daiichi Power Plant disaster, which will be analyzed in the following section.

We tend to believe that natural environmental events are characterized by randomness. In other words, we assume that all these events are unexpected and may appear at any time and in any place, which actually means that they are not determined by any factor. However, previous research has shown that not only these events are

[7] Earthquakes are divided into two types of events, the "ground movement" which is the movement on the land caused by the tectonic plate movement, and the "tsunami" which is the waves caused by the movements at the seabed (Halkos and Zisiadou, 2018a).

non-random but also, they are significantly influenced by a range of different factors. Moreover, certain circumstances may lead from an unexpected event to an environmental hazard. Regarding the occurrence of appearance, it is well known that not all the events are attached to all regions but it depends on the geographical position of each country. Countries that are “placed” exactly above the tectonic plate joints are more risk-related to the geophysical environmental events such as earthquakes. Countries that are bordered with oceans are more risk-related to tsunamis and finally, the countries that have volcanos, whether actively or not, know that there is always the case of the volcanic eruption.

It is an often phenomenon to name specific areas, not necessarily at the same continent, with titles that show the high possibility of the occurrence. To be more specific, Bolt (1988) mentions a well-known region in the Pacific Ocean, the “Ring of Fire”, by trying to illustrate that more than 65% of the significant earthquake events were observed in an area on the Pacific Ocean due to the existence of the tectonic plates. The countries that are part of the “Ring of Fire” are country members both from the Americas and Asia, which leads to the assumption that we cannot examine those events with a continent-based analysis but dividing them to high frequency and low frequency regions. Onuma et al. (2017) prove that households which have recently faced a great disaster are more prepared to a possible upcoming one compared to those who have not faced a similar disaster in the short-run. Based on Parwanto and Oyama (2014), Japan is one of the countries globally that has the best earthquake early warning systems.

One of the factors that makes an event to be a hazard or even worse a disaster is the significant impact that this may leave after its occurrence. In other words, the number of people influenced is a decisive factor to call that specific event a hazard. The same logic is followed when we want to announce that a hazard unfortunately became a disaster. Sheehan and Hewitt (1969) when tried to give a definition of disaster they presented some threshold in order to determine the lowest losses for a disaster. More specifically, a hazard can be treated as a disaster if there are at least 100 dead people, or 100 injured people, or $1 million damage. Those thresholds were re-estimated by the EM-DAT and the new criteria for a disaster assume that if there are at least 10 dead people, instead of 100, then it is called disaster.

Moreover, if there is a declaration of state of emergency and/or a need for international assistance then it is not just a simple environmental event but a disaster. A difficulty that may appear when estimating the losses is that we cannot always estimate the exact number of people influenced by the event due to the fact that the results may appear in the short-run or the long-run. For instance, we can report the number of people died during the disaster but we cannot estimate those who died few days after the event or people who may suffer from inconsistent illnesses caused due to that event. If we assume that we can make an estimation for the total number of affected people then we should take into consideration factors such as the population density. If the area of disaster is highly populated then as a consequence the number of affected people will be higher compared to the less highly populated areas. Significant role to the number of fatalities can have the time of occurrence. If the event takes place during the night hours when most of people are at their houses and probably sleeping, then they will not be able to react.

As we mentioned above, the economic loss is one of the determinants that will help us recognize if there is a disaster or not. The economic loss can be influenced by a great range of factors. Apart from the most obvious geophysical factors which are the magnitude and the intensity of the event, there are some other mainly economic factors that will influence the volume of economic loss. First of all, as Smith (1996) described, the economic position of a country, or a specific region, can have a significant impact both to the economic losses and the number of fatalities.

According to Smith (1996) "…. - the poor lose their lives while the rich lose their money." (Smith, 1996, p. 33). That leads us to the distinction between developed and developing countries hypothesizing that the developed, or based on Smith rich (MDCs), countries are going to have higher economic losses compared to the developing, and based to Smith poor, countries. Smith (1996), used a similar distinction for countries mentions the most developed countries (MDCs) as the rich countries and the least developed countries (LDCs) as the poor countries. He also mentioned the Third World countries in the explanation of the structural paradigm. He drew a connection line between underdevelopment and economic losses. The economic losses in that case derives from the fact that those countries do not have the appropriate economic ability to create emergency plans as well as constructions based on the building codes proposed by the MDCs, so even with a less significant environmental hazards, the impacts will be dramatic in those countries. Nowadays, the term "Third World" is not an appropriate categorization for countries so there is a dichotomous distinction between developed and developing countries. As Freeman (2001) mentioned, international financial institutions like World Bank are caught in the grip of two financial forces: the increasing demand from developing countries for borrowing to cope with the cost of natural hazard losses, and the stagnant budgets that have not increased with the demand on their resources. Over the past years, with the co-operation of other international finance institutions, the World Bank has sponsored or supported several research initiatives to examine the role private markets may have in supplying post-disaster reconstruction financing (Pollner, 2000). Regarding the risk management of the catastrophes, Pollner (2000) mentioned that the vulnerability of specific regions as well as other individual risk characteristics may help to create actuarial estimates of event probabilities and intensities. One of the techniques suggested is the hazard mapped locations. With this technique, which lies in the non-structural regulatory measures, may be able to reduce the underlying structural risk of physical assets, with the ensuring effect of dramatically reducing the potential "loss value" of properties at risk.

The building codes that have already been mentioned is an institutional framework that provides construction guidelines (Yamin et al. 2014). These guidelines are often used when a government building is under construction. Smith (1996) mentioned that public buildings like schools, offices, factories do follow those building codes so that they will be able to provide support while the disaster is in progress. As it is obvious, those building codes and the construction procedure are accessible by the high-income societies while the low-income societies do not have the ability to make choice on whether to settle so the location is usually an unsafe place where their main goal is to survive till the next day (Smith 1996). From that phenomenon, a new term has arisen due to the fact that the damages caused to the poorly constructed buildings are greater compared to the high-income societies. That gave the researchers the ability to create a new unofficial type of disaster called "classquake" (Smith 1996).

If we try to express the economic damage or loss as a ratio to national wealth, then the damaged occurs by a disaster mainly affects the lower income societies due to the low-income levels (Smith 1996). Although the economic damage is easily calculated, the difficulty comes when the prospect of analysis is the valuation of life. Even nowadays, the scientists have not found an approach which could give an exact value of loss concerning the life loss and including all different aspects that this loss may influence. The health expenditures could be considered as a direct impact on human loss value. However, there are omitted variables that increase the value of loss which are not easily approached.

Another difference between countries and how they consider the disaster has its roots on the past and goes from generation to generation. Few researchers have worked on that topic known as “Locus of Control” or “Act of God Syndrome” (Smith 1996; Gaillard and Texier 2010). The theoretical review on that topic was initially mentioned by Dynes and Yutzy (1965). Since then, most of the researches have ignored religion and its impact on people’s beliefs (White and Haas 1975; Hewitt 1983, 1997; Drabek 1986; Burton et al. 1993; Dynes 1994; Chester 1998; Lewis 1999; Oliver-Smith and Hoffman 1999; Wisner et al. 2004). There are specific religions which have the belief that disaster is the punishment of God for their acts. So, having that in mind, they do not try to protect themselves by creating emergency plans but they accept that “punishment” as a sign of God.

Another difference between countries is the distinction between resilience and reliability. Based on Smith (1996), the MDCs, due to the fact that they have the economic ability to financially support protective devices against hazard, use the approach of reliability when those protective devices fail. On the other hand, and due to the lack of financial support, the LDCs accept the disaster as a normal part of life and with the method of recovery after the disaster, they use a measure called resilience in order to estimate the rate of that recovery (Smith 1996). As we can see, different economic conditions lead to different disaster approaches, so there is no global estimation which will treat the world as a unit.

What is also widely known and mentioned by Smith (1996), poverty gap is increasing when a disastrous event occurs due to the lack of essentials such as food stocks. In that case the demand and supply theory come to increase the price of the limited stocks which will automatically give access only to few people, especially those who can financially afford it.

Till that part we have analyze the factor that can cause a natural environmental hazard, or make people unable or even unwilling, to avoid that hazard. What will be analyzed further is the cascade of hazard impacts (Smith 1996). As it is mentioned above, an environmental hazard can have both losses and gains, which can be either direct or indirect. The direct losses are obvious if we consider the fatalities as well as the economic damages. People may die or get injured or homeless in case of house demolitions. The production of the suffered region may be affected which will automatically affect the GDP, the GDP per capital as well as the economic growth. Moreover, as it has been mentioned that an environmental disaster can increase the poverty gap as well as the inequality in a society or across countries.

The population of the specific area will also be negatively affected due to life loss. However, having in mind that a new disaster may occur, those who will survive by that disaster will consider migration as a solution and way of protection. That has also been stated by Munro and Managi (2017) who mentioned that tsunami victims, who have survived, are not likely to return to their homes after such a hazard. However, if the survived victims appear to have household ownership and/or job opportunities may decide to return to the area of disaster as it is proved by Sanaei et al. (2016). If the disaster caused adverse impacts on the environment and probably a type of pollution such as air pollution or water pollution, those who will remain in the polluted areas will may be face different illness factors that will increase mortality and at the same time will decrease the life expectancy. High CO_2 emissions is one of the most often variables affected after an environmental disaster.

Knowing that the economy is a vicious circle and that the negative influence to an economic variable can negatively affect other economic variables leading to a continues death spiral. When the production is almost destroyed then the society cannot produce what it need; as a result, the levels of imports increase while the level of exports decrease. The economy appears to have deficit, which will lead to external debt. If the economy is "strong" enough it will be able to welcome foreign direct investments after the disaster, otherwise the economy will follow the direction of lending. All those impacts refer to the short-run, exactly after each occurrence. However, the gains, which are usually indirect, appear after same years or even after many generations. As described in the introduction, a disaster may change the whole scenery by transforming it into a new tourist attraction. This may lead to a new economic generation of growth with increased tourism which will lead to increased incomes and as a consequence increased GDP and GDP per capita.

Technology, on the other hand, is an ambiguous topic of discussion and Weisaeth (1994) emphasized its ambiguity by explaining that the right use of technology can result to growth and prosperity, however, if it is used with recklessness, adverse effects may appear. This opinion is also supported by Smith (1996), who moreover mentioned that a technological innovation may not only create a technological disaster such as a possible failure but also a natural disaster. Although the evolution of technology has established a safer environment of living still a possible technological failure can lead to unexpected losses. For instance, the dam construction may assist the society due to the benefits that offers, nevertheless, a possible dam failure that may occur will probably result to a great number of fatalities and affected citizens as well as huge economic losses. Based on Smith (1996), the construction of the dam may solve water supply issues to a community, however, a construction failure increases the risk of flood disaster.

People tend to connect the term technological disaster mainly to the industrial accidents and sometimes overlook the most common man-made accidents which belong to the transport type of disaster. The main reason may probably be the multiple consequences that an industrial disaster may cause. When such a disaster occurs, impacts may affect people, goods and services, the economy in general and the environment. As it has been mentioned by Smith (1996) and Halkos and Zisiadou (2018a), a hazard can be categorized, based on the effect it has, into hazard to people, to goods and/or to environment. When the discussion is focused on the industrial technological disasters, it is highly possible to significantly affect all three cases of hazards. Nuclear accidents are the most known and catastrophic events that have shocked the world.

The most disastrous nuclear accidents recorded in world's history are the Chernobyl Disaster in Ukraine in 26 April 1986 and the Fukushima Dai-ichi Nuclear Power Plant disaster in Japan in 11 March 2011 (Ferstl et al. 2012; Hasegawa 2012; Kawashima and Takeda 2012; Yamamura 2012; Aoki and Rothwell 2013; Kim et al. 2013; Wada et al. 201). These two significant disasters are the only events, since the beginning of the nuclear accident history, that have been rated with a score equals to 7 on the "International Nuclear Event Scale". Based on that scale, level 7 is the highest level and is called *major accident* (Webb et al. 2006) which actually means that there is a major release with widespread environmental and health impacts.

When a nuclear accident occurs, there are direct and indirect negative effects. All direct impacts take place the moment of the occurrence, when property damage, loss of lives, injuries and economic damage is observed. However, when such a nuclear disaster occurs, chain reactions tend to appear. More specifically, during the event, chemical and/or poisonous materials are released to the environment which may lead to another disastrous event such as an explosion and/or fire, or may harm the environment on the long-run, even for the next generations (Smith 1996). Those released materials were investigated by Glickman et al. (1992) and concluded that those materials can only be hazardous when they affect the exposed population through air, water or soil pollution.

Unlike the Chernobyl case, Fukushima Dai-ichi NPPD[8] can also be considered as a *na-tech* disaster, given the Showalter and Myers (1994) definition. The chronicle of the Dai-ichi disaster started when the Tōhoku earthquake with a magnitude of 9.0 (Aoki and Rothwell 2013) created a tsunami that and jointly led to the shut-down of the nuclear reactor (Aoki and Rothwell 2013; Wada et al. 2012; Managi and Guan 2017). This highly significant event proved that the natural and technological environmental hazards can be connected and when both of them occur as chain reactions the results are dramatic and place the disaster into the greatest level of the International Nuclear Event Scale. The aftermath of this event was investigated by dozens of researchers such as Ferstl et al. (2012), Hasegawa (2012), Kawashima and Takeda (2012), Yamamura (2012), Aoki and Rothwell (2013), Kim et al. (2013), and Wada et al. (2012). Another indirect impact of a technological disaster is the fact that can also adversely affect the neighbour cities, regions, or even countries. Smith (1996) described that phenomenon when discussing the Chernobyl case, mentioning that Scandinavian countries, Austria, Germany, Poland, the UK and Ireland were affected through rain. We can estimate the level of pollution in the region of an event, but it is difficult to estimate transboundary

[8] Nuclear Power Plant Disaster

pollution caused by that. Gardner and Gould (1989) showed that people tend to accept the risk of a possible technological disaster due to the numerous benefits they main gain if the industrial activity is successful.

Transport, is another common type of technological hazards that raises a lot of attention. Yagar (1984) explained that although the number of fatalities due to transport accidents increase, more and more people tend to use private or public transportation either of business or leisure purposes. All types of transport are commonly used nowadays which therefore increase the frequency of the transport-related accidents (Smith 1996). Compared to road travel, air travel case appears to be safer and this was proven by Cox et al. (1992) who showed that the ratio of victims per distance is lower in the case of air travel. McDaniels et al. (1992) referred to the "willingness-to-pay" theory as an effort to show that passengers prefer to pay more by purchasing air tickets, compared to road travel cost, in order to reduce the risk of travel.

The list of adverse effects after a technological disaster is huge and, for that reason, the developed economies such as UK and USA attempt to prepare the community on how to face and overcome the disaster impacts (Drogaris 1993; Soby et al. 1993). Reporting Systems and Preparedness Programs established on MDCs are the countries' effort to secure the countries' stability and trustworthiness. For that reason, an analysis of the high frequent areas will reinforce the need for establishment of Reporting Systems and Preparedness Programs if needed. We still examine the assumption of Smith (1996) who pointed out that "…. - the poor lose their lives while the rich lose their money." (Smith, 1996, p. 33) and that has been examined by Halkos and Zisiadou (2018a) regarding the natural environmental hazards. That leads us to the distinction between developed and developing countries hypothesizing that the developed, or based on Smith rich (MDCs) countries are going to have higher economic losses compared to the developing, or based to Smith poor, countries.

If we choose to focus on the Na-tech events, we should have in mind that geophysical phenomena are not an unexpected process in terms of appearance and frequency. More specifically, since ancient times, the existence of these phenomena has been known and tends to be detected at a higher frequency in certain areas across the globe. The continuous movement of the earth's parts combined with the changes of the weather conditions have shaped the present image of the planet. Islands have been created or destroyed by volcanic eruptions, landscapes have undergoing changes from ground movements and tidal waves, however, the intensity of the event is the main factor that will affect the final outcome. Additionally, natural disasters cause a great number of fatalities as well as supreme national catastrophes (Viscusi, 2009) An extended literature considering the terminology and the high-risk areas has been presented by Halkos and Zisiadou (2018a). Based on CRED database, 1,621 geophysical events have been recorded since 1900 causing 2,678,022 fatalities and economic damages which aggregately exceed the 781.5 billion USD (EMDAT, 2017; Halkos and Zisiadou, 2018a).

Industrial accidents on the other hand, do not have similarities with the geophysical phenomena regarding the expectancy. Nowadays, technology takes up more and more space in our lives, not only for professional but also for personal purposes. Of course, when it comes to technological accidents and disasters, the first thing that comes to mind is industrial accidents. What is important to mention is that, technological disasters include all types of accidents that may occur having technology as one of the main factors. The three main categories of technological accidents are industrial, miscellaneous and transport accidents (Halkos and Zisiadou, 2018b; 2019).

Using once again the CRED database, we can come to the conclusion that the industrial hazards are not the most often, however, they are the most disastrous. Over the last 117 years (1900-2016), 1,434 industrial events caused 57,619 fatalities and almost 43,1 billion USD economic damages (EMDAT, 2017; Halkos and Zisiadou 2018b;2019). Industrial hazards, or even disasters, include all cases that may cause production disruption or even fatalities involving industrial buildings, such as chemical spills, collapses, explosions, fires, gas leaks, oil spills, poisoning and radiation. What is really important to mention is that the amount of fatalities became greater during the last years due to the fact that the population increase on those high risk areas (Kunreuther, 1996).

Although there is a perception that natural phenomena are unexpected and occur randomly, there is evidence to suggest that, partially, the assertion of randomness is not valid. To be more specific, there is a proven regional distribution regarding the geophysical events, initially mentioned by Bolt (1988) as the "Ring of Fire". Based on CRED database (EMDAT, 2017) and with the use of R-studio packages and routines, maps of occurrence have been created both for Geophysical and Industrial hazards (Halkos and Zisiadou, 2018a; 2018b; 2018c; 2019). Figure 1(a), obviously, represents the space concentration of geophysical hazards in the high-risk area called "Ring of Fire". In other words, although the exact place and time of an upcoming geophysical event cannot be predicted, based on evidence, we know a priori, which regions are more prone to face another disaster.

Due to the possibility of a new catastrophe, governments should pay more attention to those high-risk areas as an attempt to reduce possible losses (Viscusi, 2006). What is interesting though is that, although we were expecting a space concentration regarding the natural events, the assertion of regional distribution is also observed in the case of industrial hazards. As we can see in Figure 1(b), East Asia is the most suffered region regarding industrial disasters. Although, the reasons of such a space concentration are not known, based on evidence, researchers have at their disposal data that provide them with a first illustration of the riskiest areas.

As we have already mention, investors are primarily oriented to avoid most of the risk, or at least try to protect themselves from it. If they know, therefore, in advance, the risks they adopt by investing in those regions, they may be able to diversify their portfolios to the fullest.

Before analysing the cases that will be used in our modelling, it is important to understand basic concepts related to the seriousness of the incidents included in our sample. The first basic requirement for sample creation is the date that each event occurred, as we included events from 2000 onwards for reasons of availability of stock data. The second and equally important reason is the intensity of each event. Regarding the events we examine, there are four different intensity scales. For earthquakes, either ground movements or tsunamis, there are two different scales, the Moment Magnitude M_w, also known as Richter Scale, and the Intensity Scale, also known as Mercalli Scale. Both scales are presented in Figure I (see Appendix II), with a full description about the effects and the frequencies.

Regarding the volcanic eruptions, the scale that is used as a measurement is the Volcanic Explosivity Index (VEI) which is presented in Figure II (see Appendix II). These three scales are the most common used while measuring the intensity of a natural geophysical event. Regarding the industrial events, to our knowledge, there is only one scale that is used as a tool to rate an industrial disaster. This scale is the International Nuclear and Radiological Event Scale (INES) which is created by the International Atomic Energy Agency (IAEA) and the Nuclear Energy Agency of the Organization for Economic Co-operation and Development (OECD/NEA) in 1990[9] (see Figure III, Appendix II). The values of each scale and their impact are quite useful when describing an event and explaining the reason of inclusion to the sample.

Since we have discussed the main categories of catastrophic events, it is important to pay attention to a not so new phenomenon, which however raised great concern the latest years. Terrorism, in contrast to the environmental hazards, cannot be categorised under the umbrella of the unexpected hazards, due to the fact that is a result of political or military strategies as mentioned before. Tavares (2004), apart from the examination of stock returns, investigates the main determinants causing terrorism. Based on Major (2002), the risk of terrorism is higher in comparison to other catastrophes, because is driven by both intelligence and intent. Intelligence is a factor excluded from natural unexpected catastrophes and intent is a factor excluded from industrial disasters. This makes terrorist attacks more dangerous compared to other catastrophes (Major, 2002). However, that situation may become even worse when the main weapon of terrorism is any kind of biological agent.

A terrorist may use a pathogen due to the fact that this element may not be easily detected as a potential threat. As a consequence, the pathogen will have the adequate time to spread so as to be presented as a natural disease and not as a bioterrorist attack (Dembek, 2005). Since no one can accurately answer the question whether each disease was caused naturally or was a bioterrorist attack, the available data for bioterrorism is in fact narrow. Chesney et al. (2011) examined the terrorist attacks especially on financial markets and suggested that the non-parametric methods are more appropriate

[9] https://www.iaea.org/topics/emergency-preparedness-and-response-epr/international-nuclear-radiological-event-scale-ines Accessed: 10 October 2018

for the investors or portfolio managers in order to take into consideration the risk of a terrorist attack. Procasky and Ujah (2016) come to an agreement with Chesney et al. (2011) by proposing a model for predictions that can help investors to diversify their portfolios.

From another perspective, Frey et al. (2004) investigated the terrorist attacks and the different activities that have influenced not only the market but also the associated economic impact. Their analysis provides evidence that a terrorist attack may have an outcome to eight different activities, such as tourism, investments as well as foreign direct investments, savings and consumption, foreign trade, urban economy, national income and growth and of course stock markets. This analysis provides an integrated view of the outcomes that a terrorist attack may have.

Considering the purpose per region, the terrorist attacks on the USA embassies in Kenya and Tanzania inspired (Carter et al., 1998) in their research. Although USA supports the belief that they are prepared for any terrorist attack, because terrorism for them is a serious matter, Carter et al. (1998) proved that USA is not prepared enough to face such events especially when the events have as a target the government, services or embassies.

On these lines, the terrorist attack that inspired a great number of researchers is the 11th of September 2001, which shocked the whole world. Charles and Darné (2006) examined whether this attack had a temporary or a more permanent consequence due to the huge economic result caused. Based on their findings, the international stock markets did experience both permanent and temporary shocks and figured out that if these events were taken into consideration financial risk modeling could be improved by eliminating volatility of the stock market prices. On the other hand, Bhattarai et al. (2005) investigated the results of the same terrorist attack on September 11, but not in the USA. The region of their interest was Nepal. The main reason was the fact that since 1951 there was a great tourist increase in Nepal mainly from USA which dramatically decrease exactly after the terrorist attack of 11th of September 2001.

Krueger and Malečková (2003) are also inspired by the September 11 but they tried to examine the event from the educational and economic perspectives. Their purpose was to suggest if there is any linkage to an attack with the educational level of the perpetrators including also in their research the economic viewpoint by analyzing the perpetrators' and not the victims' economic status. However, their research provided little direct connection between an attack and the existing educational and economic conditions.

Eldor and Melnick (2004) based on terrorist attacks that occurred in Israel between 1990 and 2003, proved that the markets do react after an attack. Moreover, the results from Israel can be used to other western democratic countries due to the fact that Israel is a democratic and well-established country as well. Hausken (2016), based on the 11/9/2001 terrorist attack in the USA and following the proposed methodology used by Stewart and Mueller (2013), establishes a cost benefit analysis of terrorist attack, in which three main costs are included.

The first element refers to the human cost, including any suicide attack, the second element refers to the economic cost and it deals with the required funds for each attack, while the third element refers to the influence cost for the targets, which is considered as benefit for the assaulter. Initially, the model is introducing a time discount factor, as well as a risk parameter, which includes all possible risk cases such as risk aversion, risk neutrality and risk seeking. In addition, the generalization of the models permits a multiple stakeholders' impact to the terrorist organizations, which leads to different weights in each analysis.

Rosoff and John (2009) used a simulation model with terrorist perspectives' proxies, while Shubik and Zelinsky (2009) introduced a new metric relationship. This relationship represented the linkage between the target and the assaulter and was called *Terrorist Damage Exchange Rate*. Buesa et al. (2007) studied the aftermath of the March 11 2004 terrorist attack in Madrid by evaluating the direct economic costs, while considering that human catastrophic consequences will follow. In an attempt to assess various counterterrorism procedures, Sandler et al. (2009, 2011) calculated the values of lives and casualties based on an average terrorist attack. On the other hand, Brandt and Sandler (2010) clarified the way terrorists justify the costs and benefits by adjusting the targets.

Consider the purpose per decade we may say that although authors attempted to include previous research based on per year attacks, nothing was found. Therefore, to our knowledge, there is no research trying to conclude whether the frequency of attacks has significantly changed in recent years compared to the past.

Similarly, and in terms of the analysis per religion, Jones (2006) focused his research specifically on religious terrorist attacks. His research is a theoretical psychoanalytic approach and attempts to analyze the main psychological perspectives that underlie the attacks guided by religious groups. He also tried to search if there are specific religious groups that are more prone to commit such crimes.

Another usual question is why terrorism occurs. More specifically, a number of researchers wonder which system of government is the most dangerous as a target. There is a great conflict on whether democracy tends to be the main target for a terrorist attack both from the inside of the country and also from the outside the borders. Brynjar and Skjølberg (2000) raised this question and attempted to answer it. Their findings provide information that there is a highly correlated but complex relationship between terrorism and democracy. More specifically, countries more exposed to terrorism are those on the democratic transition, which makes the well-established democratic countries a less common target.

Regarding the economic determinants, Kis-Katos et al. (2011) proved that there is a positive relationship between terrorist events and CDP per capita both on domestic and international level. Another case of examination was the one Coleman (2012) used where nine Al Qaida attacks since 1998. More specifically, Coleman (2012) examined those 9 periods around each event for market efficiency on the three forms proposed by Fama in 1998 (weak, semi-strong, strong) ad proved that markets appeared to be strong when no inside evidence exists.The empirical results of studies on terrorist attacks are quite significant. Hallahan et al. (2016), relying on the 11th of September 2001, showed that systematic risk has mainly increased due to that attack whereas there was no change due to similar attacks. Carter et al. (1998) investigated the terrorist attacks on USA embassies concluding that although USA believe terrorist attack is a serious matter, USA was not prepared enough in order to tackle such a threat of catastrophic terrorism.

In terms of religions, Jones (2006) mentioned that all religious terrorists emphasize they are tackling an apocalyptic battle with demonic forces. The terrorists' purpose is not only to divide the world into good and evil but also to purify the world. The linkage that has been fount between religion and terrorism is the violence of sacrificial killing and/or apocalyptic purification.

In terms of results per system of government, Brynjar and Skjølberg (2000) concluded that there is a complex relationship between democracy and terrorism. More specifically, they mention that although the democratic countries are a great target for the terrorists, the semi-democratic countries or countries in democratic transition are those with the most events occurring

The main contradiction is on the level of democracy and wealth. Karolyi and Martell (2010) stated that terrorist attacks on richer and more democratic countries led to a greater negative market reaction compared to the poorer and less democratic ones. Adams and Klobodu (2016) investigated 33 Sub-Saharan African countries (SSA) mentioning that the more democratic and stable countries appear to have a growth effect on the remittance given and in that way they propose to other countries to adopt similar policies. Here comes the contradiction by Tavares (2004) who claimed that the democratic countries face small market reactions.

Concerning the education level and based on the findings in Russell and Miller (1983), the majority of perpetrators are usually well educated from high-ranking universities and probably Masters Degree holders. So, the belief that terrorism is a situation caused by uneducated or less educated people cannot be proved from this paper. This statement may be well related to Hamilton and Hamilton (1983) who ended on results proving that the further impact is generated to less well-educated countries. On the other hand, Taylor (1988) mentioned that the social background as well as the educational level of the participants cannot be proved to be determinants of a terrorist attack. In terms of the results per developed/developing countries and based on the findings by Russell and Miller (1983) the majority of perpetrators usually come from the middle or even the upper classes in the respective nations or areas.

4.1 Hedging Theory

The first question that needs to be answered regarding the hedging techniques is "Who is responsible for which hedging strategy should be followed?" The answer to this question differs to the type of the investment we are handling. If this question is raised by individual investors who are placing their money to corporations' stocks or governments' bonds, then the answer is quite simple. The investment advisor will consider the risk level the investor is willing to accept and then he/she will propose possible hedging techniques to minimize the potential loss of capital. In such cases, one of the most common techniques, if not the most popular, is the portfolio diversification.

On the other hand, when this question is raised into a corporation and among the board of directors, the answer is not so plain. As mentions by Stulz (1984), shareholders do not have the ability to decide which hedging policy the corporation will follow. Responsible for such decision are the managers of the firm. In other words, the manager of a firm should be able to protect the capital of the corporation as well as the current liquidity status and the firm's reputation. For that reason, a capable manager is the one that will be well-informed and well-educated in order to know the possible threats the corporation may face as well as predict them. This knowledge will allow them to create the optimal hedging policy.

The same paper (Stulz, 1984) raised the impact of hedging cost to the managers' decision. One of the main assumptions is that the manager can implement a hedging strategy costlessly. Under that assumption, shareholders do not interfere to the managers' decisions regarding the hedging strategy. What is important to mention though, is the fact that sometimes a hedging strategy may have a remarkable cost. Although the shareholders are not those who will decide the hedging policy of the corporation, they have the right to forbid and cancel the managers' decision for a costly policy. Such an action, though, it may not have desirable results. Stulz (1984) underlined the fact that the managers may use techniques that will probably be undetectable by the shareholders. If the managers are not allowed to hedge using a straightforward hedging strategy due to the cost and the barriers set by the shareholders, then the most common technique is to reject projects with a positive net present value.

Having that said, hedging policies for unexpected phenomena have discouraging costs and may raise great conflict between managers and shareholders.

Another great question raised regarding hedging policies is in what way an optimal hedging technique will benefit a corporation. In order to be able to answer that question we need to take into consideration the statement Mello and Parsons (2000) underlined regarding the Futures. Among all hedging choices, Futures often provide the most liquid and convenient instruments for managing risk. A disadvantage though is the fact that we cannot simultaneously hedge cash flows since future contracts are marked to market. The liquidity aspect of the futures is what makes them more desirable. The reason to that is the fact that the optimal hedging policy of a corporation is the one that maximizes the firm’s liquidity in the form of excess cash and/or unused debt capacity. The benefit of such situation is that it minimizes the potential risk of financial distress.

The importance of liquidity is not so superficial. A corporation that can ensure its liquidity status can certify its credibility. More specifically, one of the main factors taken into consideration by credit rating agencies is the liquidity of a corporation, or government if a country is examined. In other words, liquidity may affect the credit rating of a corporation and/or government, a criterion commonly used by analysts when examining the trustworthiness and reputations or firms and nations. A speculative credit rating is discouraging for investors as well as for lenders. In other words, the credit rating of a country or corporation is one of the most common rates that mirror potential risk the investor is about to perceive by investing on this specific bond or stock.

Another aspect that may influence investors’ decisions is a recorder reduction of production. Reduced productivity may affect investors' perceptions causing fluctuations in the share price or even volatility in its broad of directors. If we consider in our analysis the case of unexpected disasters, both natural and technological, then we must underline the aftermath of such events. During such an occurrence, we encounter both direct and indirect impacts. Smith (1996) recorded as direct impacts the fatalities caused by the disaster, the injured citizens and as well as the loss of properties. However, those direct impact tend to cause indirect ones. The increased number of injured citizens lead to an increase of excess need of paramedic sources, leading to an increase of the governments' health expenditures. The most recent case of unexpected natural environmental hazard that underlines all the negative impacts is the COVID-19 pandemic. What is important to mention is that all the pandemic are included on the natural biological environmental hazards under the category of epidemics. A great number of researchers have investigated and discussed the consequences of that unexpected phenomenon both to the individuals and the economy in general over the last year (Gharehgozli et al. 2020, Martin et al. 2020, Mandel and Veetil 2020, Katafuchi et al. 2020, Kurita and Managi 2020). Property losses, on the other hand can affect both the individuals who eventually become homeless, and the corporations/governments which lose their facilities. Demolished building lead to loss of fixed assets which immediately decreases the productivity and increases the cost of replacement. Although disasters are associated with risk, investors tend to have a different perspective regarding the source of the disaster10.

More specifically, if a country is facing a natural disaster, where no one can be blamed for, foreign investors who may hold this country's bonds will continue to trust the country due to the "innocence" of the country. On the other hand, when a firm causes a technological disaster, such as a nuclear power plant explosion, will probably

[10] A detailed review of terminology regarding disasters and all criteria taking into consideration when characterizing an event as disaster is given in Halkos and Zisiadou (2018a).

have to face adverse effects such as defamation and its consequences. More specifically, a corporation causing an environmental accident may record client losses which will eventually lead to a decrease of liquidity with all the side effects that this may have. At the same time, investors will "punish" the firm by selling its shares at any price to avoid a bigger loss, if this corporation is publicly traded. In such cases, corporations may lose trustworthiness. However, this is not always the case. As it is mentioned by Halkos and Zisiadou (2020), specific corporations which can guarantee their high profitability such as corporations of the oil industry, do not face a negative impact of their share prices, indicating that investors may ignore the environmental disaster due to the fact of the high earnings through dividends.

Regarding the unexpected environmental disasters, another common tool corporation use in order to transfer and reduce risk is the insurance technique. By insuring their assets, the firms transfer to risk of loss to the insurance agency. This policy, however, caused a great concern to the insurance industry. O'Brien (1997) mentioned the disquiet influencing the insurance industry regarding the need of additional capital sources in order to be able to cover the financial risk posed by natural catastrophes. This disquiet meant to be the forerunner of the catastrophe insurance options. The Florida Residential Property and Casualty Joint Underwriting Association in 1995 was negotiating a 1.5-billion-dollar line of credit. A similar alternative was proposed by Samuel Fortunato, a former New Jersey Insurance Commissioner, who offered the approach of Catastrophe Risk Exchange (Catex). Those transactions were characterized by the transfer or exchange of risk among insurers or reinsurers.

Based on the common hedging policies, Chicago Board of Trade in 1992 proposed the Insurance Derivatives which were basically, catastrophe insurance futures and options. However, catastrophe insurance futures did not appear to gain interest among insurers and their trading stopped in 1995. Catastrophe insurance options, on the other hand, appeared to be more successful due to their similarity with the protection afforded by reinsurance layers. The fact that the premium estimated was based on the most recent statutory annual statement filed by the reporting companies led the insurance industry to not fully accept those options as a hedging tool. For hat reason, in 1995 the Chicago Board of Trade introduced the PCS Options, which are index options having as a measuring the amount of catastrophe claims in the region and the period of the contract.

The PCS Options have 3 main advantages over the reinsurance policy. Firstly, the options provide a standardize contract that has no negotiation with a reinsurer. Secondly, they have a rapid execution. Last but not least, the insurer has the ability to adjust the hedge throughout the contract period in response to claims experience. On the other hand, their biggest disadvantage is their effectiveness compared to the reinsurance. If the estimate of the relative claims ratio is far from the actual outcome, the pcs could be either quite pleasant or unpleasant based on the direction of the discrepancy. Another drawback is the fact that there is no generally accepted approach for the options price determination.

Although a great discussion is taking place throughout the years regarding corporations and insurance industries against the catastrophes, it is important to mention that catastrophes, both natural and technological, heavily affect the countries either on regional or national level. An interesting difference is lying between the developed and developing countries. By using a line from Smith's (1996) book, we can emphasize that difference. As Smith (1996) mentioned "…poor lose their lives and rich lose their money". And that difference, between developed and developing countries is also underlined by Freeman (2001), who made a distinction on the way those groups of countries cope with the catastrophes.

More specifically, based on Freeman (2001), World Bank as well as other International Financial Institutions encountered two financial issues occurred by natural catastrophes. On the one hand, there is the increasing demand from developing countries for financial support after a natural hazard occurrence and on the other hand, there are the non-increasing limited budgets against the demanding financial support. In an attempt to cope with that financial issue, the institution have considered the catastrophe hedges as a possible tool to provide post-disaster reconstruction financial relief to the developing countries. Additionally, as Pollner (2001) mentioned through the years World Bank and other financial institution have sponsored research attempts which investigated the role of private market to the post-disaster financing.

The option o hedging may have been proposed as a possible tool to the developing countries but as Freeman (2001) emphasized, it is important to understand if there is any benefit for a developing, or poor as it is mention, country to place its limited economic resourced to hedge against a catastrophe. The answer to that dilemma is based on a cost benefit analysis. In other words, if the cost of hedging is greater that the cost of the potential disaster, the hedging policy is rejected, and the country will bear the economic negative impact that the catastrophe will bring. Similarly, if the cost of the catastrophe is greater compared to the hedging strategy, then the hedging strategy is preferable. As it is also mentioned, if the government fails to provide risk shifting opportunities, all the disaster-related cost is bared to the victims.

Regarding the developed countries, as Freeman (2001) mentioned, natural catastrophe derivates appeared to be one of the most important innovations in the field of catastrophe risk management. Risk shifting for catastrophe losses was occurred through insurance and as it is widely proved that technique appears to be efficient when a large number of independent risks is combined. As Hodgson (1997) mentioned, under the law of large numbers, the probability of each measured event of a given type tends to approach the mean probability of all aggregated events. However, is it crucial to mention that natural catastrophes, or at least events, are not independent. There is proven to be a connection between two or more, either natural or technological, disasters. A well-known example of such a combined disaster is the Fukushima Daiichi Nuclear Power Plant disaster occurred in 2011 as described by Halkos and Zisiadou (2020). An earthquake occurred in the ocean, created a tsunami that caused a flood which eventually led to the shutdown of the reactor of the power plant. This is a strong example establishing the correlation between the catastrophes, which is against the law of the large numbers.

The catastrophe-linked derivates were also discussed by Freeman (2001) emphasizing the benefit of unlimited capacity that the capital market provides to those tools, compared to the limited capacity the path of insurance. Doherty (1997) underlined the advantage of the catastrophe-derivatives having a competitive price in the long term compared to the traditional methods, however, history proved that these derivatives were not preferable.

4.2 **Catastrophe Risk Management and Preparedness**

The insurance industry was globally challenged by the catastrophe risk. Insurers were evaluating the financial coverage of losses based on the statistically measurable and predictable distribution of events (Pollner, 2001). Moreover, as Pollner (2001) mentioned, catastrophic events are less frequent while causing a large number of potential losses. Catastrophe events, both natural and technological hazards, are characterized as unexpected processes in terms of occurrence. And this statement is actual up to a point. The scientists may not be able to predict with a high level of accuracy the place where the next unexpected event will occur or the exact magnitude this event will have, however, specific techniques which can illustrate the high-risk areas of each random event do exist. Using techniques which are based on frequencies may let us conclude to assumptions that can be used as a priori information. The first requirement, based on Pollner (2001) is to set meaningful and workable risk criteria.

Although there is a perception that natural phenomena are unexpected and occur randomly, there is evidence to suggest that, partially, the assertion of randomness is not valid. More specifically, there is a proven regional distribution regarding the geophysical events, initially mentioned by Bolt (1988) as the "Ring of Fire". In other words, although the exact place and time of an upcoming catastrophe cannot be predicted, based on evidence, we know a priori, which regions are more prone to face another disaster. This information may influence the manageable part of the risk. Based on Pollner (2001), there is a great potential for structural risk reduction based on the knowledge of the hazard prone areas. The term of structural indicated the use of building codes as well as appropriate construction materials as established by scientists. Another proposal for such cases is the extended use of protective devices when this is applicable. Apart from the structural category, there is also the non-structural category that includes features that can not be changes such as hazard-prone areas, which however if they are identified correctly can be least used, if not avoided at all.

Due to the possibility of a new catastrophe, governments and corporations should pay more attention to those high-risk areas as an attempt to reduce possible losses (Viscusi, 2006). Taking into consideration all the a priori information, and the What is interesting though is that, although we were expecting a space concentration regarding natural events, the assertion of regional distribution is also observed in the case of industrial hazards. As it has already been mentioned, one of the most important advantages a priori information can give is the ability to create better and well-structured preparedness plans. Both corporations and governments should be able to minimize the potential risk they are facing. For the risk that cannot be reduced, they should be able to handle of the direct and indirect losses that will eventually occur.

Countries which are located to specific hazard-prone areas should evaluate their building codes while at the same time examine the existing building, both private and public, in an attempt to repair any construction failure in advance. Alongside with the technical measures, the governments should inform and educate their citizens on how to react when a hazard occurs and what they should do after the occurrence. In that way, the citizens will know what they will face, and this condition will help them reduce the uncertainty and any poor risk management as individuals. This will not only increase the safety of the public during a disaster but also the trustworthiness the citizens will have for the government.

Section 5

5. Methodological Review

5.1. Proposed Methodologies

Event study analysis is the most commonly used methodology in investigating unexpected events (Eckbo et al., 1990; De Jong et al., 1992; Cowan and Sergeant, 1996; Prabhala, 1997; Binder, 1998; Maloney and Mulherin, 2003; Chen and Siems, 2004; Gaspar et al., 2005; Karolyi and Martell, 2010; Charles and Darné, 2006; Walker et al., 2006; Ambec and Lanoie, 2008; Arin et al., 2008; Brounrn and Derwall, 2010; Carpentier and Suret, 2015). What differs between these studies is the range of the event window. Some researchers use a 10-days range of the event window trying to examine the immediate and short-term impact (Charles and Darné, 2006). Others prefer a longer range of the event window like Carpentier and Suret (2015) who extended the event window up to a year due to the fact that investors have the power to pressure the management in the long-run so they do not prefer to sell over the night.

Apart from event study analysis already mentioned, Bollerslev (1986) introduced the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which appeared not to be the best approach because the estimated residuals of that model continue to have excess kurtosis as proved by Baillie and Bollerslev (1989) and Teräsvirta (1996). Many researchers have attempted to give an explanation to that problem concluding that GARCH models are not able to apprehend outliers (Balke and Fomby, 1994; Fiorentini and Maravall, 1996). For the outlier detection, Charles and Darné (2006) applied ARIMA models mentioning also two methods commonly used by researchers. The first method is Time Series Regression with ARIMA Noise, Missing Observations and Outliers (TRAMO) used by Franses and Haldrup (1994), Lo and Chan (2000), Tolvi (2001), Charles (2004) and Darné and Diebolt (2004) while Bradley and Jansen (1995) used methods like autoregressive, moving average, ARMA and ARIMA described by Tsay (1988).

Tavares (2004) determined the main factors influencing terrorism. For that reason, he applied a simple linear regression including as explanatory variables all those factors that, based on the researcher, could influence terrorist attacks. In a different manner, Major (2002) proposed the need for more than a probability when analyzing terrorism due to factors like intelligence and intent and used game theory, search theory and specific statistical methods.

Corrado (1989) developed a non-parametric methodology due to non-normality. Cam (2006), Ramiah et al. (2007) and Hallahan et al. (2016) used this methodology. Obviously, something that is unexpected cannot follow the normal distribution. Hamilton and Hamilton (1983) in one of the initial papers using dynamic models, suggested a class of stochastic models in order to prove there are arguments on the terrorism and further impacts. Moving forward, Cauley and Im (1988) exerted the intervention analysis, which is actually an interrupted time series analysis to examine how effective the security measures can be. Based on these, Enders and Sandler (1993) upgraded this approach by adding in the analysis the Vector Autoregressive Models.

Paté-Cornell and Guikema (2002), Frey et al. (2004), Dembek (2005) and Okuyama (2007) introduced various advanced techniques. Paté-Cornell and Guikema (2002) based their analysis on different scenarios. They have used opt system analysis and probabilistic approach. Dembek (2005) also used a similar method with a variety of scenarios. Both of these researches have investigated bioterrorism. Paté-Cornell and Guikema (2002) emphasize that using probabilistic approaches to bioterrorism minimize the expected biases and errors due to limited data availability. On the other hand, Dembek (2005) applied the probable scenarios as an attempt to make future predictions about the biological terrorist attacks.

Moving forward, Frey et al. (2004) initially analyzed the *traditional methods* used in order to calculate the costs of terrorism and then proposed a new method that is not only based on valuation and market. The new method takes into consideration the *life satisfaction* dimension. Specifically, the two traditional methods are the *stated preference* and the *revealed preference methods*. When using the prior method, researchers are usually operating the *contingent valuation method* while for the revealed preference method the commonly used one is the *hedonic market* approach. The new approach (Frey et al., 2004) is, as already mentioned, based on life satisfaction and aims to value the psychological impact on humans and not just the economic and market impacts.

The most advanced methods are those mentioned in Okuyama (2007). This paper analyzes the benefits and drawbacks of each method. The *Input–Output* (I/O) *method* is the most commonly used when examining terrorist attacks and natural disasters. Similarly, with *Social Accounting Matrices (SAM) method*, I/O aims to provide upper bounds when analyzing the economic impact of the terrorist attacks and natural disasters. In contrast with I/O, *Computable General Equilibrium (CGE)* is non-linear model that can estimate a long-term equilibrium; however, it is a method generally underestimating the economic impact of these events. General *Econometric Models* may provide stochastic estimates as well as the ability to make future forecast but the main drawback is the fact that a massive dataset is required in order to have accurate estimations.

Based on Okuyama (2007) there are two factors able to influence estimations and even lead to models that are more specific. These two factors are *time* and *geographical* *space.* The time of these events in duration and consequences may range from 30 s to few months, in a worst-case scenario. On the other hand, most – if not all – of economic indices are reported in an annual base. When using a static approach, the estimation cannot capture the significance of the event due to the short time span of that disaster, which usually leads to insignificant total impact estimations in the end. In order to make those models applicable to each case, researchers made some improvements such as adding lags to consider time. Improvements have been made to all models.

The dynamic version of I/O is an approach that includes lags, while *Regional Econometric Input–Output Model (REIM)*is a continuous time formulation. Due to the static factor, CGE approach is not the best choice and a dynamic CGE has also being established. When considering time, last but not least is the *Sequential Interindustry Model (SIM)*, which is used when the economic indices are reported in a quarterly base. By using I/O with the SIM modification, researchers have the ability to determine short-run estimation. The SIM approach is the most appropriate for short-run estimations, however is not flexible enough.

Concerning the geographical space it is expected that any kind of disaster will affect not only the region where the event takes place but probably the whole country or even more (Okuyama, 2007). For that reason, the space dimension should also be taken into consideration and one of the most appropriate solutions is to use the *Spatial Computable General Equilibrium (SCGE)* approach. What is also commonly used is the market efficiency by Fama (1998) and the Fama and French (1993) three-factor model.

5.2. *Methodology and Data*

The process of modelling has never been easy. Of course, it may become even more lax and chaotic if qualitative variables are included in the study, which may not be measurable (such as the investor's psychology, the credibility of a government and the reputation of a business). Of course, with the appropriate econometric methods and the use of specific variables, we can partially integrate the qualitative variables in our models. But one factor that cannot be modelled is randomness. From a theoretical point of view, it is expected that we cannot model and therefore predict the "unexpected" because then it would cease to be a random event.

Randomness and consequently uncertainty are what characterizes markets. However, significant efforts have been made to evaluate models that can determine the expected value of an asset. The most known models are the Market Model, the A.P.T and the C.A.P.M. Regarding the cases where an unexpected event or announcement occurs, the Event study analysis initially proposed by MacKinlay (1997) is the most common method of estimating the abnormality on returns (Prabhala, 1997; Binder, 1998; Maloney and Mulherin, 2003; Gaspar et al., 2005; Karolyi and Martell, 2010; Charles and Darné, 2006; Walker et al., 2006; Arin et al., 2008; Brounrn and Derwall, 2010; Carpentier and Suret, 2015; Halkos et al., 2017).

Of the three approaches mentioned above, the preferred one is C.A.P.M. Most of the financial advisors as well as many of the researchers tend to use this approach in order to estimate the systematic risk of each stock or bond (Strong, 1992; Faff, 1991; Chen, 2003; Womack and Zhang, 2003; Fernandez, 2006; Bruner et al. 2008; Adrian and Franzoni, 2009). The A.P.T, on the other hand is an alternative approach for estimating systematic risk, which compared to the C.A.P.M approach, includes more information regarding the macroeconomic conditions (Roll and Ross, 1980; Connor and Korajczyk 1986).

By estimating the systematic risk, we can therefore predict the expected returns of the asset we examine, as well as the abnormal return using the actual value of the return. When an unexpected event occurs, the question raised is whether those abnormal returns tend to be significant, showing the reaction, either positive or negative, of the investors. This is the main path that we are going to follow in this paper.

5.2.1. Hypotheses and Data

Carter and Simkins (2004) decided to investigate airline stocks after the terrorist attacks on 11 September 2001. Their findings provide information regarding the USA capital market and the returns of airline corporations. They found that after the attack, statistically significant negative abnormal returns were observed for the examined airlines. Based on that outcome, we intend to observe if the under-investigation assets follow the same path. Another significant finding by Carter and Simkins (2004) is that the results indicated a rapid drop of stock prices which led to a shock of the USA capital markets. Based on that finding, we seek to examine whether an unexpected disaster can have a similar impact on the government's bond price or the share price of a corporation[11].

Moving forward, the psychological impact of an unexpected event, which in Carter and Simkins' case (2004) is the September 11th attack, may trigger the rationality that characterizes investors and leads them to react immediately causing pricing volatility. However, it is proven by evidence that larger airline corporations took advantage of that event, while smaller airline corporations did not have that

[11] It refers to the industrial disasters, which may have been caused by anthropogenic factors.

opportunity. On the same path, we shall observe if such a condition is feasible at a country level. Finally, Carter and Simkins (2004) investigated the impact of corporations' size to market reaction giving us the priming to include countries' economic status and its impact on the investors' psychology.

The first step of our analysis is to put the underlying assumptions to determine both the course of the analysis and the time interval and the variables to be used. The main hypotheses that will be examined in this paper are listed below:

H_A: The unexpected events are not space concentrated.

H_B: The Most Developed Countries face greater economic losses; the Least Developed Countries face greater fatalities.

H_C: There is no significant abnormal return after an unexpected event.

H_D: The systematic risk of an asset remains unaffected by an unexpected event.

H_E: Macroeconomic factors of the country suffering from an unexpected event cannot influence the investors' psychology and decisions.

H_F: Religious targets for terrorist attacks do not exist.

For examining the above hypotheses, both financial and macroeconomic data are used. Regarding financial data, it is important to mention that daily stock and bond prices have been derived from open-source databases12 with a time-span of 125 days before the occurrence of the event as well as three days after the occurrence of the event to capture the possible return abnormality. When the event of analysis belongs to a

[12] The source of data is the website Investing.com: www.investing.com (accessed on 01 October 2018). We are familiar with that fact that this database is not the most accurate source due to the fact that provides data for delisted stocks nor it is adjusted for splits and dividends; however, to our knowledge, it is the only open source which provides the majority of the needed information. Sources such as Bloomberg and/or Thomson Reuters DataStream are preferable, however, no access was granted. The non-inclusion of dividend yield and/or stock spilt event certainly has an impact on our estimations. These non-adjustments may cause under/overestimation of the systematic risk. Further research would preferably include a more detailed data source which will give us the ability to include those adjustments in our estimations.

natural disaster, the asset of examination is the country's government bond, while the market index used is the corresponding Government Bond Index. In order to collect the bond data, we searched for data related to the government bond with longer time-to-maturity of each country facing a disaster. However, in some cases, the longer time-to-maturity bond had stable (same) bond price values, which would have given us bond returns equal to zero. In those cases, the exact previous bond was selected and included in our analysis. Restrictions regarding the open source data, possible exclusion of events due to lack of data, and the unavailability of dividend yields and/or stock splits have undoubtedly affected our final estimations. When the event of analysis belongs to a technological disaster, the asset of examination is the corporation's stock price, while the market index used is the corresponding market index which the corporation is listed in.

Concerning the risk-free asset that is necessary for the CAPM approach, the assumption of Barro and Misra (2016) was used; they underlined that gold can be considered as a risk-free asset since it cannot be used as a hedge against macroeconomic declines and its expected real rate of return should be close to risk-free. As already mentioned, some events have been excluded from the analysis due to lack of information, mainly because corporations are not publicly listed, or due to overlapping cases, where the examination window of one event overlaps with the estimation window of another in the same country. Using this open-source database, confronts us with the main limitation of the research, in terms of time span. This is the main reason we chose na-tech disasters which occurred since 2000. For the macroeconomic factors' variables, the reliable and recognized database of the World Bank13 was used.

[13] Source of data is the website of the World Bank: https://data.worldbank.org (accessed on 5 October 2018).

5.2.2. Frequencies and Mapping Visualizations

Although the modelling process is the most crucial part of a research, a critical step that we should not ignore is the one that gives the initial picture of the data we are analysing. Different types of measures tend to be used in this step such as descriptive statistics and frequencies. A not so common process is the mapping visualization of the data included in a research. This is a pioneer method that will be used also included in this dissertation. The maps will be created with the use of R studio routines.[14]

5.2.3. Events Study Analysis using C.A.P.M

The most widespread method for analysis of the market reactions is the event study analysis as described by MacKinlay (1997). The initial step for the following analysis is to set the estimation and the event windows. As an event window, we used a seven-day period (−3, +3) centered to the event day15 and including three days before and three days after the event, in an attempt to capture market reaction to the disaster. This event window will be used to estimate the expected return of the asset as well as the possible abnormality. As an estimation window, we used a 120-day period (−124, −4), which should not include the days of the event window. By establishing a wider estimation window, compared to the time span proposed by MacKinlay (1997), we estimated the systematic risk before the occurrence of the event with higher accuracy. This approach allowed us to predict more precisely the expected returns of the assets

[14] The R-routines are available after request.

[15] Many events occurred over multiple days. However, we consider the first day of the event as day zero due to the fact that at this moment the event was recognized as unexpected, while the aftershocks on the following days are assumed to be expected. Moreover, due to the time span of the 70-day ex-ante analysis, we included the possible reaction due to the multiple day occurrences that followed the first day of the events.

on the seven-day event window and these expected returns provided more accurate abnormal returns. After calculating systematic risk, we moved forward to the event window to approach abnormal returns.

The final step was to compute the cumulative abnormal return (CAR) which was examined for its significance. Moreover, as an extension of the proposed methodology, we decided to examine the abnormal returns of the seven-day event window for all 25 events and how they were influenced by macroeconomic factors. The initial methodology proposed by MacKinlay (1997) examined the cumulative abnormal returns using cross-sectional data analysis. However, we decided to observe separately all abnormal returns instead of their aggregations. The other extension included in the analysis was the inclusion of a dummy variable receiving the value 1 for the day of the event occurrence and the three-day span after the occurrence, and zero otherwise. The products (XjD) will shed more light on the post event reaction.

Specifically, as the abnormal return (AR) we set the actual ex post return of the security over the event window after extracting the normal return of security over the same period. The normal return equals to the expected return without occurrence of the unexpected event. For each case i and during period t the abnormal return is given by (1), where ARit, RAit, E(RAit|Xt), RMit, RFit, and e_{it} stand for abnormal, actual, normal returns, return of market and risk-free assets and residuals, respectively during the period t and Xt refers to the conditioning information (MacKinlay 1997):

$$CAR_t = \sum_{t=-3}^{3} AR_t \qquad (1)$$

For each case i and during period t the abnormal return is given by (2), where AR_{it}, RA_{it}, $E(RA_{it}|X_t)$, R_{Mit}, R_{Fit} and e_{it} stand for abnormal, actual, normal returns, return of market and risk-free assets and residuals respectively during the period t (MacKinlay, 1997):

$$AR_{it} = e_{it} = RA_{it} - E(RA_{it}|X_t) \qquad (2)$$

Based on CAPM specification, systematic risk known as β_i, is defined as the covariance of RA_{it} with R_{Mit} over some estimation period (Cov[RAit, R_{Mit}] divided by the variance of R_{Mit} over the same period (Var[R_{Mit}]) (Jagannathan and Wang. 1993; Armitage, 1995).

$$E[RA_{it}] = R_{F_{it}} + \beta_i [E(R_{M\,it}) - R_{F_{it}}] + \varepsilon_{it} \tag{3}$$

$$E(\varepsilon_{it}) = 0 \qquad Var(\varepsilon_{it}) = \sigma^2_{\varepsilon_{it}}$$

with ε_{it} the disturbance term with the usual properties.

Using matrix algebra, expression (3) can be expressed as a regression system,

$$RA_i = X_i \beta_i + \varepsilon_i \tag{4}$$

where RA_i=[RA_{it-3}……RA_{it+3}]′ is a (L_1×1) vector of event-window returns, X_i=[R_{Mit-3}….R_{Mit+3}] is a (L_1×2) matrix of market return observations, and β_i=[β_i]′ is the (1×1) parameter vector. The OLS estimators of CAPM parameter using an estimation window L_1 observations are

$$b_i = (X_i' X_i)^{-1} X_i' RA_i \tag{5}$$

$$\hat{\sigma}^2_{\varepsilon_i} = \frac{1}{L_1 - 2} e_t' e_t \tag{6}$$

$$e_t = RA_i - X_i b_i \tag{7}$$

$$Var(b_i) = (X_i' X_i)^{-1} \sigma^2_{\varepsilon_i} \tag{8}$$

Provisional on market return over the event window, abnormal returns will be distributed normally with zero conditional mean and matrix V_i as shown in (9) and (10) below.

$$E(e_i^* \big| X_i^*) = E[RA_i^* - X_i^* b_i \big| X_i^*] = E[(RA_i^* - X_i^* b_i) - X_i^*(b_i - \beta_i) \big| X_i^*] = 0 \tag{9}$$

$$\begin{aligned} V_i &= E(e_i^* e_i'^{*'} \big| X_i^*) = E\big([\varepsilon_i^* - X_i^*(b_i - \beta_i)\big)][\varepsilon_i^* - \varepsilon_i^*(b_i - \beta_i)]' \big| \mathrm{X}_t^* = \\ &= E[\varepsilon_i^* \varepsilon_i^{*'} - \varepsilon_i^*(b_i - \beta_i)' X_i^* - X_i^*(b_i - \beta_i)\varepsilon_i^{*'}] + X_i^*(b_i - \beta_i)(b_i - \beta_i)' X_i^* \big| X_i^*] = \\ &= I\sigma^2_{\varepsilon_i} + X_i^*(X_i' X_i)^{-1} X_i^{*'} \sigma^2_{\varepsilon_i} \end{aligned} \tag{10}$$

where I is the identical matrix.

Under the null hypothesis (H_0) of event study analysis that the event occurred has no impact on the mean and variance of returns, we can use (9) and (10) and the joint normality of abnormal returns to draw inferences. Under H_0 for the vector of event-window sample abnormal returns we have

$$e_i^* \sim N(0, V_i) \tag{11}$$

This last expression (11) gives us the distribution for any single abnormal return observation. We next build on this result and consider aggregation of abnormal returns as shown in (1) (Campbell et al. 1997).

What is important to mention though, is that, to the best of our knowledge, similar papers examining market reactions using event study analysis, do not examine the model specification for the OLS hypotheses violations regarding time series analysis. In other words, and since we are dealing with time series data, it is crucial to evaluate our estimation outputs for autocorrelation and autoregressive conditional heteroskedasticity (ARCH) effect possible problems, and if any assumption is violated, to correct the model before forecasting. There is no need for specification error diagnostics since we are using an established model.

5.2.4. *Event Study Analysis using APT*

The A.P.T estimation has many similarities with the C.A.P.M estimation. More specifically, the initial procedure (eq. 01 and eq.02) mentioned above remain the same. The change occurs on eq. 03, where apart from the Returns of Assets and the Returns of the Market, we should include some macroeconomic factors. The most common macroeconomic factors used in the A.P.T approach are the inflation, the gross national product, the GDP. However, what happens in our case is that the returns are reported on a daily base, while the macroeconomic factors are reported in an annual base.

That makes the independent variables, also mentioned macroeconomic variables, to have a repetitive value through all the estimation window period. In other words, the macroeconomic factors will have the same value for 120 days. Such an estimation is impossible due to near singular matrices. Other proposes is to include prices of commodities and exchange rates in the RHS of the estimation. Having in mind that we use the price of gold as risk free asset, the independent variables we will include in order to establish our model will be the price of crude oil as well as exchange rates.

The exchange rates that will be used in our model specification are based on the five most common currencies (USD, Euro, British Pound, Swiss Franc and Japanese Yen). More specifically, in each case we will include the country's exchange rate to those five currencies as well as the price of crude oil. If the country of the event uses as national currency one of these five, this exchange rate will be excluded because its value will equal to 1.

$$E[RA_{it}] = R_{F_{it}} - \beta_i\left[E\left(R_{M_{it}}\right) - R_{F_{it}}\right] + \beta_i \sum_{i=1}^{5} \Delta\left(\frac{Currency_{c_{it}}}{Currency_{it}}\right) + \beta_i Crude_{oil_{it}} + e_{it} \qquad eq. 12$$

where Currency_C stands for the currency of the country facing the unexpected events, Currency stands for the five most common currencies mentioned above and Cr_Oil stands for Crude oil prices.

Using matrix algebra, equation 12 can be expressed as a regression system,

$$RA_i = X_i\theta_i + e_i \qquad eq. 13$$

where RA_i= $[RA_{it-3}......RA_{it+3}]'$ is a (L_1×1) vector of estimation-window returns, Xi=[RM Currencies Crude_oil] is a (L_1×7) matrix of market return observations, the currency exchanges and the price of the crude oil, and θi=[θi]′ is the (7×1) parameter vector. The OLS estimators of the Arbitrage Pricing Theory parameters using an estimation window L_1 observations is

$$\widehat{\theta_i} = (X_i'X_i)^{-1}X_iRA_i \qquad eq. 14$$

$$\widehat{\sigma_{e_i}^2} = \frac{1}{L_1 - 2}\widehat{e_i}'\widehat{e_i} \qquad eq. 15$$

$$\widehat{e_i} = RA_i - X_i\widehat{\theta_i} \qquad eq. 16$$

$$Var\left[\widehat{\theta_i}\right] = (X_i'X_i)^{-1}\sigma_{e_i}^2 \qquad eq. 17$$

Conditional on the market return over the estimation window, the abnormal returns will be jointly normally distributed with a zero conditional mean and conditional matrix V_i as shown in eq. 16 and eq.17 respectively.

$$
\begin{aligned}
E[\widehat{e_i^*}|X_i^*] &= E\left[RA_i^* - X_i^*\widehat{\beta_\iota}\middle|X_i^*\right] \\
&= E\left[(RA_i^* - X_i^*\theta_i) - X_i^*\left(\widehat{\theta_\iota} - \theta_i\right)\middle|X_i^*\right] \\
&= 0 \qquad\qquad eq. 18
\end{aligned}
$$

$$
\begin{aligned}
V_i &= E\left[\widehat{e_i^*}\widehat{e_i^*}'\middle|X_i^*\right] \\
&= E\left[\left[e_i^* - X_i^*\left(\widehat{\theta_\iota} - \theta_i\right)\right]\left[e_i^* - e_i^*\left(\widehat{\theta_\iota} - \theta_i\right)\right]'\middle|X_i^*\right] \\
&= E\left[e_i^*e_i^{*\prime} - e_i^*\left(\widehat{\theta_\iota} - \theta_i\right)'X_i^{*\prime} - X_i^*\left(\widehat{\theta_\iota} - \theta_i\right)e_i^{*\prime}\right] + X_i^*\left(\widehat{\theta_\iota} - \theta_i\right)\left(\widehat{\theta_\iota} - \theta_i\right)'X_i^{*\prime}|X_i^*
\end{aligned}
$$

$$
\begin{aligned}
&= I\sigma_{e_i}^2 \\
&+ X_i^*(X_i{}'X_i)^{-1}X_i^{*\prime\sigma_{e_i}^2} \qquad\qquad eq. 19
\end{aligned}
$$

Under the null hypothesis (H_0) of the event study analysis that the event occurred has no impact on the mean and variance of the returns, we can use eq. 18 and eq. 19 and the joint normality of the abnormal returns to draw inferences. Under H_0 for the vector of event-window sample abnormal returns we have

$$\widehat{e_i^*} \sim N(0, V_i) \qquad\qquad eq. 20$$

Equation 20 gives us the distribution for any single abnormal return observation. We next build on this result and consider the aggregation of abnormal returns as shown in eq. 1 (Campbell et al. 1997).

All the previous analysis assumes the non-violation of the OLS assumption. What is important to mention though, is that, to the best of our knowledge, similar papers examining the market reactions using the event study analysis, do not examine the model specification for the OLS violations regarding the time series analysis. In other words, and since we are dealing with time series data, it is crucial to evaluate our estimation outputs for a number of issues. Initially, we should check our variable for non-stationarity. For that purpose, we are going to use the Augmented Dickey Fuller Diagnostic Test. If all variables are stationary, we will continue with the estimation, otherwise stationary should be reached.

Moving forward to the next possible violation, we should diagnose the residuals of the estimation for autocorrelation by using the Breusch-Godfrey lm test and for ARCH effect issues by using the ARCH lm test. and if any assumption is violated, correct the model using Durbin two step model or ARCH estimations respectively before the forecasting procedure. For the case of ARCH estimations, if it occurs, we will examine all possible specifications (ARCH, GARCH, IGARCH, TGARCH, EGARCH and PARCH) and the best estimation will be indicated by the Akaike Information Criterion Criterion (AIC) as it is shown in equation 21 (Gujarati, 2003, p. 537), where k indicates the number of regressors including the intercept if exists, and n indicated the number of observations. However, for mathematical convenience eq. 21 is written as is it shown in eq. 22.

$$AIC = e^{2k/n}\frac{\sum \widehat{u_i^2}}{n} = e^{2k/n}\frac{RSS}{n} \qquad eq. 21$$

$$lnAIC = \left(\frac{2k}{n}\right) + \ln\left(\frac{RSS}{n}\right) \qquad eq. 22$$

For the C.A.P.M specification, there is no need for specification error diagnostics since we are using a reliable model. Moreover, since the C.A.P.M ends to a two-variable model, there is also no need for multicollinearity testing. However, for the APT model, both specification error and multicollinearity violations should be tested. For the specification error we will use the Ramsey RESET test under the null hypothesis H_0 that there is no specification error, while for the multicollinearity, the test that will be used is the Variance Inflation Factor (VIF) (Halkos, 2011).

ARCH specification

A great variety of parametric specifications for the time varying conditional variance have been proposed in the literature. The linear ARCH(q) specification was originally introduced by Engle (1982) as

$$\sigma_t^2 = \omega + \sum_{i=1,q} \alpha_i \varepsilon_{t-1}^2 \equiv \omega + \alpha(L)\varepsilon_{t-1}^2 \qquad eq.23$$

where L denotes the lag operator, $L_{y_t}^i \equiv y_{t-i}$.

GARCH specification

An extension of the ARCH specification was created in order to solve the issue of the long lag length and the large number of parameters. Bollerslev (1986) proposed the generalized ARCH (GARCH) model in an attempt to solve the existing problem. The GARCH model is written as

$$\sigma_t^2 = \omega + \sum_{i=1,q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1,p} \beta_j \sigma_{t-j}^2 \equiv \omega + \alpha(L)\varepsilon_{t-1}^2 + \beta(L)\sigma_{t-1}^2 \qquad eq.24$$

IGARCH specification

As Ali (2013) mentioned, GARCH models apply both an autoregressive and moving average structure to the variance, σ^2. The integrated GARCH (IGARCH) is specified as

$$\varepsilon_t = \sigma_t z_t;\ \sigma_t^2 = \omega + \sum_{i=1,q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1,p} \beta_j \sigma_{t-j}^2 \qquad eq. 25$$

TGARCH specification

In order to allow the inclusion of non-linear oscillatory behavior in volatility, Rabemananjara and Zakoian (1993) relaxed the non-negativity constraints. The σ_t variable does no longer define the typical conditional standard deviation due to the fact that it is allowed to be negative. As a result, it appears to be normal to include a threshold effect in the past values of volatility. Thus, the general TGARCH model has been created as

$$\varepsilon_t = \sigma_t Z_t$$

$$\sigma_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i^+ \varepsilon_{t-i}^+ - \alpha_i^- \varepsilon_{t-i}^- + \sum_{j=1}^{p} \alpha_j^+ \sigma_{t-j}^+ - \alpha_j^- \sigma_{t-j}^- \qquad eq. 26$$

$$(Z_t) i.i.d, \qquad E(Z_t) = 0, \quad var(Z_t) = 1, \quad Z_t\ independent\ of\ (\varepsilon_{t-1})$$

EGARCH specification

As Bollerslev et al (1994), the GARCH models are able to capture the thick tailed returns and volatility, however, they are not capable to adopt the leverage effects. This led to the creation of the exponential version of such a specification by Nelson (1991), known as exponential GARCH (EGARCH), where σ^2_t depends on both the size and the sign of lagged residuals and is written as

$$\ln(\sigma_t^2) = \omega + \left(1 + \sum_{i=1,q} \alpha_i L^i\right)\left(1 - \sum_{j=1,p} \beta_j L^j\right)^{-1} \{\theta z_{t-1} + \gamma[|z_{t-1}| - E|z_{t-1}|]\} \quad eq. 27$$

APARCH specification

Last but not least, it is important to take into consideration the fact that sometimes time series may follow linearity, and a possible example of that is the exponential GARCH. However, some other cases may need asymmetric approaches. For that reason, Ding et al. (1993), introduced the general asymmetric power ARCH specification which indicated the variance as

$$\sigma_t^d = \alpha_0 + \alpha_1(|\varepsilon_{t-1}| + \gamma_1 \varepsilon_{t-1})^d + \beta_1 \sigma_{t-1}^d \qquad eq. 28$$

When the value of β1 equals to zero then the model is called APARCH, and APGARCH otherwise.

Regarding the diagnostic tests, we will test our estimation outputs for all violations mentioned above, however, due to the fact that we now have a multiple regression, we will examine the results for Specification errors by using the Ramsey RESET test and for multicollinearity by using the VIF test, and if any assumption violation occurs we will correct it using the proposed techniques (Halkos, 2011).

5.2.5. Ex-ante and Ex-post Systematic Risk Comparison

Moving forward, we will re-examine our events under a second hypothesis, that is related to the comparison of systematic risk before and after the event. This approach has one similarity with the event study analysis regarding the estimation window, however the contrast comes to the period after the event. Firstly, we will set the pre-event estimation window which in this case will have a time span of 70-days. The pre-event estimation window will begin just the day before the event [-70, -1].

The next step will be to create the post-event estimation window using the same technique and setting the time span to [+1, +70]. Day 0 is the day of the disaster occurrence and it has been excluded from both estimation windows. Once again, all appropriate diagnostic tests are taken into consideration. This procedure provides us with different systematic risks (betas) before and after the occurrence which we assume will provide us useful information regarding investors' perspectives.

5.2.6. Pooled Panel Regressions

In an attempt to understand investors' possible reaction after an unexpected hazard, we tried to investigate the causes or factors that may influence this possible abnormality. Thus, the final part of the analysis evaluated all results of possible abnormal returns and combined them with macroeconomic factors. The main idea was to observe if there are specific macroeconomic factors that may influence investors to react positively or negatively to the asset price after the event. The idea behind the macroeconomic factors derives from the credit rating methodology, which uses fundamental variables of each economy to rate its creditability and reliability. As already mentioned, credit rating is one of the main elements investors use to diversify their portfolios. Consequently, the question raised is "Does the economic status of a country affect the final decision?"

For that purpose and due to small panel data with even within country differentiations, pooled OLS regressions specifications were used of the form

$$Y_{it} = \alpha_0 + \alpha_1 X_{1it} + ... + \alpha_k X_{kit} + \beta_1 X_{1it} D_{1t} + ... + \beta_k X_{kit} D_{kt} + u_{it} \tag{29}$$

where Yit, Xit, Di, and uit are the dependent variable, independent variables, dummy, and disturbance term (with the usual properties), respectively. As dependent variable, we set the abnormal returns that occurred after an unexpected event. For the calculation of the abnormal returns we used the beta estimations computed using a 120-day estimation window. These betas were then used for a seven-day forecast, in which the abnormality was then estimated. In other words, each case of examination included abnormal returns of seven days. The whole dataset used for the estimation has 175 observations (25 events × 7 days abnormal returns). Although the number of observations per event are equal among all events, the period of the occurrence differs, meaning that each event occurred in a separate historical moment, making dynamic cross-sectional panel estimations a non-appropriate approach of estimation.

Section 6

6. Results and Discussion

This Section presents all the results of our analysis in an attempt to give answers to the research questions we raised by either accepting or rejection the hypotheses mentioned in Section 5. Before we start examining all types of events separately, it is helpful to have a general overview of the cases we examine. Table 1 displays all events that have been recorded. As we can see, over the last 117 year (1900-2016), 18,553 natural environmental hazards have occurred with almost 33 million fatalities, over 8 billion affected citizens and a total of almost 3 trillion USD economic damages. The most often category of natural hazards is the biological, while the most disastrous regarding the economic damage is the meteorological hazards.

Moving forward to the technological hazards, over the last 117 years (1900-2016), 8,310 events occurred with transport being the most often. Industrial hazards though are those which caused the most fatalities as well as the most economic damages. Complex hazards are the least often category of environmental hazards. Although a lot of people were affected, there is no economic damage.

Table 1: Total Values of Events and their Impacts

	Occurrence	Deaths	Injured	Affected	Homeless	Total Affected	Economic Damage ('000$)
Biological	*6,011*	*11,040,941*	*1,313,247*	*553,680,241*	*9,371,132*	*564,364,620*	*32,187,389*
Climatological	*1,122*	*10,535,271*	*7,914*	*2,636,212,659*	*255,468*	*2,636,476,041*	*200,671,880*
Geophysical	*1,612*	*2,678,022*	*2,925,533*	*172,798,483*	*23,184,433*	*198,908,449*	*781,558,525*
Hydrological	*5,354*	*7,015,542*	*1,370,944*	*3,562,133,398*	*96,414,272*	*3,659,918,614*	*741,027,652*
Meteorological	*4,453*	*1,577,903*	*3,344,440*	*1,058,160,932*	*53,295,852*	*1,114,801,224*	*1,136,734,132*
Extra-Terrestrial	*1*	*0*	*1,491*	*300,000*	*0*	*301,491*	*33,000*
Natural Hazards	**18,553**	**32,847,679**	**8,963,569**	**7,983,285,713**	**182,521,157**	**8,174,770,439**	**2,892,212,578**
Industrial	*1,434*	*57,619*	*222,359*	*3,246,606*	*595,109*	*4,064,074*	*43,061,040*
Miscellaneous	*1,385*	*67,177*	*77,020*	*2,854,648*	*561,326*	*3,492,994*	*2,630,370*
Transport	*5,491*	*237,000*	*120,046*	*115,065*	*15,550*	*250,661*	*1,147,700*
Technological Hazards	**8,310**	**361,796**	**419,425**	**6,216,319**	**1,171,985**	**7,807,729**	**46,839,110**
Complex	**14**	**5,610,000**	**0**	**19,686,114**	**0**	**19,686,114**	**0**
Terrorist Attacks	**180,799**	**390,187**	**522,921**	**NR**[16]	**NR**	**NR**	**NR**

16 NR: Not Reported

Last but not least, the terrorist attacks appear to be the most often phenomenon. More specifically, in only 48 years (1960-2017) there were 180,799 events which is almost 10 times higher than the natural hazards. The fatalities and the injuries though are lower compared to the environmental hazards. Regarding the economic losses, there was no record on the official database we used.

6.1. Frequencies and Mapping Visualizations

6.1.1. Biological Hazards

As it has already been mentioned we will follow the same flow with the terminology so the first group of hazards that will be analyzed is the biological hazard. Based on Table 2, it is clear enough that the region that has suffered more by the biological hazards if the African Continent. Having in mind all the described subtypes that are included in the biological hazards, we can understand the reason of such a result. Epidemics and Insect Infestation are more prone to occur in Least Developed areas where the access to sanitation and drinking water is not taken for granted. What is also expected is to have increased fatalities, considering the great difference on the number of occurrences.

The African Continent is the most vulnerable on biological hazards and if we take a closer look to Table 2 we can understand that more than 90% of all biological hazards occurred in Africa. More specifically, 5,416 events of the total 6,011 events occurred in African giving us a ratio equal to 90.1%. Based on that score, we have significant evidence to support the acceptance of the hypothesis 1 and suggest that biological hazards are space concentrated events which is also presented in Map 1.

Moving forward, we are trying to either accept or reject the hypothesis concerning the division between Least Developed Countries and Most Developed Countries and the losses they face. However, taking into consideration the fact that more than 90% of the events occurred in Africa, we expect both fatalities and possible economic losses to be gathered on the same continent.

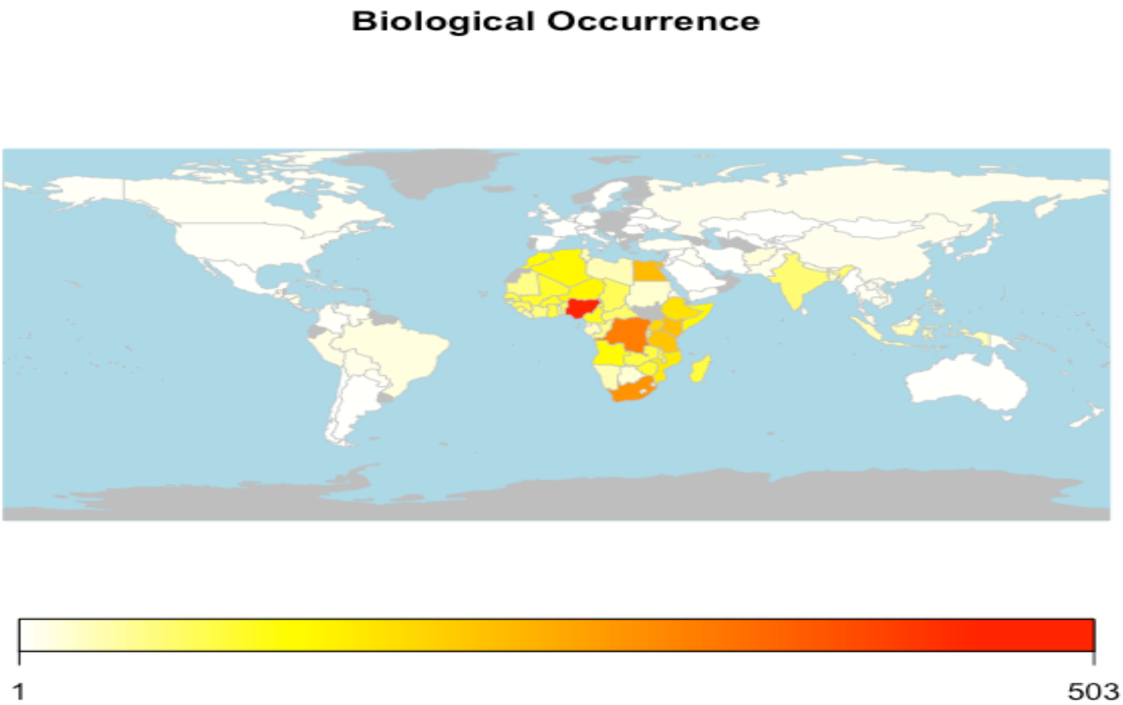
Table 2: Biological Hazards - Regional Results

					Biological			
Continent	**Region**	**Occurrence**	**Deaths (‘000)**	**Injured (‘000)**	**Affected (‘000)**	**Homeless (‘000)**	**Total Affected (‘000)**	**Economic Damage ('000,000$)**
Africa	Eastern Africa	1,777	1,078	168	323,000	3,804	326,972	6,491
Africa	Middle Africa	837	68	28	19,545	694	20,267	140
Africa	Northern Africa	793	238	92	39,801	2,537	42,430	17,213
Africa	Southern Africa	396	10	10	31,619	109	31,738	6,242
Africa	Western Africa	1,613	533	144	108,000	2,227	110,371	1,875
Americas	Caribbean	29	7.5	278	466	0	744	0
Americas	Central America	50	1.5	15	315	0	330	7
Americas	South America	79	15	80	2,750	0	2,830	104
Americas	Northern America	12	51	0	2,416	0	2,416	0
Asia	Central Asia	13	0.3	0.141	26	0	26.1	0
Asia	Eastern Asia	28	1.56	0.185	2,310	0	2,310.1	0
Asia	Southern Asia	167	4,957	0.211	4,210	0	4,210.2	0
Asia	South-Eastern Asia	112	9	124	1,296	0	1,420.1	1
Asia	Western Asia	33	1	2	221	0	223	0
Europe	Eastern Europe	22	2,500	0	18,173	0	18,173	0
Europe	Northern Europe	9	0.073	0	2	0	2	0
Europe	Southern Europe	12	0.047	0	14	0	14	0
Europe	Western Europe	7	0.034	0	1	0	1	0
Oceania	Australia & New Zealand	5	7	0	0.007	0	0.007	120
Oceania	Melanesia	10	0.451	372	13	0	385	0
Oceania	Micronesia	3	0.042	0	4	0	4	0
Oceania	Polynesia	4	0.008	0	3	0	3	0
		6,011	**9,478.481**	**1,268.537**	**554,185.007**	**9,371**	**564,869.507**	**32,193**

As it can be seen in Table 3, the ten countries with the most recorded biological events are located in African Continent. Moreover, the same table presents the fatalities and economic losses per event17 which let us draw more conclusions about the hazards and its effects. Regarding deaths, it is shown that the four countries noting the most deaths are located in Eurasia, and not in Africa as it was expected, giving us the notion that although biological hazards are not that frequent on Eurasia, the times these

[17] The rest columns have been calculated by dividing the aggregated value of each fatality or economic loss to the occurrence in an attempt to estimate the average level of deaths, injuries, affected people, homeless people and economic losses respectively, using as a weight the value of appearance.

occurred led to more deaths compared to the African fatalities (Halkos and Zisiadou 2018). Moving to the most Injured country of biological hazards we are surprised by the extremely high value recorder in Solomon Is18 (Halkos and Zisiadou 2018). Once again, regarding injuries, it is shown that the four countries noting the most deaths are located in Oceania, America and Asia, and not in Africa as it was expected, giving us the notion that although biological hazards are not that frequent on those continents, the times these occurred led to more deaths compared to the African fatalities (Halkos and Zisiadou 2018).



Map 1: Biological Hazards – Occurrence

In contrast to deaths and injuries, the values of homelessness following a biological occurrence goes in line with the occurrence and the expectations these caused to us. In other words, all ten most suffered countries regarding the homelessness are

[18] The average injured people in Solomon Is due to biological hazards equals to 186,000 and to be precise, biological hazards (and more specifically viral disease) occurred once in 2013 and one in 2016 causing none injured and 372,000 injured respectively leading to (372,000/2=186,000) per event.

located in African continent as it is presented by Halkos and Zisiadou (2018). The highest economic losses are also mainly located in African continent if we exclude Australia (place 2) and Colombia (place 6) of the most suffered areas (Halkos and Zisiadou 2018).

Table 3: Biological Hazards - Most suffered areas

	Country Name	Occurrence		Country Name	Total Deaths ('000)		Country Name	Injured ('000)		Country Name	Affected ('000)
1	Nigeria	503	1	Soviet Union	1,250	1	Solomon Is	186	1	Soviet Union	9,000
2	Congo[19]	318	**2**	China	142	**2**	Haiti	40	**2**	Japan	667
3	South Africa	287	**3**	India	66	**3**	Philippines	6	**3**	Eritrea	510
4	Egypt	228	**4**	Bangladesh	13	**4**	Peru	6	**4**	Ethiopia	468
5	Kenya	223	**5**	Canada	7	**5**	Guatemala	2	**5**	Kenya	295
6	Sudan	220	**6**	Cabo Verde	3	**6**	Ghana	0.63	**6**	Malawi	290
7	Tanzania	212	**7**	New Zealand	3	**7**	Tanzania	0.56	**7**	Canada	287
8	Uganda	186	**8**	Ethiopia	2.5	**8**	Liberia	0.52	**8**	South Sudan	218
9	Ethiopia	171	**9**	Uganda	2	**9**	Sierra Leone	0.4	**9**	Mozambique	209
10	Mozambique	155	**10**	Niger	2	**10**	Iraq	0.3	**10**	Niger	201

	Country Name	Homeless ('000)		Country Name	Total Affected[20] ('000)		Country Name	Total Damage ('000$)
1	Madagascar	12	**1**	Soviet Union	9,000	**1**	Algeria	92,079
2	Algeria	7	**2**	Japan	667	**2**	Australia	40,000
3	Sudan	7	**3**	Eritrea	511	**3**	Mauritius	30,822
4	Benin	5	**4**	Ethiopia	469	**4**	Madagascar	24,488
5	Mozambique	4	**5**	Kenya	295	**5**	South Africa	20,898
6	Malawi	4	**6**	Malawi	294	**6**	Colombia	20,800
7	Somalia	4	**7**	Canada	287	**7**	Reunion Is	15,875
8	Ghana	2	**8**	South Sudan	218	**8**	Morocco	15,782
9	Uganda	2	**9**	Mozambique	213	**9**	Tunisia	1,1020
10	Togo	2	**10**	Niger	202	**10**	Mozambique	7,322

Based on all the evidence, we once again have the ability to mention that the biological events are mainly noticed in African continent however, regarding its effects,

[19] (the Democratic Republic of the)

[20] Total Affected is that summation of Injured Affected and Homeless.

we cannot come to conclusion whether they affect significantly the Least Developed Countries or Most Developed Countries based on that statistically analysis and therefore, an advanced econometric analysis is proposed.

6.1.2. Climatological Hazards

Climatological Hazards is the next classification of the natural environmental hazards that we will analyse. Compared to the biological hazards, we can notice that the total amount of occurrence over the last 117 years is much lower. Based on Table 4, it is not clear enough which region has suffered more by the biological hazards due to the fact that all regions have recorded almost some frequencies of climatological hazards. The region that faces the highest number of deaths, although the occurrence level is not that high, is the Southern Asia with 6,150 thousand deaths in total over the last century, as well as the affected people, reaching almost the 1.5 billion people.

Compared to the deaths, the injured people suffered from the climatological hazards appeared to be significantly lower, with a maximum value of 2 thousand people in Eastern Europe. Finally, the region with the highest economic damage is the Northern America reaching the 76,217 million USD. In total almost 2.7 billion people have been affected (injured, affected and homeless) over the last century due to climatological hazards, while 10,647.7 thousand people lost their lives globally. The total economic damage due to climatological hazards equals to 200,670 million USD.

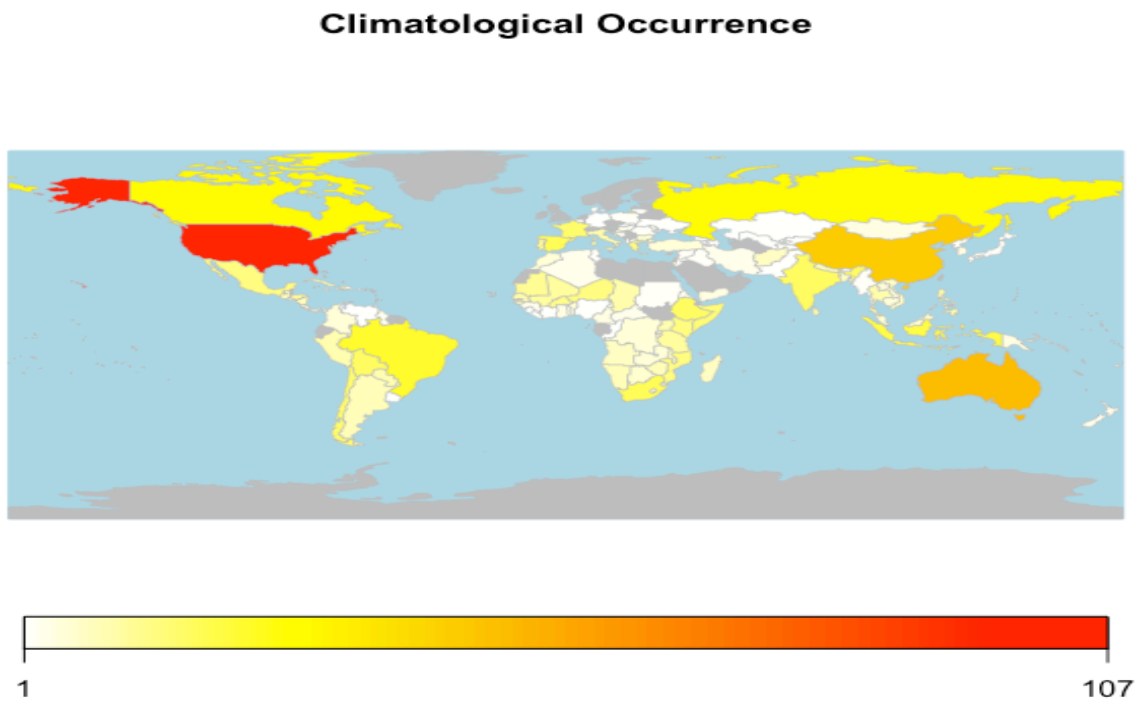
The African Continent is once again the most vulnerable on biological hazards and if we take a closer look to Table 4 having 339 events in total which equals to almost 30% of all climatological hazards occurred globally. Table 4 also provides evidence that climatological hazards cause higher economic losses compared to the biological hazards. Based on Map 2, and analysing the country level results, we can suggest that the most suffered country is USA which is also proven by Table 5 giving 107 events and the first place of Occurrence to USA. As we can see both in Map 2 and Table 5, the regions with the highest frequencies tend to be in America and Asia.

Table 4: Climatological Hazards - Regional Results

Climatological									
Continent	**Region**	**Occurrence**	**Deaths ('000)**	**Injured ('000)**	**Affected ('000)**	**Homeless ('000)**	**Total Affected ('000)**	**Economic Damage ('000,000$)**
Africa	Eastern Africa	136	544	0.028	249,752	3	249,755	372
Africa	Middle Africa	31	3	0	13,837	4	13,841	85
Africa	Northern Africa	21	150	0	27,654	0.105	27,654.1	900
Africa	Southern Africa	45	0.630	0.530	27,763	6	27,769.5	3,605
Africa	Western Africa	106	170	0.200	81,821	14	81,835.2	507
Americas	Caribbean	34	0	0	8,332	0	8,332	199
Americas	Central America	58	0.211	0	10,388	0	10,388	2,485
Americas	South America	100	0.187	1	90,092	9	90,102	14,365
Americas	Northern America	135	1	0.912	1,650	62	1,713	76,217
Asia	Central Asia	5	0	0	6,408	0	6,408	107
Asia	Eastern Asia	95	3,504	0.303	542,315	11	542,326.3	34,157
Asia	Southern Asia	54	6,151	0	1,477,985	54	1,478,039	6,177
Asia	South-Eastern Asia	68	10	0.478	66,009	23	66,032.5	12,778
Asia	Western Asia	26	0.120	0.154	5,493	21	5,514	802
Europe	Eastern Europe	48	0.220	2	5,562	24	5,588	2,827
Europe	Northern Europe	3	0	0	0	0	0	1,030
Europe	Southern Europe	71	0.280	0.460	10,446	5	10,451.5	27,327
Europe	Western Europe	18	112	0.161	6	0.006	6.1	1,620
Oceania	Australia & New Zealand	51	1	1	7,149	20	7,170	14,990
Oceania	Melanesia	10	0.084	0	3,430	0	3,430	90
Oceania	Micronesia	3	0	0	119	0	119	0
Oceania	Polynesia	4	0	0	1	0	1	31
		1,122	**10,647.732**	**4.226**	**2,636,212**	**256.111**	**2,636,475.2**	**200,671**

Moreover, the same table presents the fatalities and economic losses per event which allow us to draw more conclusions about the hazards and its effects. Regarding deaths, it is shown that Soviet Union recorded the most fatalities per event over the last century (Halkos and Zisiadou 2018). Moving to the most Injured country of biological hazards we are surprised by the extremely high value recorder in Russian Federation with almost 83 injured people per event (Halkos and Zisiadou 2018). In contrast to deaths and injuries, the higher values of homelessness following a climatological occurrence are located in African continent as it is presented by Halkos and Zisiadou (2018). The highest economic losses are also mainly located in Eurasia (Halkos and Zisiadou 2018).

What we should take into consideration is that climatological hazards refer to both droughts and wildfires as it has already been described on previous section. Each subtype has its own consequences leading to the fact that droughts appear to be almost twice more often than wildfires. Moreover, the fatalities and the affected people by wildfires are less compared to those from droughts. What is more, apart from the high levels of fatalities, and affected people, droughts appear to have 2.5 times higher economic losses than wildfires (Halkos and Zisiadou 2018). That statement underlines once again the importance of a scientifically detailed dataset which takes into consideration all different subtypes of each possible natural environmental hazard.



Map 2:Climatological Hazards – Occurrence

As we can see, the greater number of fatalities per event is noticed in developing countries such as Bangladesh, India, China etc, while the great economic losses per event are noticed in developed countries such as Denmark, USA, Spain etc.

So, regarding the Climatological Hazards, and based on the database of CRED for the period 1900-2016, we do not have the ability to mention whether climatological hazards are space concentrated events but we can accept the hypothesis about the fact that the Most Developed Countries face greater economic losses compared to the Least Developed Countries which face greater fatalities is also accepted in this case, however the evidence is not highly significant based on that statistically analysis and therefore, an advanced econometric analysis is proposed.

Table 5:Climatological Hazards - Most suffered areas

	Country Name	Occurrence		Country Name	Total Deaths ('000)		Country Name	Injured		Country Name	Affected ('000)
1	USA	107	**1**	Soviet Union	600	**1**	Russian Federation	83	**1**	India	81,873
2	Australia	48	**2**	Bangladesh	271	**2**	Chile	64.5	**2**	Iran21	12,542
3	China	43	**3**	India	250	**3**	Benin	40	**3**	China	12,048
4	Hong Kong	40	**4**	China	81	**4**	South Africa	29.4	**4**	Korea[22]	10,500
5	Canada	28	**5**	Ethiopia	24	**5**	Australia	25.8	**5**	Ethiopia	4,538
6	Russian Federation	28	**6**	Sudan	15	**6**	Indonesia	23.9	**6**	Bangladesh	3,572
7	Brazil	23	**7**	Cabo Verde	8.5	**7**	Israel	15.5	**7**	Kenya	3,486
8	Indonesia	20	**8**	Mozambique	7	**8**	Portugal	15.5	**8**	Brazil	3,428
9	South Africa	18	**9**	Niger	6	**9**	Mongolia	15.25	**9**	Ghana	3,128
10	Spain	18	**10**	Somalia	2.6	**10**	Lebanon	15	**10**	Malawi	3,047

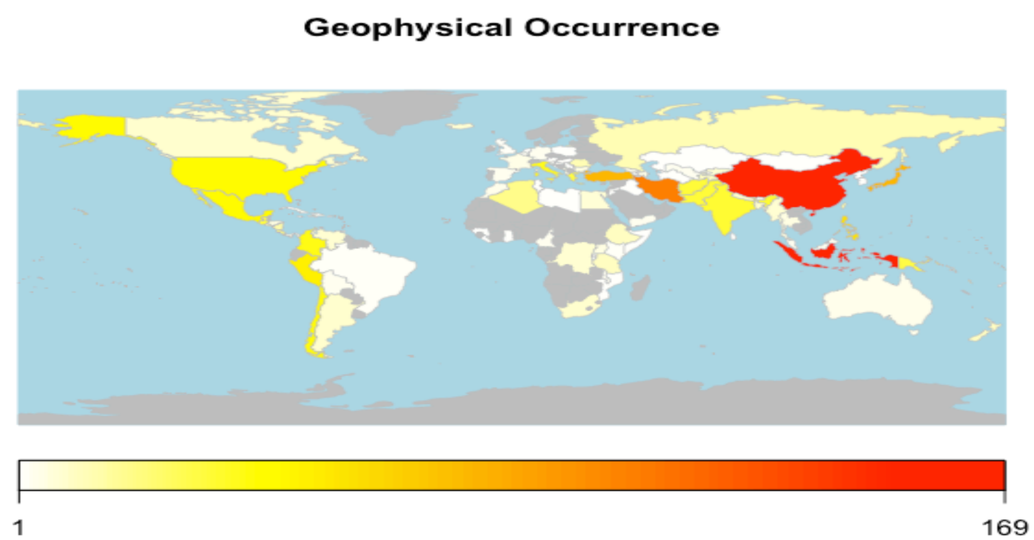
	Country Name	Homeless		Country Name	Total Affected ('0000		Country Name	Total Damage ('000,000$)
1	Myanmar	10,000	**1**	India	81,873	**1**	Ukraine	1,690
2	Nepal	6,750	**2**	Iran [23]	12,542	**2**	Iran [24]	1,100
3	Yemen	5,000	**3**	China	12,048	**3**	China	752
4	Sierra Leone	2,257	**4**	Korea [25]	10,500	**4**	Denmark	752
5	Benin	1,151,8	**5**	Ethiopia	4,538	**5**	Spain	745
6	Canada	651.2	**6**	Bangladesh	3,572	**6**	USA	607
7	Congo[26]	579	**7**	Kenya	3,486	**7**	Indonesia	552
8	Malaysia	500	**8**	Brazil	3,428	**8**	Brazil	489
9	Gambia	500	**9**	Ghana	3,128	**9**	Mongolia	455
10	Australia	424.5417	**10**	Malawi	3,047	**10**	Portugal	410

[21] (Islamic Republic of)
[22] (the Democratic People's Republic of)
[23] (Islamic Republic of)
[24] (Islamic Republic of))
[25] (the Democratic People's Republic of)
[26] (the Democratic Republic of the)

6.1.3. Geophysical Hazards

Geophysical Hazards is the next classification of the natural environmental hazards that we will analyze. Compared to the climatological hazards, we can notice that the total amount of occurrence over the last 117 years is almost at the same level. In order to be more precise, the total amount of climatological hazards is 1,122 events over the last 117 years while the geophysical events are just 1,612 events (Table 6) over the last 117 years. Another similarity that we can spot is that the geophysical events are spread almost all over the globe with the most frequent region to be America once again, however, this time it is South America where there were 183 geophysical events in total.

The region that faces the highest number of deaths is the Eastern Asia with 1,089 thousand deaths in total over the last century, as well as the affected people, reaching the 72,102 thousand people. In total 198,907 thousand people have been affected (injured, affected and homeless) over the last century due to geophysical hazards, while 2,678 thousand people lost their lives globally. The total economic damage due to geophysical hazards equals to 781,599.5 million USD.



Map 3: Geophysical Hazards – Occurrence

Table 6: Geophysical Hazards - Regional Results

		Geophysical						
Continent	**Region**	**Occurrence**	**Deaths ('000)**	**Injured ('000)**	**Affected ('000)**	**Homeless ('000)**	**Total Affected ('000)**	**Economic Damage ('000,000$)**
Africa	Eastern Africa	47	0.681	3	535	81	619	795
Africa	Middle Africa	11	2	2	33	172	207	16
Africa	Northern Africa	35	21	57	612	839	1,508	11,996
Africa	Southern Africa	9	0.071	0.165	3	0	3.1	20
Africa	Western Africa	5	0.338	1	24	5	30	0
Americas	Caribbean	21	256	300	3,595	0.255	3,895.2	8,075
Americas	Central America	131	70	164	11,215	1,952	13,331	12,263
Americas	South America	183	182	518	18,395	2,435	21,348	43,168
Americas	Northern America	51	3	13	42	26	81	42,602
Asia	Central Asia	24	0.202	0.954	265	41	306.9	203.5
Asia	Eastern Asia	258	1,089	841	72,102	4,960	77,903	485,285
Asia	Southern Asia	228	436	667	37,756	8,290	46,713	30,200
Asia	South-Eastern Asia	243	240	200	16,299	1,676	18,175	15,114
Asia	Western Asia	97	92	101	6,795	1,254	8,150	27,088
Europe	Eastern Europe	65	160	30	1,779	971	2,780	19,434
Europe	Northern Europe	10	0.001	0.008	10	0.069	10.08	125
Europe	Southern Europe	102	119	24	2,412	416	2,852	58,640
Europe	Western Europe	12	0.124	0.164	3	0.200	3.4	362
Oceania	Australia & New Zealand	15	0.621	2	643	0.720	645.7	25,797
Oceania	Melanesia	56	6	1	263	65	329	121
Oceania	Micronesia	2	0	0.071	0	0	0.071	120
Oceania	Polynesia	7	0.197	0.342	16	0.500	16.84	135
		1,612	**2,678.235**	**2,925.704**	**172,797**	**23,184.744**	**198,907.291**	**781,599.5**

Map 3 provides information about the occurrence of geophysical hazards over the last century (1900-2016), suggesting that the Asian Continent appears to suffer more from those events. So, based on those evidence we can also confirm the statement of the Ring of Fire. The area that is described as Ring of Fire, focalizes the most often geophysical events during the last century. More specifically, Indonesia is the country with the most geophysical events over the last 117 years (Map3, Table 7) that equals to 169 events and China is the second country with 164 events for the same period of time.

As we have mentioned, the Ring of Fire is not a region that is placed over one continent. Instead it is mentioned that it contains one part of the Asia and one part of the Americas. That has also been proven by the top 10 countries with the most geophysical occurrences (Table 7) showing that apart from Iran and Turkey all the other countries are part of the well-known Ring of Fire. Table 7 also provides information about the fatalities per occurrence[27]. As we can see, the greater number of fatalities per event is noticed in developing countries such as Sri Lank and Haiti (Halkos and Zisiadou 2018), while the great economic losses per event are noticed in developed countries such as Japan or New Zealand (Halkos and Zisiadou 2018).

What was interesting with geophysical hazards is the fact that with the term *earthquake* we could either describe the ground movement or the tsunami, and as it has been mentioned, that proves once again the complexity and the difficulty of the analysis. For that reason, we decided to present separately the Ground Movements (Halkos and Zisiadou 2018) and the Tsunamis (Halkos and Zisiadou 2018). The results indicate that the most often phenomenon appear to be the Ground Movement (1,251 events the last 117 years compared to just 64 tsunamis over the last century). Based on that statement, we assume to have greater economic losses on Ground Movements compared to Tsunamis due to the great difference on occurrence. Surprisingly, although the ration Tsunami to Ground Movement equals to almost 5% (eq.30) making the Ground Movement the most frequent geophysical phenomenon, the ratio of their economic losses equals to almost 49% (eq.31), making Tsunamis the most disastrous phenomenon economically speaking.

$$\frac{Tsunami}{Ground\ Movement} = \frac{64}{1{,}251} = 0.051 \quad (eq.30)$$

$$\frac{Economic\ Loss_{tsunami}}{Economic\ Loss_{ground\ movement}} = \frac{254{,}101{,}440}{523{,}315{,}137} = 0.485 \quad (eq.31)$$

[27] Those amounts have been calculated by dividing the total amount of each fatality or loss of each country to the occurrence of each country. That gives us the average fatality or loss per occurrence.

So, regarding the Geophysical Hazards, and based on the database of CRED for the period 1900-2016, we can accept the hypothesis of the space concentrated appearance of events, by proving the existence of the Ring of Fire. Moreover, the hypothesis about the fact that the Most Developed Countries face greater economic losses compared to the Least Developed Countries which face greater fatalities is also accepted in this case, by proving that the victim per events are higher in Haiti and Sri Lanka, while the economic losses are higher in Japan.

Table 7: Geophysical Hazards - Most suffered areas

	Country Name	Occurrence		Country Name	Total Deaths ('000)		Country Name	Injured ('000)		Country Name	Affected ('000)
1	Indonesia	169	**1**	Haiti	111	**1**	Haiti	150	**1**	Haiti	1,700
2	China	164	**2**	Sri Lanka	35	**2**	Sri Lanka	23	**2**	India	770
3	Iran [28]	106	**3**	Martinique	15	**3**	Ecuador	7	**3**	Nepal	701
4	Turkey	78	**4**	China	5	**4**	India	6.5	**4**	Sri Lanka	516
5	Japan	77	**5**	Soviet Union	5	**5**	Morocco	6	**5**	China	432
6	Philippines	57	**6**	Pakistan	4	**6**	Pakistan	4.5	**6**	Chile	215
7	Peru	49	**7**	Morocco	3	**7**	China	4	**7**	El Salvador	190
8	Mexico	42	**8**	Italy	3	**8**	Argentina	34	**8**	Guatemala	168
9	USA	42	**9**	Japan	2.5	**9**	Peru	3	**9**	Azerbaijan	144
10	Chile	40	**10**	India	2	**10**	Nepal	3	**10**	Yemen	133

	Country Name	Homeless ('000)		Country Name	Total Affected ('000)		Country Name	Total Damage ('000,000$)
1	Sri Lanka	480	**1**	Haiti	1,850	**1**	Japan	4,673
2	Pakistan	157	**2**	Sri Lanka	1,019	**2**	Haiti	4,010
3	India	63.5	**3**	India	840	**3**	New Zealand	2,253
4	Algeria	40	**4**	Nepal	708	**4**	Sri Lanka	1,316.5
5	Guatemala	38	**5**	China	464	**5**	Italy	1,297
6	Chile	33	**6**	Chile	250	**6**	Taiwan	1,080.5
7	China	28	**7**	Pakistan	220	**7**	USA	1,014
8	El Salvador	25	**8**	El Salvador	218	**8**	Chile	903
9	Soviet Union	24	**9**	Guatemala	209	**9**	China	673
10	Malawi	23.5	**10**	Yemen	147	**10**	Yemen	667

6.1.4. Hydrological Hazards

Hydrological Hazards is the next classification of the natural environmental hazards that we will analyse. Hydrological Hazard appeared to be a more often phenomenon compared to climatological and geophysical hazards. Actually, it is

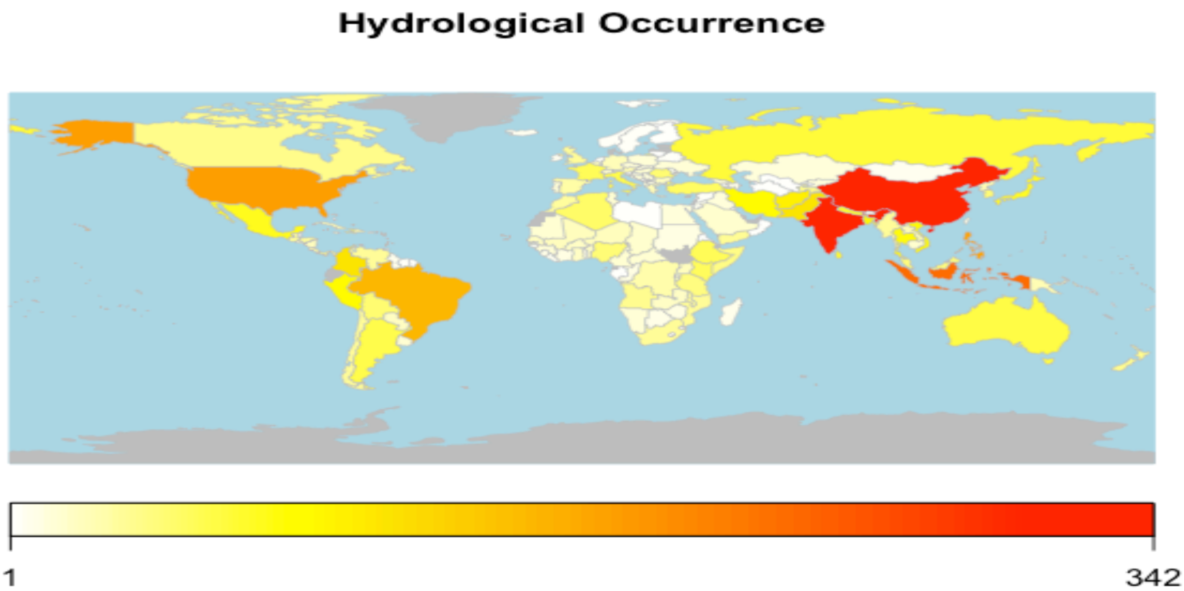
[28] (Islamic Republic of)

almost as often as the biological hazards. In order to be more precise, the total amount of biological hazards is 6,011 events over the last 117 years while the hydrological events are just 5,354 events (Table 8) over the last 117 years. A similarity that we can spot between climatological, geophysical and hydrological hazards is that all those hazards are spread almost all over the globe with the most frequent region to be Southern Asia once where there were 857 hydrological events in total.

Table 8: Hydrological Hazards - Regional Results

			Hydrological					
Continent	**Region**	**Occurrence**	**Deaths (‘000)**	**Injured (‘000)**	**Affected (‘000)**	**Homeless (‘000)**	**Total Affected (‘000)**	**Economic Damage ('000,000$)**
Africa	Eastern Africa	388	13	3	31,896	1,750	33,649	2,072.5
Africa	Middle Africa	126	2	2	3,451	473	3,926	36
Africa	Northern Africa	148	9	21	7,562	1,684	9,267	3,150
Africa	Southern Africa	64	2	0.377	2,238	65	2,303.4	1,732
Africa	Western Africa	250	3	4.5	20,946	2,142	23,092.5	1,271
Americas	Caribbean	150	7	9	4,237	194	4,440	980
Americas	Central America	253	51.5	20	8,852	338	9,210	7,370
Americas	South America	624	63	28	67,257	3,400	70,685	36,456
Americas	Northern America	220	4	0.429	12,877	53	12,930.4	84,999
Asia	Central Asia	67	2	1	1,029	103	1,133	1,303
Asia	Eastern Asia	532	6,628	841	1,981,089	45,870	2,027,800	272,158
Asia	Southern Asia	857	170	147	1,241,864	35,247	1,277,258	102,918
Asia	South-Eastern Asia	695	29	263	157,767	2,173	160,203	63,208
Asia	Western Asia	167	5	1	5,146	865	6,012	6,857
Europe	Eastern Europe	238	16	10	8,789	321	9,120	29,100
Europe	Northern Europe	54	0.390	0.078	417	30	447	23,327
Europe	Southern Europe	212	6	18	4,487	1,580	6,085	42,485
Europe	Western Europe	152	3	0.214	1,052	0.260	1,052.5	46,431
Oceania	Australia & New Zealand	101	0.378	0.088	337	7	344	14,828
Oceania	Melanesia	46	0.701	0.42	837	118	955.4	295
Oceania	Micronesia	5	0	0	1	0.085	1	0
Oceania	Polynesia	5	0.029	0.014	0.500	0	0.514	51.5
		5,354	**7,014.998**	**1,370.12**	**3,562,131.5**	**96,413.345**	**3,659,914.714**	**741,028**

The region that faces the highest number of deaths is the Eastern Asia with 6,628 thousand deaths in total over the last century, as well as the affected people, reaching the 1,981,089 thousand people. In total 3,659,914 thousand people have been affected (injured, affected and homeless) over the last century due to geophysical hazards, while almost 7,015 thousand people lost their lives globally. The total economic damage due to geophysical hazards equals to 741,028 million USD.



Map 4: Hydrological Hazards – Occurrence

Following the same procedure, Map 4 provides information about the occurrence of hydrological hazards over the last century (1900-2016), suggesting that the American and Asian Continents appear to suffer more from those events. Specifically, the highest frequency of hydrological hazard is spotted in Asia. In order to be more specific, three Asian countries China, India and Indonesia with 342, 324 and 233 total events respectively, showing that those countries are the most suffering from the hydrological hazards. However, although in the American Continent, the appearance is not that often, the hydrological hazards tend to be observed across the whole continent and not in specific areas (Map 4, Table 9).

So, regarding the Hydrological Hazards, and based on the database of CRED for the period 1900-2016, we cannot significantly accept the hypothesis of the space concentrated appearance of events, based on Map 4. However, the hypothesis about the fact that the Most Developed Countries face greater economic losses compared to the Least Developed Countries which face greater fatalities is also accepted in this case, by proving that the victim per events are higher in China, while the economic losses are higher in Germany.

Table 9: Hydrological Hazards - Most suffered areas

	Country Name	Occurrence		Country Name	Total Deaths		Country Name	Injured		Country Name	Affected ('000)
1	China	342	**1**	China	19,316	**1**	Yugoslavia	2,500	**1**	China	5,727
2	India	324	**2**	Guatemala	1,188	**2**	China	2,423	**2**	Bangladesh	3,402
3	Indonesia	233	**3**	Venezuela	899	**3**	Bangladesh	1,315	**3**	India	2,549
4	USA	181	**4**	Bangladesh	559	**4**	Indonesia	1,098	**4**	Cambodia	719
5	Philippines	175	**5**	Soviet Union	540.4	**5**	El Salvador	1,000	**5**	Thailand	692
6	Brazil	156	**6**	Netherlands	500.25	**6**	Taiwan	671.4	**6**	Pakistan	670.5
7	Colombia	113	**7**	India	229	**7**	Sudan	570	**7**	Korea [29]	474
8	Pakistan	112	**8**	Japan	195	**8**	Czech Republic	185	**8**	Viet Nam	372
9	Afghanistan	101	**9**	Pakistan	159	**9**	Haiti	159	**9**	Myanmar	352
10	Bangladesh	94	**10**	Lebanon	147	**10**	Russian Federation	115	**10**	Mozambique	271,

	Country Name	Homeless		Country Name	Total Affected ('000)		Country Name	Total Damage ('000,000$)
1	China	128,626	**1**	China	5,858	**1**	Germany	1,126
2	India	69,190	**2**	Bangladesh	3,449	**2**	Korea [30]	702
3	Sri Lanka	56,870	**3**	India	2,618	**3**	China	692
4	Bangladesh	45,270	**4**	Cambodia	738	**4**	UK	661
5	Korea [31]	44,003	**5**	Pakistan	708	**5**	Thailand	567
6	Sudan	42,749	**6**	Thailand	695	**6**	Poland	567
7	Pakistan	37,868	**7**	Korea[32]	518	**7**	Italy	443
8	French Guiana	35,000	**8**	Viet Nam	377	**8**	Czech Republic	442
9	Italy	25,081	**9**	Myanmar	361	**9**	USA	422
10	Benin	22,957	**10**	Mozambique	273	**10**	Spain	277

6.1.5. <u>Meteorological Hazards</u>

Meteorological Hazards is the last classification of the natural environmental hazards that we will analyze. Hydrological Hazard appeared to be a more often

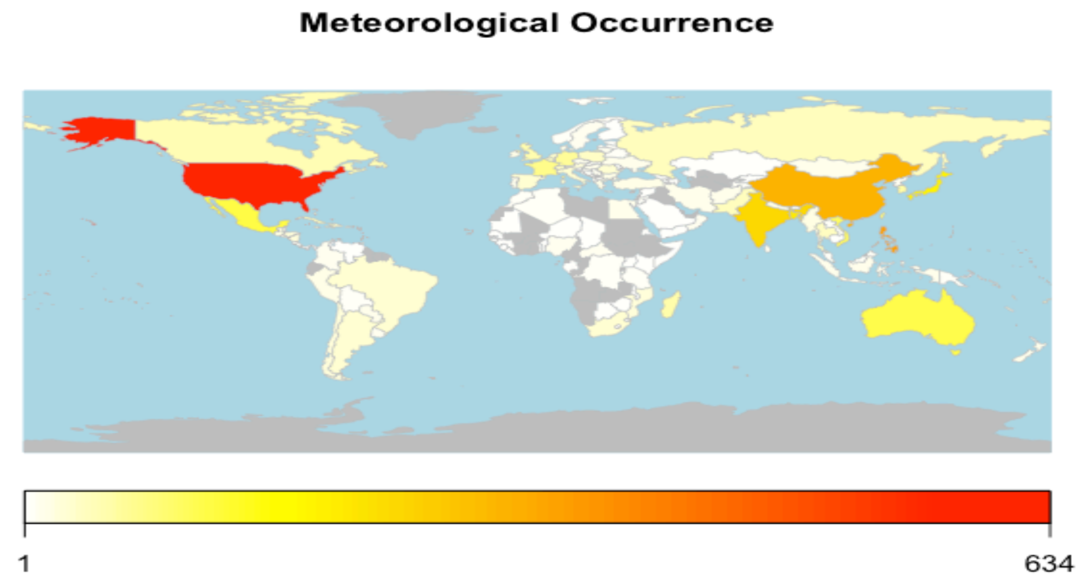
[29] (the Democratic People's Republic of)

[30] (the Democratic People's Republic of)

[31] (the Democratic People's Republic of)

[32] (the Democratic People's Republic of)

phenomenon compared to climatological and geophysical hazards but less often compared to biological and hydrological hazards. Actually, in order to be more precise, the total amount of meteorological hazards is 4,453 events over the last 117 years (Table 10). A similarity that we can spot between climatological, geophysical, hydrological and meteorological hazards is that all those hazards are spread almost all over the globe with the most frequent region to be Eastern Asia once again where there were 699 meteorological events in total, as well as the affected people, reaching the 574,922 thousand people. In total 1,058,161 thousand people have been affected (injured, affected and homeless) over the last century due to geophysical hazards, while 1,577 thousand people lost their lives globally. The total economic damage due to geophysical hazards exceeds the 1,136,736 million USD.



Map 5:Meteorological Hazards – Occurrence

Following the same procedure, Map 5 provides information about the occurrence of meteorological hazards over the last century (1900-2016), suggesting that the American and Asian Continents appear to suffer more from those events. Specifically, the highest frequency of hydrological hazard is spotted in America. In order to be more specific, United States of America records almost the double value of meteorological events (634 meteorological events) compared to the second of the classification which is Philippines (335 meteorological events) and the third one which is China (294 meteorological events) showing that those countries are the most suffering from the hydrological hazards. (Map5, Table 11).

Table 10: Meteorological Hazards - Regional Results

			Meteorological					
Continent	**Region**	**Occurrence**	**Deaths (‘000)**	**Injured (‘000)**	**Affected (‘000)**	**Homeless (‘000)**	**Total Affected (‘000)**	**Economic Damage ('000,000$)**
Africa	Eastern Africa	141	4.5	9	13,046	1,796	14,851	3,201
Africa	Middle Africa	20	0.095	3	101	38	142	0.282
Africa	Northern Africa	31	0.577	0.589	932	0	932.6	1,203
Africa	Southern Africa	41	0.393	1	1,273	20	1,294	818
Africa	Western Africa	32	0.655	0.606	1,120	41	1,161.6	56
Americas	Caribbean	312	31	20	21,588	2,083	23,691	33,867
Americas	Central America	220	42	24	15,219	792	16,035	43,545
Americas	South America	135	4	1,829	5,369	229	7,427	2,955
Americas	Northern America	688	37	15	13,693	441	14,149	639,681
Asia	Central Asia	13	0.147	0.062	2,617	1.5	2,618.5	843
Asia	Eastern Asia	699	245	328	574,922	15,869	591,119	199,756
Asia	Southern Asia	524	839	966	174,470	20,459	195,895	28,652
Asia	South-Eastern Asia	516	217	104.5	208,804	11,208	220,116.5	33,089
Asia	Western Asia	66	0.728	10	3,442	11.5	3,463.5	6,544
Europe	Eastern Europe	182	64	24	3,689	35	3,748	3,711
Europe	Northern Europe	114	6	0.163	1,108	0	1,108.2	23,350
Europe	Southern Europe	134	42	1	1,022	15	1,038	16,344
Europe	Western Europe	272	41	2	4,346	0.800	4,348.8	75,507
Oceania	Australia & New Zealand	123	0.805	4	8,690	17	8,711	19,893
Oceania	Melanesia	103	1	1.5	2,090	134	2,225.5	1,658
Oceania	Micronesia	22	0.082	0.731	57	23	80.7	1,019
Oceania	Polynesia	65	0.448	0.382	563	82	645.4	1,044
		4,453	**1,577.43**	**3,344.533**	**1,058,161**	**53,295.8**	**1,114,801.3**	**1,136,736.282**

So, regarding the Hydrological Hazards, and based on the database of CRED for the period 1900-2016, we cannot significantly accept the hypothesis of the space concentrated appearance of events, based on Map 4. However, the hypothesis about the fact that the Most Developed Countries face greater economic losses compared to the Least Developed Countries which face greater fatalities is also accepted in this case, by proving that the victim per events are higher in Myanmar, Peru, Lao and China, while the economic losses are higher in United States of America.

Table 11:Meteorological Hazards - Most suffered areas

	Country Name	Occurrence		Country Name	Total Deaths		Country Name	Injured		Country Name	Affected ('000)
1	USA	634	**1**	Myanmar	7,615	**1**	Peru	114,062	**1**	China	1,900
2	Philippines	335	**2**	Bangladesh	3,251	**2**	Bangladesh	4,800	**2**	Moldova	652
3	China	294	**3**	Russian Federation	1,418	**3**	Costa Rica	1,071	**3**	Philippines	465
4	India	234	**4**	Honduras	1,119	**4**	Myanmar	1,069	**4**	Viet Nam	440
5	Bangladesh	196	**5**	India	780	**5**	Ukraine	1,027	**5**	India	418
6	Japan	181	**6**	Italy	705	**6**	Syrian Arab Republic	963	**6**	Tajikistan	401
7	Mexico	117	**7**	China	596	**7**	Japan	725	**7**	Bangladesh	364
8	Australia	110	**8**	Spain	544	**8**	Belarus	674	**8**	Mongolia	340
9	Viet Nam	99	**9**	Haiti	387	**9**	China	637	**9**	Israel	333
10	Taiwan	81	**10**	Hong Kong	377	**10**	Sri Lanka	560	**10**	Liberia	333

	Country Name	Homeless		Country Name	Total Affected ('000)		Country Name	Total Damage ('000$)
1	Lao [33]	200,000	**1**	China	1,953	**1**	USA	995,998
2	China	52,248	**2**	Moldova	658	**2**	Korea [34]	678,946
3	Bangladesh	51,161	**3**	Viet Nam	484	**3**	Oman	574,667
4	Viet Nam	44,099	**4**	Philippines	481	**4**	Cayman Is.	499,511
5	India	42,713	**5**	India	461	**5**	Germany	488,489
6	Mozambique	26,889	**6**	Bangladesh	420	**6**	France	423,220
7	Korea [35]	24,739	**7**	Tajikistan	401	**7**	China	375,236
8	Maldives	23,849	**8**	Peru	379	**8**	Sweden	371,250
9	Haiti	23,784	**9**	Mongolia	340	**9**	Japan	350,717
10	Madagascar	20,587	**10**	Liberia	335	**10**	Italy	311,431

[33] People's Democratic Republic (the)

[34] (the Democratic People's Republic of)

[35] (the Democratic People's Republic of)

6.1.6. Extra-terrestrial Hazards

The case of Extra-terrestrial Hazards is unique. To be more specific, during the period of 117 years, there is only one event recorded as it can be seen in Table 1. For that reason, frequency table and map visualization are non applicable.

6.1.7. Industrial Hazards

As it has already been mentioned we will follow the same flow with the terminology so the first group of hazards that will be analyzed is the industrial hazard. Based on Table 12, it is clear enough that the region that has suffered more by the industrial hazards is the Asian Continent and more specifically the Eastern Asia and Southern Asia regions. Having in mind that the industrial hazards include the nuclear accidents, we can understand the reason of such a result. Eastern Asia is the most suffered region, which counts 562 over the last 117 year as it can be seen in Table 12. The second most suffered region is Southern Asia with 156 events the last century.

This is even more obvious when we take a look at Figure 6, where the China is proven to be the most suffered country with 525 events, a statement that is also mentioned by Halkos and Zisiadou (2018c, Table 1, Appendix I). Following the same path, Eastern Asia and Southern Asia counts 18,690 and 9,424 deaths respectively in total caused by industry-related accidents. The greatest life losses per event belong to Iraq with a record of 411 deaths per event as presented in Halkos and Zisiadou (2018c, Table 1, Appendix I) and Figure 1 at Halkos and Zisiadou (2018c, Appendix II).

Apart from the greatest life losses, Southern and Eastern Asia enumerate the most injured citizens with 109,421 and 36,954 injured citizens respectively, where once again Iraq recorded the most injured citizens reaching 2,055 per event as it can be seen at Figure 2 (Halkos and Zisiadou 2018c, Appendix II) and Table 1 (Halkos and Zisiadou 2018c, Appendix II). Although Asia enumerates the greatest effects regarding humans, the hugest economic loss due to industry-related hazards is recorded in Algeria reaching the value of 800 million US dollars (Table 1 Halkos and Zisiadou 2018c Appendix I; Figure 6 Halkos and Zisiadou 2018c Appendix II). In aggregated terms, Southern Europe recorded more that 10 billion US dollar economic damage caused by industrial accidents (Table 12).

Table 12: Industrial Hazards - Regional Results

				Industrial				
Continent	**Region**	**Occurrence**	**Deaths**	**Injured**	**Affected**	**Homeless**	**Total Affected**	**Economic Damage ('000$)**
Africa	Eastern Africa	23	1,012	932	1,750	0	2,682	3,700
Africa	Middle Africa	17	434	136	0	0	136	0
Africa	Northern Africa	16	384	4,487	0	4,000	8,487	818,400
Africa	Southern Africa	20	1,261	406	1,835	0	2,241	67,700
Africa	Western Africa	58	3,862	1,328	114,431	350	116,109	18,700
Americas	Caribbean	6	56	416	3,500	0	3,916	22,400
Americas	Central America	49	1,427	11,136	225,189	23,160	259,485	1,840,800
Americas	South America	59	4,965	3,485	593,993	1,603	599,081	87,000
Americas	Northern America	100	1,523	8,305	608,030	300	616,635	21,567,500
Asia	Central Asia	6	144	619	1,747	0	2,366	8,400
Asia	Eastern Asia	562	18,690	36,954	309,319	320,000	666,273	342,311
Asia	Southern Asia	156	9,424	109,421	662,665	0	772,086	877,980
Asia	South-Eastern Asia	78	2,371	4,653	57,181	41,030	102,864	126,642
Asia	Western Asia	50	2,871	7,098	509	3	7,610	79,000
Europe	Eastern Europe	97	3,222	3,788	538,002	13,202	554,992	5,150,000
Europe	Northern Europe	23	796	305	17,600	1,461	19,366	1,345,300
Europe	Southern Europe	32	1,157	21,906	59,434	190,000	271,340	10,095,407
Europe	Western Europe	75	3,969	6,279	35,921	0	42,200	597,800
Oceania	Australia & New Zealand	6	40	645	15,500	0	16,145	0
Oceania	Melanesia	1	11	60	0	0	60	12,000
Oceania	Micronesia	0	0	0	0	0	0	0
Oceania	Polynesia	0	0	0	0	0	0	0
		1,434	**57,619**	**222,359**	**3,246,606**	**595,109**	**4,064,074**	**43,061,040**

As an overview, over the last century 1,434 industrial accidents took place globally from which almost 51% were caused by explosions and were responsible for 61% of the total deaths. More specifically, 730 explosions led to 35,225 life losses as well as the greatest economic losses costing more that 25 billion US dollars. Although explosions are the most fatal type of industrial accidents, gas leak appears to be the most harmful regarding the injured citizens based on the fact that almost 52% of the injuries are due to gas leak. All this information is presented on Table 5 (Halkos and Zisiadou 2018c Appendix I). To sum up, regarding the hypotheses we tend to examine and based on the statistical and visual representation, we can assume that industrial hazards tend to be space concentrated and affecting mainly the Asian Continent. The second hypothesis regarding the life losses, it is proven that the highest fatalities are recorded in low-income regions, such as Asia, while the highest economic losses are recorded in high-income regions, such as Southern Europe.

What is important to mention though is that we concluded to those results based only on statistical and visual representations as an initial attempt of research. It is crucial to used advanced econometric approaches in order to come to significantly stated conclusions, which will be the next step of research. These econometric approaches will allow us to examine if there are specific reasons that may lead to space concentration hazards such as the lack of security and protection systems and programs.

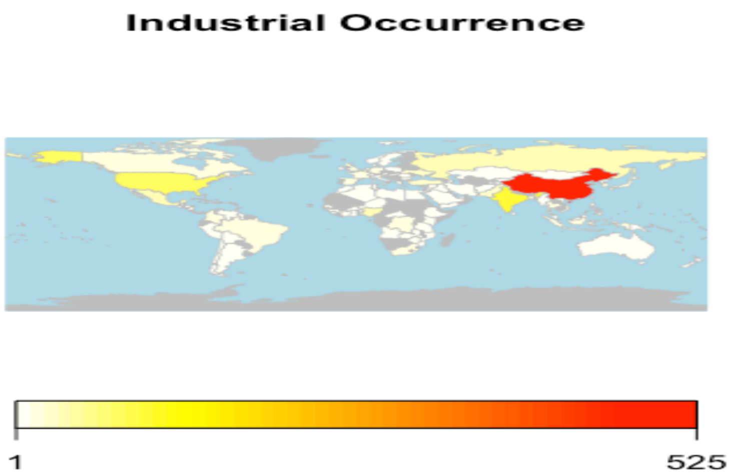


Figure 6: Industrial Hazards – Occurrence

6.1.8. Miscellaneous Hazards

Based on Table 13, it is clear enough that the region that has suffered more by the miscellaneous hazards is the Asian Continent and more specifically the Southern Asia and South-Eastern Asia regions which counts 212 and 195 events respectively over the last 117 year as it can be seen in Table 13. This is even more obvious when we take a look at Figure 7, where the China is proven to be the most suffered country with 129 events, a statement that is also mentioned by Halkos and Zisiadou (2018c, Table 2, Appendix I). Following the same path, Eastern Asia and Western Asia counts 14,408 and 9,950 deaths respectively in total caused by miscellaneous accidents. The greatest life losses per event belong to Paraguay with a record of 390 deaths per event as presented in Halkos and Zisiadou (2018c, Table 2, Appendix I) and Figure 7 at Halkos and Zisiadou (2018c, Appendix II).

Apart from the greatest life losses, Southern and Eastern Asia enumerate the most injured citizens with 14,375 and 9,422 injured citizens respectively, where the Congo recorded the most injured citizens reaching 1,638 per event as it can be seen at Figure 8 (Halkos and Zisiadou 2018c, Appendix II) and Table 2 (Halkos and Zisiadou 2018c, Appendix I). Although Asia enumerates the greatest effects regarding humans, the hugest economic loss due to miscellaneous hazards is recorded in Portugal reaching the value of more than 83 million US dollars (Table 1 Halkos and Zisiadou 2018c Appendix I; Figure 12 Halkos and Zisiadou 2018c Appendix II). In aggregated terms, Western Europe recorded more that 733 million US dollar economic damage caused by miscellaneous accidents (Table 13).

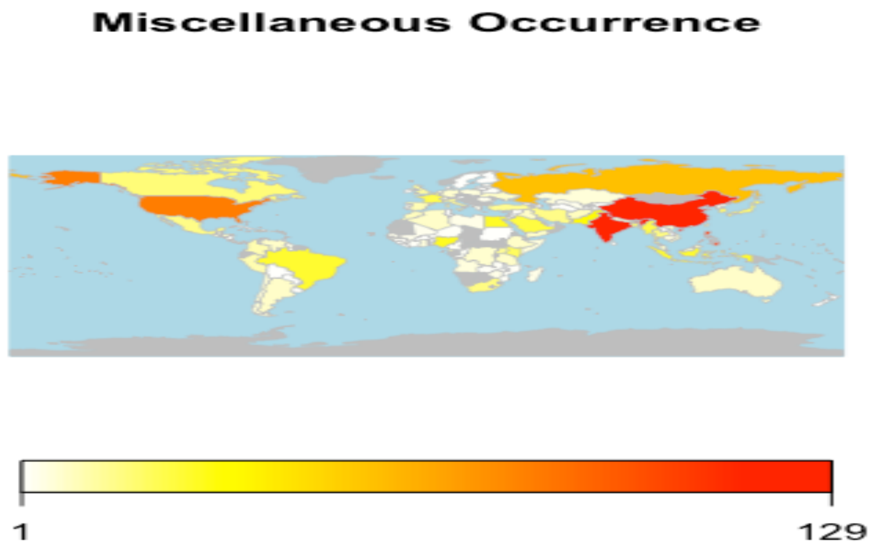


Figure 7: Miscellaneous Hazards - Occurrence

As an overview, over the last century 1,385 miscellaneous accidents took place globally from which almost 49.3% were caused by fire and were responsible for 50.3% of the total deaths. More specifically, 682 fires led to 33,803 life losses as well as the greatest economic losses costing almost 1.8 billion US dollars. All this information is presented on Table 6 (Halkos and Zisiadou 2018c Appendix I). To sum up, regarding the hypotheses we tend to examine and based on the statistical and visual representation, we can assume that miscellaneous hazards tend to be space concentrated and affecting mainly the Asian Continent. The second hypothesis regarding the life losses, it is proven that the highest fatalities are recorded in low-income regions, such as Asia, while the highest economic losses are recorded in high-income regions, such as Western Europe.

What is important to mention though is that we concluded to those results based only on statistical and visual representations as an initial attempt of research. It is crucial to used advanced econometric approaches in order to come to significantly stated conclusions, which will be the next step of research. These econometric approaches will allow us to examine if there are specific reasons that may lead to space concentration hazards such as the population density.

Miscellaneous

Continent	Region	Occurrence	Deaths	Injured	Affected	Homeless	Total Affected	Economic Damage ('000$)
Africa	Eastern Africa	70	1,647	3,426	69,641	173,806	246,873	0
Africa	Middle Africa	27	867	3,844	10,509	6,900	21,253	0
Africa	Northern Africa	60	1,403	1,958	5,627	9,335	16,920	0
Africa	Southern Africa	17	322	302	534	18,000	18,836	0
Africa	Western Africa	57	2,389	2,093	120,062	24,755	146,910	0
Americas	Caribbean	24	657	448	523,215	855	524,518	50,300
Americas	Central America	43	1,728	2,077	998,049	888	1,001,014	11,224
Americas	South America	82	5,633	7,657	284,128	6,092	297,877	96,534
Americas	Northern America	100	7,627	5,689	1,662	9,031	16,382	264,600
Asia	Central Asia	13	293	370	20,800	7,160	28,330	0
Asia	Eastern Asia	190	14,408	9,422	44,239	17,781	71,442	257,077
Asia	Southern Asia	212	9,626	14,375	267,015	62,450	343,840	183,320
Asia	South-Eastern Asia	195	3,577	6,903	457,557	219,851	684,311	474,995
Asia	Western Asia	79	9,950	7,640	10,259	2,750	20,649	289,220
Europe	Eastern Europe	86	2,644	3,584	6,849	0	10,433	11,200
Europe	Northern Europe	22	855	1,605	200	0	1,805	2,300
Europe	Southern Europe	34	1,033	1,960	13,087	1,000	16,047	253,000
Europe	Western Europe	62	2,393	3,654	8,555	0	12,209	733,300
Oceania	Australia & New Zealand	9	106	9	660	672	1,341	3,300
Oceania	Melanesia	0	0	0	0	0	0	0
Oceania	Micronesia	1	1	4	12,000	0	12,004	0
Oceania	Polynesia	2	18	0	0	0	0	0
		1,385	**67,177**	**77,020**	**2,854,648**	**561,326**	**3,492,994**	**2,630,370**

Table 13: Miscellaneous Hazards - Regional Results

6.1.9. Transport Hazards

Moving forward, based on Table 14, it is clear enough that the region that has suffered more by the transport hazards is the Asian Continent and more specifically the Southern Asia and Western Africa regions which counts 1,053 and 492 events respectively over the last century. This is even more obvious when we take a look at Figure 8, where the India is proven to be the most suffered country with 493 events, a statement that is also mentioned by Halkos and Zisiadou (2018c, Table 3, Appendix I). Following the same path, Southern Asia and South-Eastern Asia counts 47,206 and 26,796 deaths respectively in total caused by transport accidents. The greatest life losses per event belong to Estonia with a record of 912 deaths per event as presented in Halkos and Zisiadou (2018c, Table 3, Appendix I) and Figure 13 at Halkos and Zisiadou (2018c, Appendix II).

Apart from the greatest life losses, Southern Asia and Northern America enumerate the most injured citizens with 22,859 and 15,123 injured citizens respectively, where the Democratic People's Republic of Korea recorded the most injured citizens reaching more than 252 per event as it can be seen at Figure 14 (Halkos and Zisiadou 2018c, Appendix II) and Table 3 (Halkos and Zisiadou 2018c, Appendix I). Regarding the transport-related hazards Asia enumerates the greatest effects regarding humans as well as the hugest economic loss recorded in the Democratic People's Republic of Korea reaching the value of more than 68 million US dollars (Table 1 Halkos and Zisiadou 2018c Appendix I; Figure 18 Halkos and Zisiadou 2018c Appendix II). In aggregated terms, Eastern Asia recorded more that 477 million US dollar economic damage caused by transport-related accidents (Table 14).

As an overview, over the last century 5,491 transport accidents took place globally from which almost 45,7% were road-related accidents while the water-related accidents are almost the 24.5% of all transport accidents and were responsible for 42.5% of the total deaths. More specifically, 1,349 water accidents led to 100,630 life losses. All this information is presented on Table 7 (Halkos and Zisiadou 2018c Appendix I). To sum up, regarding the hypotheses we tend to examine and based on the statistical and visual representation, we can assume that miscellaneous hazards tend to be space concentrated and affecting mainly the Asian Continent.

Table 14: Transport Hazards - Regional Results

					Transport			
Continent	**Region**	**Occurrence**	**Deaths**	**Injured**	**Affected**	**Homeless**	**Total Affected**	**Economic Damage ('000$)**
Africa	Eastern Africa	377	14,572	7,261	52,161	0	59,422	40,000
Africa	Middle Africa	248	10,609	4,600	2,348	0	6,948	0
Africa	Northern Africa	391	14,887	6,974	1,982	0	8,956	0
Africa	Southern Africa	153	2,987	5,745	603	0	6,348	0
Africa	Western Africa	492	18,606	4,932	845	0	5,777	2,800
Americas	Caribbean	93	6,155	1,645	873	0	2,518	0
Americas	Central America	151	4,617	4,431	25	0	4,456	0
Americas	South America	475	14,326	8,429	1,358	0	9,787	62,000
Americas	Northern America	235	12,258	15,123	7,100	6,000	28,223	258,000
Asia	Central Asia	18	521	63	3	0	66	0
Asia	Eastern Asia	384	22,641	11,732	32,281	9,250	53,263	477,900
Asia	Southern Asia	1,053	47,206	22,859	1,582	0	24,441	38,000
Asia	South-Eastern Asia	446	26,796	5,977	7,963	0	13,940	3,300
Asia	Western Asia	248	8,391	3,832	721	0	4,553	0
Europe	Eastern Europe	223	8,940	3,070	237	200	3,507	0
Europe	Northern Europe	99	5,618	4,631	2,355	0	6,986	0
Europe	Southern Europe	198	9,161	3,867	1,964	100	5,931	145,700
Europe	Western Europe	164	6,797	4,537	459	0	4,996	120,000
Oceania	Australia & New Zealand	29	1,157	334	127	0	461	0
Oceania	Melanesia	11	432	4	24	0	28	0
Oceania	Micronesia	1	228	0	0	0	0	0
Oceania	Polynesia	2	95	0	54	0	54	0
		5,491	**237,000**	**120,046**	**115,065**	**15,550**	**250,661**	**1,147,700**

The second hypothesis regarding the life losses is controversary in this part of analysis and we do not feel confident enough to accept or reject this hypothesis based only on the current analysis. Moreover, the statement raised by Cox et al. (1992), that the air transport is the safest method of transportation is proven based on the dataset we used due to the fact that it has not the highest percentages regarding the occurrence, fatalities or even economic losses.

What is important to mention though is that we concluded to those results based only on statistical and visual representations as an initial attempt of research. It is crucial to used advanced econometric approaches in order to come to significantly stated conclusions, which will be the next step of research. These econometric approaches will allow us to examine if there are specific reasons that may lead to space concentration hazards such as the population density.

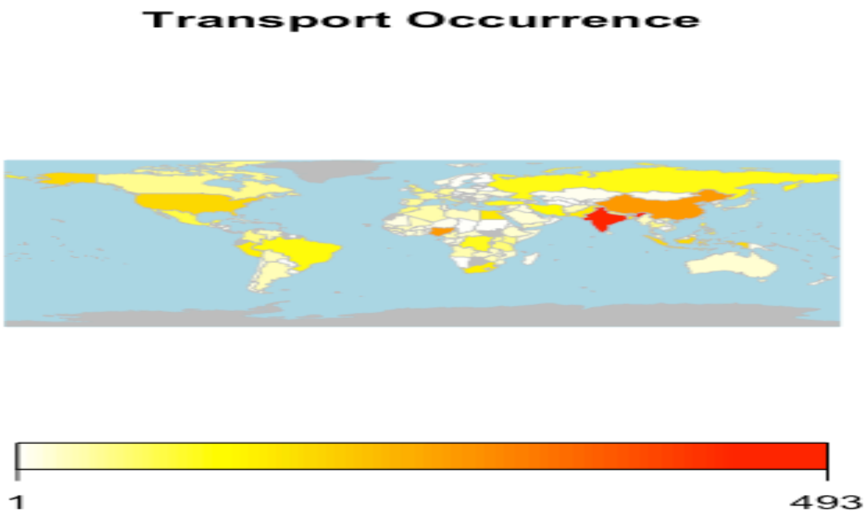


Figure 8: Transport Hazards - Occurrence

6.1.10. <u>*Complex Hazards*</u>

The last but not least part of this analysis is the Complex hazards. We should mention that on the recent history which includes the last 117 years of analysis, only 14 events occurred globally. This lack of evidence makes the analysis even trickier. Based on Table 15, it is clear enough that almost all regions have suffered once or twice by a complex hazard. More specifically, Eastern Africa, Central America, Southern Asia and Western Asia have faced a complex hazard twice in the history of the last century. Following the same path, Eastern Europe and Eastern Asia counts 5 million and 610 thousand deaths respectively in total caused by complex hazards. The greatest life losses per event belong to Soviet Union with a record of 5 million deaths per event and the Democratic People's Republic of Korea recorded the second highest value of fatalities with 610 thousand deaths per event as presented in Halkos and Zisiadou

(2018c, Table 4, Appendix I). Apart from the greatest life losses, the Democratic People's Republic of Korea enumerates the most affected citizens with 8 million as it can be seen at Table 4 (Halkos and Zisiadou 2018c, Appendix I).

As an overview, over the last century 14 complex hazards took place globally from which only one event took place in Europe, an evidence that emphasizes the hypothesis of difference between MDCs and LDCs (Halkos and Zisiadou 2018c Table 4 Appendix I). To sum up, regarding the hypotheses we tend to examine and based on the statistical and visual representation, we cannot assume if complex hazards tend to be space concentrated based on the fact that they affected mainly the Asian Continent due to the lack of a high number of evidences.

Table 15:Complex Hazards - Regional Results

					Complex			
Continent	**Region**	**Occurrence**	**Deaths**	**Injured**	**Affected**	**Homeless**	**Total Affected**	**Economic Damage ('000$)**
Africa	Eastern Africa	2	0	0	2,300,000	0	2,300,000	0
Africa	Middle Africa	1	0	0	45,000	0	45,000	0
Africa	Northern Africa	1	0	0	2,600,000	0	2,600,000	0
Africa	Southern Africa	0	0	0	0	0	0	0
Africa	Western Africa	1	0	0	50,000	0	50,000	0
Americas	Caribbean	0	0	0	0	0	0	0
Americas	Central America	2	0	0	15,500	0	15,500	0
Americas	South America	0	0	0	0	0	0	0
Americas	Northern America	0	0	0	0	0	0	0
Asia	Central Asia	0	0	0	0	0	0	0
Asia	Eastern Asia	1	610,000	0	8,000,000	0	8,000,000	0
Asia	Southern Asia	2	0	0	838,400	0	838,400	0
Asia	South-Eastern Asia	1	0	0	900,000	0	900,000	0
Asia	Western Asia	2	0	0	4,937,214	0	4,937,214	0
Europe	Eastern Europe	1	5,000,000	0	0	0	0	0
Europe	Northern Europe	0	0	0	0	0	0	0
Europe	Southern Europe	0	0	0	0	0	0	0
Europe	Western Europe	0	0	0	0	0	0	0
Oceania	Australia & New Zealand	0	0	0	0	0	0	0
Oceania	Melanesia	0	0	0	0	0	0	0
Oceania	Micronesia	0	0	0	0	0	0	0
Oceania	Polynesia	0	0	0	0	0	0	0
		14	**5,610,000**	**0**	**19,686,114**	**0**	**19,686,114**	**0**

The second hypothesis regarding the life losses is controversary in this part of analysis and we do not feel confident enough to accept or reject this hypothesis based only on the current analysis. What is important to mention though is that we concluded to those results based only on statistical and visual representations as an initial attempt of research. It is crucial to used advanced econometric approaches in order to come to significantly stated conclusions, which will be the next step of research. These econometric approaches will allow us to examine if there are specific reasons that may lead to space concentration hazards such as the population density.

6.1.11. Terrorist Attacks

Based on Table 16, it is clear enough that the region that has suffered more by the terrorist attacks is the Asian Continent and more specifically the Southern Asia and Western Asia regions which counts 45,530 and 42,509 events respectively over the last 48 year as it can be seen in Table 16. Moreover, Western Asia counts the most fatalities and injuries in total with 116,120 life losses 193,489 injuries respectively. The lack of economic damage data, does not allow as to compare the economic losses of a terrorist attack with those from environmental hazards.

As we can see, both in Table 17 and Figure 9, the most suffered country over the last 48 years is Iraq with 24,632 attacks in total. Those attacks caused 78,409 life losses and 134,969 injured citizens. The countries that faced the most attacks are located either to Asia or Americas. In other words, there tends to be space concentration regarding the terrorist attacks.

Table 16: Terrorist Attacks - Regional Results

		Terrorist Attacks		
Continent Name	**Region Name**	**Occurrence**	**Fatalities**	**Injuries**
Africa	*Eastern Africa*	7,095	24,118	24,878
Africa	*Middle Africa*	2,048	11,736	7,307
Africa	*Northern Africa*	8,553	11,949	19,982
Africa	*Southern Africa*	2,211	2,945	4,994
Africa	*Western Africa*	5,126	27,646	13,093
Americas	*Caribbean*	479	525	606
Americas	*Central America*	10,300	28,863	9,040
Americas	*South America*	18,838	28,594	16,680
Americas	*Northern America*	2,897	4,135	20,846
Asia	*Central Asia*	273	425	1,359
Asia	*Eastern Asia*	790	1,149	9,212
Asia	*Southern Asia*	45,530	102,236	145,103
Asia	*South-Eastern Asia*	12,424	15,573	26,138
Asia	*Western Asia*	42,509	116,120	193,489
Europe	*Eastern Europe*	4,206	6,801	10,921
Europe	*Northern Europe*	5,769	3,590	5,993
Europe	*Southern Europe*	7,030	2,690	8,134
Europe	*Western Europe*	4,443	930	4,895
Oceania	*Australia & New Zealand*	130	24	106
Oceania	*Melanesia*	143	126	132
Oceania	*Micronesia*	0	0	0
Oceania	*Polynesia*	4	0	13
	International	1	12	0
		180,798	**390,175**	**522,921**

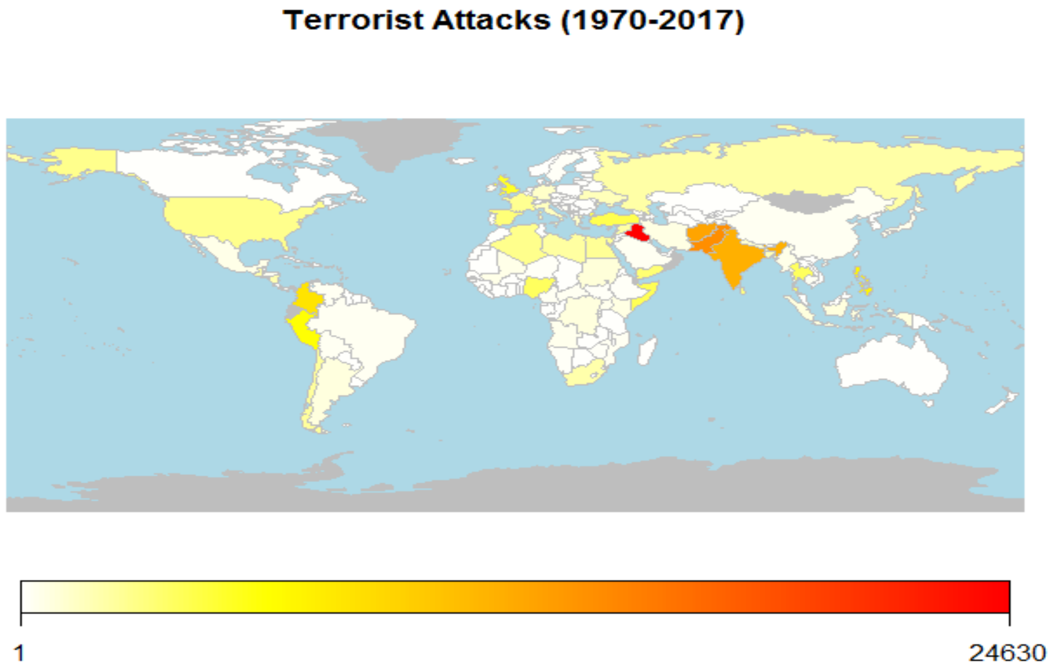


Figure 9: Terrorist Attacks - Occurrence

Table 17: Most suffered areas

Attacks			**Fatalities**			**Injuries**		
1	*Iraq*	24,632	**1**	*Iraq*	78,409	**1**	*Iraq*	134,969
2	*Pakistan*	14,329	**2**	*Afghanistan*	39,108	**2**	*Afghanistan*	44,400
3	*Afghanistan*	12,719	**3**	*Pakistan*	23,514	**3**	*Pakistan*	4,1743
4	*India*	11,933	**4**	*Nigeria*	22,622	**4**	*India*	2,8881
5	*Colombia*	8,233	**5**	*India*	19,249	**5**	*USA*	2,0700
6	*Philippines*	6,862	**6**	*Sri Lanka*	15,476	**6**	*Sri Lanka*	1,5555
7	*Peru*	6,059	**7**	*Syrian Arab Republic*	14,982	**7**	*Syria*	1,4382
8	*El Salvador*	5,277	**8**	*Colombia*	14,571	**8**	*Philippines*	1,3323
9	*UK*	5,207	**9**	*Peru*	12,647	**9**	*Lebanon*	1,0851
10	*Turkey*	4,266	**10**	*El Salvador*	12,005	**10**	*Colombia*	1,0319

6.2. Descriptive Statistics

Compared to the first section of this Section that includes all the recorded events through history, all the following sections are based on the 65 events described in Section 4. Descriptive Statistics is the initial step for any further estimation. Apart from the mean values and standard deviation, the descriptive statistics show us whether our variables follow the normal distribution, with the use of Jarque Bera test.

6.2.1. <u>Na-tech Events</u>

Regarding the na-tech events, all descriptive statistics are presented in Tables I-III (see Appendix I), Table I presents the descriptive statistics for the 120 days estimation window used in the event study analysis both for C.A.P.M and A.P.T approach. As we can see, based on the Augmented Dickey Fuller test values, all null hypotheses are rejected due to the fact the p-value is less the α[36], meaning that the variables do not have a unit root, on in other words, the variables are stationary. That fact allows us to continue with our estimation procedures due to the fact that the model variables are stationary at the same order, which is levels in all our cases. Tables II and III present the descriptive statistics for 70 days ex-ante and ex-post analysis respectively. Similar to the explanation above, all variables reject the null hypothesis of Augmented Dickey Fuller unit root test, thus all variables are stationary at levels.

6.2.2. <u>Terrorist Attacks</u>

Regarding the terrorist attacks, all descriptive statistics are presented in Tables IV-VI (see Appendix I), Table IV presents the descriptive statistics for the 120 days estimation window used in the event study analysis both for C.A.P.M and A.P.T approach. As we can see, based on the Augmented Dickey Fuller test values, all null hypotheses are rejected due to the fact the p-value is less the α, meaning that the variables do not have a unit root, on in other words, the variables are stationary. That fact allows us to continue with our estimation procedures due to the fact that the model variables are stationary at the same order, which is levels in all our cases. Tables V and VI present the descriptive statistics for 70 days ex-ante and ex-post analysis respectively. Similar

[36] For the three α levels (0.10, 0.05, 0.01)

to the explanation above, all variables reject the null hypothesis of Augmented Dickey Fuller unit root test, thus all variables are stationary at levels.

6.3. <u>Event Study Analysis Results (C.A.P.M)</u>

After securing our ability to use the variables for estimations, we continue with the C.A.P.M estimations for the event study analysis using the 120 days estimation window and 7 days event window on which we calculate the abnormal returns and the cumulative abnormal returns as described by equation 1 to 11 in Section 5.

6.3.1. <u>Na-tech Event</u>

As we have already described our initial attempt was to estimate the systematic risk during the estimation window which will afterwards be used for computing the Expected Returns and the abnormality. Thought, as mentioned in section 5.2.3 it is crucial to examine our estimations for autocorrelation and ARCH effect. Table VI (see Appendix I) presents the estimated systematic risk per event of analysis. Specifically, column (1) represents the initial estimations of beta (β) along with the diagnostic test for Autocorrelation (Breusch Godfrey lm test), ARCH effect, and Normality (Jarque Bera). The parentheses appose the t-statistics of the systematic risks, while the brackets appose the probability values for the coefficients as well as the diagnostic tests.

As we can see, most of the cases pass all the diagnostics test, though some events due face either the violation of autocorrelation or ARCH effect. For those cases, appropriate correction methods have been used in purpose of expunging the existing problem. The final results are presented in column (2), when corrections were needed. Moreover, for the case of ARCH effects, various estimations of the ARCH-family have been used, and the most appropriate has been chosen based on AIC (see Table IX,

Appendix I). The results in Table VI, strengthen our belief that all estimations must be tested for all possible OLS violations.

Based on the 120-days C.A.P.M analysis, after the corrections needed due to OLS violations, all final betas are statistically significant at 95% level of significance. Having p-value as a benchmark, 24 events are statistically significant at 99% level of significance with a probability value lower than 0.01 and only 1 event (Event 14) is statistically significant at 95% level of significance with p-value=0.0174. Results are presented on Table VII, Appendix I.

Based on the Coefficient of Determination (R^2), 5 out of 25 regressions have a really low goodness of fit (0.00-0.20), showing that less than 20% of the market returns can explain the returns of the assets. Similarly, 12 out of 25 regressions have a low goodness of fit (0.20-0.50), showing that less than 50% of the market returns can explain the returns of the assets, while 5 out of 25 regressions have a mediocre goodness of fit (0.50-0.80), showing that less than 80% of the market returns can explain the returns of the assets. Finally, 2 out of 25 regressions have a high goodness of fit (over 0.80) showing than more than 80% of the market returns can explain the returns of the assets, while only one regression has a negative R^2, indicating that the regression is probably missing the constant term. This is a true statement, however, based on C.A.P.M specification, no constant term is included on the final estimation.

After estimating the final systematic risk for each event, we computed both the Abnormal Returns in the event window as well as the Cumulative Abnormal Return. Using the Simple Hypothesis testing (Table 18), we do not reject the null hypothesis of the test as p-value is greater for than usual levels of significance ($\alpha = 0.1, 0.05$ or 0.01), thus we cannot come to conclusions whether the events caused an impact on the bond/stock returns or not. Having that in mind, we cannot give a clear answer on the H_C of our research, so the hypothesis is still debatable.

Table 18: Na-tech Events Simple Hypothesis testing Results - CAR

Simple Hypothesis Testing		
Cumulative Abnormal Return	t-statistics	p-value
CAPM	-0.697154	0.4924

6.3.2. Terrorist Attacks

As we have already described our initial attempt was to estimate the systematic risk during the estimation window which will afterwards be used for computing the Expected Returns and the abnormality. Thought, as mentioned in section 5.2.3 it is crucial to examine our estimations for autocorrelation and ARCH effect. Table VII (see Appendix I) presents the estimated systematic risk per event of analysis. Specifically, column (1) represents the initial estimations of beta (β) along with the diagnostic test for Autocorrelation (Breusch Godfrey lm test), ARCH effect, and Normality (Jarque Bera). The parentheses appose the t-statistics of the systematic risks, while the brackets appose the probability values for the coefficients as well as the diagnostic tests.

As we can see, most of the cases pass all the diagnostics test, though some events due face either the violation of autocorrelation or ARCH effect. For those cases, appropriate correction methods have been used in purpose of expunging the existing problem. The final results are presented in column (2), when corrections were needed. Moreover, for the case of ARCH effects, various estimations of the ARCH-family have been used, and the most appropriate has been chosen based on AIC (see Table X, Appendix I). The results in Table VII, strengthen our belief that all estimations must be tested for all possible OLS violations.

Based on the 120-days C.A.P.M analysis, after the corrections needed due to OLS violations, 37 final betas are statistically significant at 95% level of significance. Having p-value as a benchmark, 36 events are statistically significant at 99% level of significance with a probability value lower than 0.01 and only 1 event (Event 12) is statistically significant at 95% level of significance with p-value=0.0231. Moreover, 3 betas are not statistically significant (Events 23, 26 and 28). Results are presented on Table VIII, Appendix I.

Based on the Coefficient of Determination (R^2), 21 out of 40 regressions have a really low goodness of fit (0.00-0.20), showing that less than 20% of the market returns can explain the returns of the assets. Similarly, 11 out of 40 regressions have a low goodness of fit (0.20-0.50), showing that less than 50% of the market returns can explain the returns of the assets, while 6 out of 40 regressions have a mediocre goodness of fit (0.50-0.80), showing that less than 80% of the market returns can explain the returns of the assets. Finally, 1 out of 40 regressions has a high goodness of fit (over 0.80) showing than more than 80% of the market returns can explain the returns of the assets, while only one regression has a negative R^2, indicating that the regression is probably missing the constant term. This is a true statement, however, based on C.A.P.M specification, no constant term is included on the final estimation.

After estimating the final systematic risk for each event, we computed both the Abnormal Returns in the event window as well as the Cumulative Abnormal Return. Using the Simple Hypothesis testing (Table 19), we do not reject the null hypothesis of the test as p-value is greater for than usual levels of significance ($\alpha = 0.05$ or 0.01), thus we cannot come to conclusions whether the events caused an impact on the bond returns or not for 95% and 99% level of confidence, however, we reject the null hypothesis for 90% level of confidence and we may say that with a 90% probability, there may be a significant Abnormal Return on the bond prices when a terrorist attack occurs. Having that in mind, we cannot give a clear answer on the H_C of our research, so the hypothesis is still debatable.

Table 19: Terrorist Attacks Simple Hypothesis testing Results - CAR

Simple Hypothesis Testing CAR		
Cumulative Abnormal Return	t-statistics	p-value
CAPM	-1.859489	0.0705

In the case of the CAPM model specification and in analysing the coefficients, it is important to take into consideration both the use of additive and multiplicative dummies. More specifically, when an event occurs in a country which major religion is Muslim, the effect caused by the Muslim victims to the abnormality equals to 0.018428 (0.200070 − 0.181642), while the influence on the slope of fatalities equals to 0.0005783 (−0.67E−05 +0.000595).

Roman Catholics or Orthodox. In the case of Orthodox the constant term also decreases to 0.051489 (0.200070−0.148581) as in Muslim and the effect on slope decreases as well and equals to 0.0002823 (−1.67E−5 + 0.000299). On the other hand, the case of Roman Catholics differs from the previous cases, where, the constant term is influenced in a way that increases the total effect from 0.200070 to 0.350542 (0.200070 + 0.150472) and the effect on the slope is higher and equals to −0.0347547 compared to −1.67E−05 that is the slope of the fatalities. In some cases, the religion dummy can influence only the constant term or the slope and not both of them. Such cases are the Buddhist, Republic and Developed variables, which only influence the constant term by decreasing it to 0.068512, 0.126204 and 0.071002 respectively.

A variable that influences only the slope of fatalities is the Christian religion, which leads to an influence of −0.0018457 when fatalities occur in a Christian country. If none of these cases occurs and the religions are different, then the constant influence on the Cumulative Abnormal Returns equals to the constant term (0.200070) and the influence of the fatalities equals to −1.67E−05. In other words, we can assume that some religions do have an impact of the investors' decision and cause abnormalities. Based on analysis in section 6.1 where we proved that there is space concentration in Asia and Americas, and having in mind that these areas are mainly habited by Muslims and Roman Catholics respectively, we may think that those religions are the most suffered, however, we have no significant evidence to accept H_F and assume that the religion is the main reason on attack.

In the same way, we can estimate the effects caused when the event victims belong to specific religions. What we should not forget though is that terrorist groups tend to use their religion as their main initiative and tend to attack to the opposite religions. Such examples are all the resent attacks of ISIL against European countries.

Table 20: Cumulative Abnormal Returns (C.A.R.) in CAPM

Variables	C.A.R. CAPM	C.A.R. CAPM
Constant	0.15492 (1.9431) [0.0662]	0.20007 (2.9859) [0.0066]
Fatalities	0.009797 (1.1632) [0.2584]	−1.67E−05 (−1.4471) [0.1614]
Protestants	0.058545 (0.9220) [0.3675]	
Roman Catholic	0.204683 (3.2118) [0.0044]	0.150472 (3.6159) [0.0015]
Buddhist	−0.086692 (−1.1160) [0.2776]	−0.131558 (−2.3960) [0.0251]
Orthodox	−0.100825 (−1.4522) [0.1620]	−0.148581 (−2.7618) [0.0111]
Muslim	−0.134710 (−1.8716) [0.0760]	−0.181642 (−3.170118) [0.0043]
Republic	−0.076472 (−2.8220) [0.0105]	−0.073866 (−2.8378) [0.0093]
Developed	−0.141016 (−2.615) [0.0166]	−0.129068 (−2.5298) [0.0187]
Fatalities Muslim	−0.009210 (−1.0940) [0.2870]	0.000595 (2.3774) [0.0261]
Fatalities Orthodox	−0.009514 (−1.1296) [0.2720]	0.000299 (2.6241) [0.0152]
Fatalities Buddhist	−0.009786 (−1.1611) [0.2593]	
Fatalities Christian	−0.010877 (−1.3909) [0.1795]	−0.001829 (−2.0167) [0.0556]
Fatalities Roman Catholic	−0.044748 (−5.1138) [0.0001]	−0.034738 (−21.6906) [0.0000]
Fatalities Protestant	−0.009813 (−1.1651) [0.2577]	
Adjusted R^2	96.46%	96.72%
Akaike Info Criterion	−3.700444	−3.805767
Normality	1.1664 [0.5581]	1.0838 [0.5816]
ARCH effect	0.1412 [0.7096]	0.3032 [0.5351]
Breusch–Pagan	0.1818 [0.8352]	0.0953 [0.9095]
Ramsey RESET	0.3980 [0.6951]	0.0823 [0.9352]

6.4. Event Study Analysis Results (A.P.T)

The A.P.T approach is assumed to be a more advanced model due to the fact that contains more variables and as a result gives more information to the researchers. Table 21 presents the estimated systematic risk of one event of analysis. Specifically, column (1) represents the initial estimations of beta (β) along with the diagnostic test for Autocorrelation (Breusch Godfrey lm test), ARCH effect, and Normality (Jarque Bera) and Ramsey RESET test. Regarding the VIF test, there were two variable that scores VIF values greater than 10 (EUR/USD and GBP/USD). Those variables were excluded from the final estimation for two reasons. First of all, those two independent variables were highly correlated and secondly, non of them were statistically significant.

The parentheses appose the t-statistics of the systematic risks, while the brackets appose the probability values for the coefficients as well as the diagnostic tests. As we can see, the model passes all the diagnostic tests regarding the autocorrelation, ARCH effect, specification error and multicollinearity. Moreover we have already examined the stationarity violation for the variables and all variables are stationary at level order. However, as we can see most independent variables appear to be statistically insignificant as indicated by the t-statistics and p-coefficients. In order to improve the final estimation, we excluded insignificant variables in having as a rule of thumb the decrease of Akaike Information Criterion. The lowest value of AIC is reached when all exchange rates were excluded as well as the crude oil variable and the constant term. This specification gives as the lowest value of AIC while at the same time is the C.A.P.M specification. The final results are presented in column (2).

Table 21: A.P.T estimation example

	(1)	(2)
Constant	-0.001637	
	(-1.225227)	
	[0.2231]	
RM	0.553906	0.566306
	(4.571222)	(4.770721)
	[0.0000]	[0.0000]
EUR/USD	0.508357	
	(0.792645)	
	[0.4297]	
GBP/USD	-0.977112	
	(-1.363826)	
	[0.1754]	
JPY/USD	0.042774	
	(0.089193)	
	[0.9291]	
CHF/USD	0.361518	
	(1.181004)	
	[0.2401]	
Crude Oil Price	-0.041314	
	(-0.567224)	
	[0.5717]	
R^2	0.149497	0.156842
Fstat	4.456895	4.770721
	0.000441	0
Breush-Godfrey	0.8544	0.6864
ARCH lm test	0.2442	0.2231
JB test	8.960751	6.125573
Prob (JB)	0.011329	0.0457
Ramsey RESET test	0.7421	
AIC	-5.579246	-5.636574

We present only one[37] of the 65 events of the analysis due to the fact that all events appeared to follow the same flow and have as a more appropriate model specification the C.A.P.M. We do not support the idea that A.P.T is not a trustable or useful model for financial estimation. What we mention is that it is not proved to be preferable on the events we analyze. Different data may lead to different outcomes.

[37] The event presented on Table 21 is Event 1 of Na-tech Events

6.5. Ex-ante and Ex-post Systematic Risk Comparison

Our next attempt is to examine the H_D, and whether there is a significant difference between the systematic risk estimators before and after an unexpected event. For that purpose, we are going to use the analysis described in section 5.2.5. Based on the Event Study Analysis we are able to observe the abnormality that appears on the systematic risk following an unexpected event as well as examine whether the cumulative reaction has a significant impact on the systematic risk. The fact that this abnormality is observed over the event window, which in our case includes a 7-days' time span, captures a short-term reaction of the investors.

On the other hand, we used the ex-ante and ex-post analysis, where a longer time span was used (70 days), in an attempt to capture the increase/decrease of the systematic risk in the long-run. The level and the signal of the change will help up to understand the investors' psychology after the occurrence of the unexpected event.

6.5.1. Na-tech Events

Starting by the na-tech events, we observed 25 events, for 70 days before the occurrence of the event (ex-ante) as well as 70 days after the occurrence (ex-post). We estimated the systematic risks before and after the event, which once again were diagnosed for all possible OLS violations and if any occurred, was solved using the appropriate econometric approaches. The systematic risk results from the ex-ante and ex-post analysis are presented at Table XI (Appendix I) as well as at Figure 10 which visualizes the under-examination difference of the estimators. As it is obvious, in most cases the systematic risk increases after the occurrence of the disaster. More specifically, from the 25 events of the analysis, the 14 events present a greater systematic risk after the event and 11 events receive a lower systematic risk.

Although the Denali earthquake in Alaska in 2002 terrified the investors causing an increase of the systematic risk from 0.604627 to 0.692331, the 14.50% change is assumed to be low compared to other higher changes. However, we should always bear in mind that all these changes are multiplied with a great amount of capital investments and may cause huge losses. The Indian Ocean region belongs to the Ring of Fire, giving us the a priori information that there is an 80% perception of an earthquake occurrence, the Mw=9.3 earthquake that took place in Thailand in 2004, which then led to a tsunami causing 227,838 fatalities and $15 billion total damage, led also to a 35.42% increase on the systematic risk of the country's government bond from 0.627643 to 0.850764, giving us the belief that the investors were scared that Thailand will not be able to cover their requirements.

Though the great earthquake of 2005 in Pakistan caused a remarkable number of fatalities and injuries, the systematic risk of the government's bond decreased by 19.80%. More specifically, the systematic risk before the earthquake occurrence was 0.995803, however after the unexpected event the value of the systematic risk dropped at 0.798632 showing the investors' attempt to support the country and keeping their trust against to Pakistani Government. The Chinese earthquake at 12.05.2008 appears to have the same flow with the previous event. Once again, the number of causalities and economic losses are remarkable, thought the systematic risk mentions a 12.83% decrease from 0.954242 to 0.831756.

The next nat-ech analyzed is the Tohoku earthquake which is connected to the Fukushima Daiichi Power Plant disaster. The most interesting part of this analysis is the fact that the systematic risk of the Japanese Government mentioned a 25.84% decrease (from 0.677096 to 0.477908) giving the belief that investors based on government's reputation showed trust to a possible overcome. Moreover, Japan is placed on the region known as the Ring of Fire, a region with a high earthquake occurrence. On the other hand, the systematic risk of the corporation shares dramatically increased from 0.657127 to 3.078681. The 368.50% increase pictures the investors' tendency to sell the corporation's shares at any cost, in an attempt to avoid further losses. In that way, investors show their disappointment against the firm, or in other words punishing the corporation for its actions. However, it is important to mention that in this case, the disaster did not occur due to firm's fallacy; however, it is the most devastating nuclear disaster of the new Millennium.

To the same path of the Japanese government's bond after the earthquake occurrence, we can find the systematic risk of the New Zealand's case after the earthquake on 22 February 2011, which led to a 35.32% decrease, from 0.663115 to 0.428907. New Zealand kept its trustworthiness and persuaded the investors to support the country securing their capitals.

Moving forward, the next 4 events present mentionable increases on the systematic risks. More specifically the two earthquakes in Indonesia (Event 7 and Event 9), as well as the earthquake in Argentina led to systematic risk increases reaching the 17.36%, 47.47% and 50.80% positive change. Both regions belong to the Ring of Fire, and the fact that earthquakes are a common phenomenon on those countries, the high frequency is probably what terrifies the investors. Instead of being informed and prepared for a possible upcoming earthquake, they may assume that an earthquake, which may follow, will be even worse and probably devastating. The first volcanic eruption of the analysis is the one that occurred in New Zealand in 2011. Some volcanic activities appear to have a great impact on the investors' psychology. Probably the fact that a volcanic eruption is not a common as a ground movement, terrifies the citizens. Moreover, the outcomes after a volcanic eruption are way more disastrous comparted to a high intensity earthquake. An example of such a case is the 2011 New Zealand's case, where the systematic risk sharply increased from 0.500411 to 0.854470 (70.75%).

A remarkable case is the unique phenomenon of a tsunami into a lake, which is also connected to a volcanic activity. This Icelandic case, however, recorded a negative change on the systematic risk of the Iceland's government bond. The beta decreased from 0.466809 to 0.193990 (58.44%). The past volcanic activity experience in Iceland and the fact that they can take an advantage of such a case in that country, may have influenced the investors to support the country after the event's occurrence. That theory is also supported by following events (Event 15 and Event 16), reporting that Iceland tends to record negative change (decrease) on the systematic risk of its government's bonds after an unexpected volcanic eruption. The next volcanic activity in New Zealand, which occurred 5 years after the previous events, found the investors more prepared and the beta of the bond recorded a 45.54 decrease. On the other hand, some unexpected eruptions, such as Event 13 and Event 14, may have caused a small-scale reaction, and in these cases decrease, on the systematic risk (5.05% and 9.31% respectively).

Italy on the other hand, although it has a huge history regarding the volcanic activity, such as Mount Vesuvius and Etna, faced a dramatic systematic risk increase from 0.532475 to 0.949284 (78.27%) after the unexpected 2013 Etna's eruption. Similar reactions are also reported in cases of Japan and Chile with a 32.94% and 17.21% increase respectively after the volcanic eruption occurrence (Event 18 and Event 20). Indonesia's systematic risks on the other hand, tend to record negative changes after a volcanic eruption such as the 2014 and 2016 cases where the betas decreased by 14.14% and 33% respectively.

The last category analyzed on na-tech events are the technological disasters, and more specifically 3 oil spills and a nuclear disaster. We have already analyzed the Daiichi Nuclear disaster in this section, mentioning the remarkable systematic risk increase. The other three cases, though, do not appear to have similar impact on the investor's actions. Initially, the two oil spills occurred in Gulf of Mexico by BP, did not influence the corporation's shares in a negative way. The systematic risk decreased 4.85% and 22.47% respectively with firm's announcements trying to save the corporations reputation and investors supporting the corporation's trustworthiness. The huge environmental disaster occurred to the ecosystem did not influence the investors' beliefs and actions since the corporation announced that will "clean" the oil spill from the Gulf, ignoring the already existing damage. The Exxon Mobil oil spill case slightly increased the corporation's beta from 0.949111 to 0.966894, and once again, investors tend to ignore the devastating environmental result, due to the fact that petroleum industry is highly lucrative. All the estimated betas are presented in Table XI (see Appendix I).

Table 22: Na-tech Events Simple Hypothesis testing Resutls - Δ(β)

Simple Hypothesis Testing		
Change of the Systematic Risk	t-statistics	p-value
Δ(β)	0.719877	0.4786

Though, we cannot jump to conclusions based on a simple histogram or the percentage of change description. For that reason, we are going to compute the Δ(β)[38] which is the change of the systematic risk. Using the Simple Hypothesis testing (Table

[38] $\Delta(\beta)=\beta_{post\text{-}event}-\beta_{pre\text{-}event}$

22), we do not reject the null hypothesis of the test as p-value is greater for than usual levels of significance (α = 0.1, 0.05 or 0.01), thus we cannot come to conclusions whether the change of the systematic risk is significant. Having that in mind, we cannot give a clear if the systematic risk of an asset remains unaffected by an unexpected na-tech disaster, so the hypothesis is still debatable.

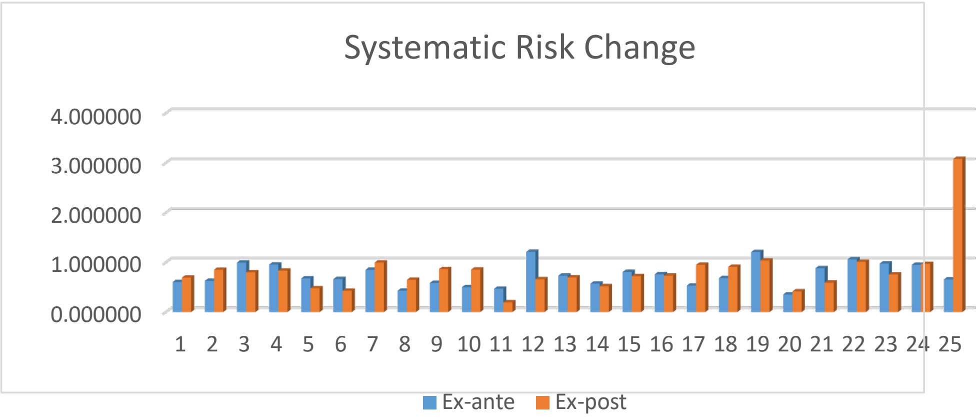


Figure 10: Na-tech Events Systematic Risk Change (ex-ante and ex-post analysis)

To be more analytical let us consider each event in turn. Although the Denali earthquake in Alaska in 2002 terrified investors causing an increase of the systematic risk from 0.604627 to 0.692331, the 14.50% change is assumed to be low compared to other higher changes. However, we should always bear in mind that all these changes are multiplied by a great amount of capital investments and may cause huge losses. The Indian Ocean region belongs to the Ring of Fire, giving us the a priori information that there is an 80% perception of an earthquake occurrence; the Mw = 9.3 earthquake that took place in Thailand in 2004, which then led to a tsunami causing 227,838 fatalities and 15 billion USD total damage, also led to a 35.42% increase in the systematic risk of the country's government bond from 0.627643 to 0.850764, giving us the belief that investors were scared that Thailand would not be able to cover their requirements.

Though the great earthquake of 2005 in Pakistan caused a remarkable number of fatalities and injuries, the systematic risk of the government's bond decreased by

19.80%. More specifically, the systematic risk before the earthquake occurrence was 0.995803, however after the unexpected event the value of the systematic risk dropped to 0.798632 showing the investors' attempt to support the country and keeping their trust against the Pakistani Government. The Chinese earthquake on 12 May 2008 appears to have the same flow as the previous event. Once again, the number of causalities and economic losses is remarkable, and systematic risk mentions a 12.83% decrease from 0.954242 to 0.831756.

The next na-tech analyzed is the Tohoku earthquake connected to the Fukushima Daiichi Power Plant disaster. The most interesting part of this analysis is the fact that the systematic risk of the Japanese Government mentioned a 25.84% decrease (from 0.677096 to 0.477908) giving the belief that investors showed trust in the government's reputation to possibly overcome this. Moreover, Japan is located on the Ring of Fire, a region with high earthquake occurrence. On the other hand, the systematic risk of the corporation shares dramatically increased from 0.657127 to 3.078681. The 368.50% increase shows investors' tendency to sell the corporation's shares at any cost, in an attempt to avoid further losses. In that way, investors show their disappointment against the firm, or in other words, punish the corporation for its actions. However, it is important to mention that in this case, the disaster did not occur due to the firm's fallacy; however, it is the most devastating nuclear disaster of the new millennium.

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Moving forward, the next four events present mentionable increases in the systematic risks. More specifically, the two earthquakes in Indonesia (Event 7 and Event 9), as well as the earthquake in Argentina. led to systematic risk increases reaching 17.36%, 47.47%, and 50.80% in positive change. Both regions belong to the Ring of Fire, and the fact that earthquakes are a common phenomenon in those countries probably terrifies investors. Instead of being informed and prepared for a possible upcoming earthquake, they may assume that an earthquake, which may follow, will be even worse and probably devastating. The first volcanic eruption of the analysis is the one that occurred in New Zealand in 2011. Some volcanic activities appear to have a great impact on investors' psychology. Probably the fact that a volcanic eruption is not as common as a ground movement, terrifies citizens. In addition, outcomes after volcanic eruptions are more disastrous compared to a high intensity earthquake. An example is New Zealand's case in 2011, where systematic risk sharply increased from 0.500411 to 0.854470 (70.75%).

A remarkable case is the unique phenomenon of a tsunami into a lake, which was also connected to volcanic activity. This Icelandic case, however, recorded a negative change on the systematic risk of Iceland's government bond. The beta decreased from 0.466809 to 0.193990 (58.44%). The past volcanic activity experience in Iceland and the fact that they can take an advantage of such a case in that country, may have influenced the investors to support the country after the event's occurrence. That theory is also supported by the following events (Event 15 and Event 16), which indicates that Iceland tends to record negative change (decrease) on the systematic risk of its government's bonds after an unexpected volcanic eruption. The next volcanic activity in New Zealand, which occurred five years after the previous events, found the investors more prepared and the beta of the bond recorded a 45.54% decrease. On the other hand, some unexpected eruptions, such as Events 13 and 14, may have caused a small-scale reaction with a decrease in the systematic risk (5.05% and 9.31%, respectively).

Italy on the other hand, although it has a huge history regarding volcanic activity, such as Mount Vesuvius and Etna, faced a dramatic systematic risk increase from 0.532475 to 0.949284 (78.27%) after Etna's unexpected eruption in 2013. Similar reactions are also reported in cases of Japan and Chile with a 32.94% and 17.21% increase, respectively, after the volcanic eruption occurrence (Event 18 and Event 20). Indonesia's systematic risks on the other hand, tend to record negative changes after a volcanic eruption such as the 2014 and 2016 cases where the betas decreased by 14.14% and 33%, respectively.

The last category analyzed on na-tech events was the technological disasters, and more specifically the three oil spills and a nuclear disaster. We already analyzed the Daiichi nuclear disaster in this section, mentioning the remarkable systematic risk increase. The other three cases, though, do not appear to have a similar impact on the investors' actions. Initially, the two oil spills that occurred in the Gulf of Mexico by BP did not influence the corporation's shares in a negative way. The systematic risk decreased 4.85% and 22.47%, respectively with the firm's announcements trying to save the corporation's reputation and investors supporting the corporation's trustworthiness. The huge environmental disaster that occurred in the ecosystem did not influence investors' beliefs and actions since the corporation announced they would "clean" the oil spill from the Gulf, ignoring the already existing damage. The Exxon Mobil oil spill case slightly increased the corporation's beta from 0.949111 to 0.966894, and once again, investors tended to ignore the devastating environmental result, due to the fact that the petroleum industry is highly lucrative. As can be seen, some events caused an increase in the systematic risk after the occurrence of the event, however, there are some cases where a decrease in the beta indicates a possible support for the country and/or corporation. This support may be due to the reputation of the country or corporation.

To conclude, although earthquakes are a really common phenomenon, in most cases considered they tended to have a moderate-to-high increase in the systematic risk of the bonds analyzed after the occurrence of each event. Regarding the moderate cases, five events caused a moderate increase in the systematic risk and were observed in countries with known tectonic plate movement activity such as the USA (Event 1), Indian Ocean (Event 2), Pakistan (Event 3), China (Event 4), and New Zealand (Event 12). Moving forward, there were four more cases recording a high-to-significantly high increase in the systematic risk, also observed in countries with high risk of occurrence. In Indonesia, which also lays on the Indian Ocean, Events 7 and 9 caused two significantly high increase of betas, while the other two countries were Chile (Event 8) and New Zealand (Event 10). As it appears, although high-risk areas exist and frequent earthquake activity is recorded, investors tend to have an immediate reaction after those events. A potential new earthquake may increase the risk of a country (or even a region) facing a possible new disaster.

It is also important to mention that there are three cases where the occurrence of an earthquake reduced beta. More specifically, Japan (Event 5), New Zealand (Event 6), and Iceland (Event 12) caused negative changes on the betas. These results raise great interest. Initially, the case of Japan was connected to the Fukushima Daiichi nuclear disaster. The earthquake which caused a tsunami leading to an industrial accident has raised a lot of attention from the media. However, the systematic risk of the Japanese bond revealed a significant decrease. In other words, the investors kept supporting the country which faced a natural disaster and a devastating nuclear hazard at the same time. What is crucial though is the Fukushima Daiichi share price faced an unprecedented shock (Event 25). The systematic risk of the stock dramatically increased giving the belief that the investors “punished” the corporation for causing the largest historical nuclear disaster of the new millennium. The ruined reputation of the corporation as well as its uncertain future probably scared the investors who reacted rapidly.

The last two negative cases on earthquake reactions were observed in New Zealand (Event 6) and Iceland (Event 11). The fact that in some cases New Zealand has negative changes and in other cases has high positive changes may be because of the possible expectance of such an event due to previous smaller earthquakes. Iceland is also observing negative changes to the systematic risk of the government bonds. Most countries analyzed regarding earthquakes are placed on the Ring of Fire area, a well-known area that concentrates the majority of earthquakes annually. Although these unexpected events are more likely to occur in these countries, investors are not prepared for such cases and immediately react.

Moving forward to the volcanic eruptions, it is surprisingly interesting to observe that the majority of the unexpected events caused negative changes in the systematic risk. Volcanic eruptions in most cases do not raise a lot of attention. The two cases that raised a lot of attention regarding the volcanic eruptions occurred in Italy (Event 17) and Japan (Event 18) and caused significantly high change on the ex-post analysis. Initially, the Etna case may have caused such a reaction because two years prior, this specific volcano recorded 38 basaltic fountains, which possibly increased the probability of a greater volcanic explosion. Finally, the Japanese case may have caused a significant reaction due to the fact that it is the only volcanic eruption which encountered fatalities. More specifically, 63 people lost their lives due to that eruption. Such outcomes may have influenced the behavior of the investors.

Last but not least is the oil spill disasters. The research included three oil spill events that occurred since 2000. Although, an increase of the systematic risk was expected due to the environmental disaster caused from those oil spills, investors appeared to decrease the betas in two cases—Prudhoe Bay (Event 22) and Deepwater Horizon (Event 23)—and a slight increase in the case of Mayflower (Event 24). Based on those results, we may assume that the investors, knowing that the oil industry is very profitable, tended to ignore the environmental impact of such disasters.

6.5.2. Terrorist Attacks

Continuing to the terrorist attacks, we observed 40 events, for 70 days before the occurrence of the event (ex-ante) as well as 70 days after the occurrence (ex-post). We estimated the systematic risks before and after the event, which once again were diagnosed for all possible OLS violations and if any occurred, was solved using the appropriate econometric approaches. The systematic risk results from the ex-ante and ex-post analysis are presented at Table XII (Appendix I) as well as at Figure 11 which visualizes the under-examination difference of the estimators. As it is obvious, in most cases the systematic risk increases after the occurrence of the attack. More specifically, from the 40events of the analysis, the 22 events present a greater systematic risk after the event and 18 events receive a lower systematic risk.

To be more analytical, the first and most known event of the analysis is the 911 terrorist attack by Al-Qaida in September 11, 2001. Although this terrorist attack shocked the globe, the immediate announcement by the US President reassured the citizens and the investors, saving USA's trustworthiness. More specifically, the systematic risk of the US Government Bond decreased by 53.58% based on those actions. Investors kept supporting the government and their actions after such a terrifying attack. Philippines on the other hand, apart from the hug number of losses had also to deal with a dramatic increase on the government's bond systematic risk after the terrorist attacks in 2004 and 2013, when the betas increased by 102.83% and 327.69% respectively. The investors felt the fear of the government's debacle.

Russian Federation faced a terrorist attack in 2005 with a great number of fatalities and injuries. Surprisingly, the systematic risk of the Russian Government bond decreased from 0.246784 to 0.073867, recording the highest decrease after a terrorist attack (70.07%). Nigeria in 2015 faced 3 terrorist attacks, from which two of them caused skyrocket increases on the betas. More specifically, Event 22 caused a 315.18% increase (from 0.085609 to 0.355435) and Event 23 caused a 118.57% increase (from 0.285819 to 0.624725). Both Philippines and Nigeria prove that the investors resent about the LDC's countries trustworthiness.

The great wave of Islamic Extremism in Europe started by the Charlie Hebdo attack, which may have caused a slight decrease in the French systematic risk (12.65%). All the under-examination events occurred in France since then caused further significant decrease on the bond's systematic risk. More specifically, after the Bataclan attack the systematic risk decrased from 0.226983 to 0.174816 (22.98%), while after the Marseille attack the beta decreased from 0.969342 to 0.826967 (14.69%). Belgium, which is assumed to be the heart of European Union, was terrified after ISIL attack in 2016. The markets reacted to the fact that the Islamic Extremism achieved to attack to the heart of European Union and democracy. The systematic risk of the Belgian government bond increased from 0.128191 to 0.491711 causing the second highest change, on the under-examination cases, recording a 283.58% increase on the risk.

All the following terrorist attacks that were triggered by the Islamic Extremism and specifically ISIL, surprisingly led to systematic risk decreases. Germany, Turkey, United Kingdom, Spain as well as USA, faced the ISIL terror, however, the investors were not influenced from such actions. The MDCs kept the reputations and their trustworthiness, sending the message of unity against terrorism.

Table 23: Terrorist Attacks Simple Hypothesis testing Results - Δ(β)

Simple Hypothesis Testing		
Change of the Systematic Risk	t-statistics	p-value
Δ(β)	0.553635	0.5830

Though, we cannot jump to conclusions based on a simple histogram. For that reason, we are going to compute the Δ(β) which is the change of the systematic risk. Using the Simple Hypothesis testing (Table 23), we do not reject the null hypothesis of the test as p-value is greater for than usual levels of significance (α = 0.1, 0.05 or 0.01), thus we cannot come to conclusions whether the change of the systematic risk is significant. Having that in mind, we cannot give a clear if the systematic risk of an asset remains unaffected by a terrorist attack, so the hypothesis is still debatable.

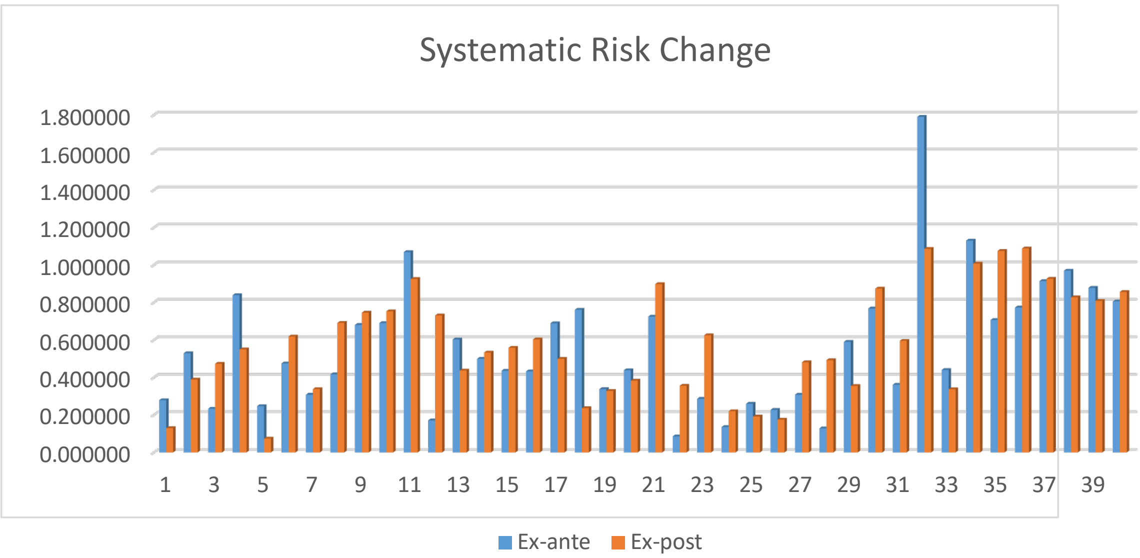

Figure 11: Terrorist Attacks Systematic Risk Change (ex-ante and ex-post analysis)

6.6. Pooled Regression Results

Moving to the final part of the analysis, we are going to determine the abnormal returns of the 25 and 40 events respectively by notable macroeconomic factors. In this part of the analysis, we will use the method described in section 5.2.6 where the dummy variable included indicates with 1 the days affected by the unexpected event, and 0 otherwise.

6.6.1. Na-tech Events

Moving to the final part of the analysis, we sought to determine the abnormal returns of the 25 events by notable macroeconomic factors. The importance of this analysis is to examine whether widely known and available macroeconomics can influence investors' actions and either support an investment or not. In other words, a well-stated economy that exudes reliability and credibility can positively affect investors, which will then lead to lower and probably insignificant abnormal returns. In this part of the analysis, the dummy variable included indicates with 1 the days affected by the unexpected event, and zero otherwise.

Table 24 presents the results from the pooled panel regression. As we can see, most of the macroeconomic variables have a significant impact on the abnormal returns. By including variables, such as tourism expenditures and tourist arrivals, we assume that similar independent variables may affect the dependent in the same way. However, as observed in Table 24, tourism expenditures and tourism arrivals have different impact on abnormal returns. More specifically, the former appears to have a negative sign, which actually means that when the number of arrivals increases, the abnormal returns of the asset examined decrease. This gives us the feeling that investors tend to react less to countries with increased tourism. However, expenditures of tourism appear to have the exact opposite impact on abnormal returns.

What is interesting to observe is how the aftermath of an unexpected event may affect abnormalities. For that purpose, we used the products of estimation with dummies, where 1 is for the days after the event occurrence. As observed, tourism arrivals have a positive sign to abnormal returns. In other words, more tourism arrivals lead to more abnormality probably due to the increased level of uncertainty. Investors may recognize each country as a risky place to visit due to a potential outbreak of a new disaster. On the other hand, increased revenues from tourists (tourism expenditures) decrease the abnormality, possibly due to the fact that more revenues may allow the country to pay the bond coupons as well as keep stability and credibility.

The purpose of GDP growth inclusion is the fact that the percentage of GDP growth through the years may be used as a proxy to the economic growth of a country. Based on the results, we can see that there is a positive relation between economic growth (GDP growth) and abnormal returns, which means that the more GDP growth, the greater the abnormal returns. Based on our assumptions, we were expecting the exact opposite relation due to the fact that a higher GDP growth will make investors believe that the country can cope with the disaster. What was interesting to observe was the results referring to the period after the occurrence of an event (GDP growth*D). The expected negative sign of the explanatory variable that represents the reduction of abnormalities caused by investors was proven in the case of the dummy influence. In other words, while increasing the growth of an economy, the country becomes more trustworthy and the investors are less negatively influenced.

Table 24: Na-tech Events Pooled Panel Regression Results

Variable	Pooled AR	Pooled AR
Constant	-0.024887 (-6.604322) [0.0000]	-0.027235 (-9.871251) [0.0000]
GDP growth	0.005188 (10.20047) [0.0000]	0.005497 (13.52677) [0.0000]
GDP/c	8.44E-07 (4.507790) [0.0000]	8.36E-07 (6.603492) [0.0000]
Population Density	-5.64E-05 (-3.643325) [0.0003]	-6.41E-05 (-5.781233) [0.0000]
FDI	3.66E-13 (5.470146) [0.0000]	4.12E-13 (9.534101) [0.0000]
Household Consumption	-6.21E-14 (-7.121643) [0.0000]	-6.46E-14 (-10.71255) [0.0000]
Imports	1.02E-13 (3.938239) [0.0001]	1.10E-13 (5.931378) [0.0000]
Inflation	-0.000355 (-0.842450) [0.3996]	
Tourism Expenditures	4.76E-12 (8.670022) [0.0000]	4.87E-12 (11.61634) [0.0000]
Tourism Arrivals	-4.52E-10 (-2.937924) [0.0033]	-4.10E-10 (-3.352551) [0.0008]
Exports	-9.29E-14 (-6.229301) [0.0000]	-9.85E-14 (-8.532868) [0.0000]
Gov. Health Expenditures/c	-4.89E-06 (-2.065084) [0.0390]	-4.61E-06 (-3.023661) [0.0025]
GDP growth*D	-0.001366 (-2.419998) [0.0156]	-0.001745 (-5.958745) [0.0000]
GDP/c*D	-6.04E-08 (-0.270809) [0.7866]	
Population Density*D	-0.000116 (-5.693055) [0.0000]	-9.82E-05 (-9.961197) [0.0000]
FDI*D	7.64E-14 (0.900765) [0.3678]	
Household Consumption*D	2.14E-14 (1.925287) [0.0543]	2.67E-14 (6.228393) [0.0000]
Imports*D	1.60E-13 (4.740005) [0.0000]	1.44E-13 (9.023375) [0.0000]
Inflation*D	0.004192 (9.399820) [0.0000]	0.004057 (13.28318) [0.0000]
Tourism Expenditures*D	-4.92E-12 (-7.071382) [0.0000]	-5.17E-12 (-12.58543) [0.0000]
Tourism Arrivals*D	1.63E-09 (8.021313) [0.0000]	1.61E-09 (10.86971) [0.0000]
Exports*D	-7.00E-14 (-3.673465) [0.0002]	-6.02E-14 (-5.329575) [0.0000]
Gov. Health Expenditures/c*D	-5.09E-06 (-1.651309) [0.0988]	-5.48E-06 (-9.441656) [0.0000]
R^2	0.28813	0.288651
F-statistics	75.03277 [0.000000]	98.15229 [0.000000]
AIC	-4.088925	-4.090998

Similar to GDP growth, we included GDP/c as an explanatory variable expecting to observe a negative impact to abnormalities. The GDP/c is a variable that is weighted by population. Higher levels of GDP/c represent better economic conditions for the population of a nation and probably a better economic status as a total. Once again, the interest would have been gathered on the product of dummy variable (GDP/c*D), however, this is a statistically insignificant variable, possibly implying for the cases considered that abnormal returns and therefore investors, are not influenced by such a factor.

In addition, there was an increase both in inflation and imports to abnormal returns after the events' occurrence. The increase in imports may be affected by the need for supplies for the suffered regions, even for basic everyday goods. If the country needs more imports this may indicate a difficulty in covering their basic needs, placing the country in an unstable condition and increasing the risk for investors. A possible increase in inflation indicates a decrease of the value of the country's currency which once again increases the risk for investors. Based on those results, investors tend to be influenced by macroeconomic factors regarding the decision to keep investing on a bond/stock after a na-tech event.

6.6.2. Terrorist Attacks

Moving forward to terrorist attacks, Table 25 presents the results from the pooled panel regression. As we can see, most of the macroeconomic variables have a significant impact on the abnormal returns. Based on the results, we can see that there is a positive relation between economic growth (GDP growth) and abnormal returns, which means that an increase on the GDP growth will cause greater abnormal returns. Based on our assumptions, we were expecting the exact opposite relation due to the fact that a higher GDP growth will make the investors believe that the country can cope with the disaster. As it is also shown there is an increase both of the inflation and the imports to the Abnormal Returns after the event's occurrence.

The increase of imports may be affected by the need of supplies for the suffered regions even on basic everyday goods. If the country needs more imports may indicate a difficulty in covering their basic needs placing the country in an unstable condition and increasing the risk for investors. The increase of inflation indicates a decrease of the value of the country's currency which once again increases the risk for investors. What is also important to mention is that a possible increase on the GDP/c will lead to a decrease on the abnormal returns meaning that higher incomes lead to lower abnormalities, showing that in cases of terrorist attacks investors are influenced by the economic conditions. Thus, investors tend to be influenced by macroeconomic factors regarding the decision to keep investing on a bond after a terrorist attack.

Table 25: Terrorist Attacks Pooled Panel Regression Results

Variable	Pooled AR	Pooled AR
Constant	0.005321	0.005321
	(1.900.834) [0.0570]	(1.903938) [0.0570]
GDP growth	0.001295	0.001136
	(4.732927) [0.0000]	(4.721368) [0.0000]
GDP/c	-0.00000108	-0.0000011
	(-7.729510) [0.0000]	(-7.97695) [0.0011]
Population Density	-0.0000235	-0.0000205
	(-3.082230) [0.0021]	(-3.273320) [0.0011]
FDI	3.47E-14	3.59E-14
	(4.071954) [0.0000]	(4.244074) [0.0000]
Household Consumption	-3.29E-15	-2.82E-15
	(-2.068004) [0.0387]	(-2.131870) [0.0331]
Imports	3.55E-14	3.12E-14
	(2.047437) [0.0407]	(2.118074) [0.0342]
Inflation	-0.000794	-0.000791
	(-6.125340) [0.0000]	(-6.131630) [0.0000]
Tourism Expenditures	-1.25E-10	-1.15E-10
	(-3.443260) [0.0006]	(-3.440130) [0.0006]
Tourism Arrivals	0.000319	0.00036
	(1.884738) [0.0595]	(2.910351) [0.0036]
Exports	-5.05E-14	-4.82E-14
	(-4.002080) [0.0001]	(-4.36247) [0.0000]
Gov. Health Expenditures/c	0.0000118	0.0000119
	(7.81237) [0.0000]	(7.898958) [0.0000]
GDP growth*D	-0.001692	-0.001414
	(-4.923910) [0.0000]	(-5.497420) [0.0000]
GDP/c*D	0.00000126	0.00000129
	(7.017712) [0.0000]	(7.343710) [0.0000]
Population Density*D	0.00000529	
	(0.692917) [0.4884]	
FDI*D	-9.11E-14	-9.32E-14
	(-8.244210) [0.0000]	(-8.551410) [0.0000]
Household Consumption*D	-4.33E-15	-5.16E-15
	(-2.107970) [0.0351]	(-3.824170) [0.0001]
Imports*D	7.22E-14	7.97E-14
	(3.162897) [0.0016]	(4.886294) [0.0000]
Inflation*D	0.000451	0.000445
	(3.251992) [0.0012]	(3.255701) [0.0011]
Tourism Expenditures*D	8.45E-11	6.76E-11
	(2.090135) [0.0367]	(2.093884) [0.0363]
Tourism Arrivals*D	0.0000729	
	(0.361591) [0.7177]	
Exports*D	-3.48E-14	-3.89E-14
	(-2.085090) [0.0371]	(-3.04935) [0.0023]
Gov. Health Expenditures/c*D	-0.0000149	-0.0000151
	(-7.571930) [0.0000]	(-7.695180) [0.0000]
R^2	0.115148	0.115245
F-statistics	22.52516 [0.000000]	24.70017 [0.000000]
AIC	-5.237054	-5.23771

Section 7

7. Conclusion and Further Research

The main purpose of this dissertation was to investigate whether investors, in their attempt to avoid risk and secure their capital, tend to react after unexpected events. Risk aversion is the main determinant that influences investors' choices. Thus, when investment advisors diversify a portfolio, they should always take into consideration the investors' preferences and their tolerance to risk as well as any aspect that may lead to money loss. Uncertainty, on the other hand, is the main characteristic of capital markets, with the idea that "the more you risk, the more you gain". Although analysis techniques for stock performances exist, these models cannot capture the potential risk of "unexpected". Environmental hazards, which are assumed to be random, have a significant impact on society and influence everyone's life. In this research, we decided to examine four hypotheses regarding the influence that certain unexpected events may have on investors' decisions.

Initially, we analysed all possible unexpected events may occur regarding the environmental hazards, both natural and technological, and acts of terrorism. What is also important to mention is that regarding the terminology and literature review as well as the frequency analysis, we covered the cases of complex hazards, which are mainly the famine case; however, the small amount of events observed led us to the decision on exclusion on the final sample of analysis.

After the first part of the analysis we concluded that the most hazards technological events, yet not the most often, are the Industrial accidents, which based on literature are highly connected to the natural hazards and most specifically the geophysical hazards. Giving as a great example the case of Fukushima Daiichi Nuclear Power Plant Failure, we decided to investigate the 25 events that belong to the category known as na-tech. At this point we should remind that the events which belong to that category since 2000 are more than 25, however, most cases of industrial accidents belong to corporations that are not publicly listed, so data or stock prices were not available.

Moving forward to the category of terrorist attacks, we followed the same procedure by displaying the historical trend of these events and created a sample of 40 significant events. The events included had either great number of fatalities or raised a lot of attention worldwide. Of course, the analysis starts with the most known event of September 11, 2001 and included all latest events occurred in Europe and triggered by ISIL.

The first hypothesis was accepted due to the fact that map visualizations and statistical analysis emphasized the high and low risk areas. We proved that neither natural, and more specifically geophysical, nor technological, and more specifically industrial, hazards are random. Based on our previous research (Halkos and Zisiadou 2018, 2019) both cases have high- and low-risk areas, so the probability of occurrence may be predicted up to a certain point. A remarkable example that has also been proven is the Ring of Fire that indicated the region with the most earthquakes on an annual base. Knowing a priori the risks we are exposed at, may allow us to either be prepared for their appearance, if we are this region's governments or citizens, or protect or capitals using portfolio diversification or hedging techniques. Using the regional results presented on tables in Section 6, we indicated that higher number of fatalities or injuries observed on Least Developed Countries, while higher economic damages observed on Most Developed Countries. Based on that information we can accept our second hypothesis, which is based on Smith's statement and state that people from regions with lower income tend to lose their lives while people from regions with higher income tend to lose their money. A reasonable answer to this statement may derive from the construction code. Low-income areas do not own luxurious and highly equipped building, which makes a possible demolition cause less economic damage compared to the luxurious constructions. The revision of construction codes is more than necessary due to the fact that if new constructions follow those building rules may be more durable to an upcoming hazard.

Using econometric techniques and based on C.A.P.M and A.P.T approaches we examined the investors' behavior after an unexpected event. We observed that the hypothesis of no significant Abnormal Return after a na-tech event is not rejected leaving more space of research due to the fact that the statement is still questionable. In the case of terrorist attacks the hypothesis is rejected on 90% level of confidence, however, is still debatable on 95% and 99%. The ex-ante and ex-post analysis allowed us to investigate whether there is a difference between the systematic risk before and after the event. All 65 cases have diversifications on their systematic risks, with 37 events having increased systematic risks and 28 events having decreased systematic risks. Both for the na-tech events and the terrorist attacks, thy hypothesis of non-affected systematic risks before and after the events is not rejected, giving more space for further research on that topic.

Based on the analysis followed the results, we can mention that regarding the nat-ech events and more specifically the earthquakes, Ring of fire is a highly frequent earthquake region, however, the occurrence of an unexpected event on that region tend to increase the systematic risk. Either the investors are not well informed about the high frequency and are terrified by such events or the fear the possible next greater earthquake. Regarding the volcanic activity, surprisingly, Iceland is the only country, which repetitively records decreases on the systematic risk after the volcanic eruptions, and probably this is connected to the history of the Icelandic volcanic activities and their beneficial aspects to the country.

The technological disasters, which are those that cause the greatest and most devastating disaster to the environment are unfortunately those that not only do not cause an increase on the systematic risk of the corporation's share, but also proves the investors support to the industry. Specifically, the petroleum industry cause 3 huge oil spill accidents, two of them in the Gulf of Mexico, and investors, having in mind the high profitability of the petroleum industry, grabbed the opportunity of the corporation's announcements regarding the water purification, firmly supported the corporations and their actions. The only corporations, from those examined, that has not the whole blame of the disaster occurred was the Daiichi Nuclear Power Plant in Japan, which however caused the highest and most rapid increase of the systematic risk, of all cases analyzed. The investors probably assumed that after such a disaster both the environment and the corporation's settlements, the corporation would not be able to cover the investors requirements.

Regarding the terrorist attacks, the LDCs tend to suffer from a rapid increase of the systematic risk after a terrorist activity. What is crucial to mention is that the the government's actions and announcements immediately after an attack may save the market volatility. Such a case is the attack on the World Trade Center in September 11, 2001. The US government saved its reputation, as well as the fluctuation of the markets. Finally, if we exclude the Belgian attack in 2016, all the terrorist attacks triggered by ISIL, led to a decrease of the systematic risk of the governments' bonds showing that the Islamic Extremism may have terrified the citizens regarding their lives, by not the investors, regarding their capitals.

At this point, we should underline once again the importance of diagnostic tests on all estimations. Most researchers working on the financial field tend to ignore the econometric diagnostics tests on their estimations giving non-accurate estimations on systematic risks. More specifically, we have proven that almost 30% of the initial estimations were inaccurate due to OLS violations. In addition, we proved that the OLS estimation is not always the most preferable and in some cases, the ARCH specifications are those which allow us to model our data on the best way. The most common ARCH specifications were GARCH and EGARCH, though in some cases PARCH specification was indicated by the AIC.

The third under-examination hypothesis is not rejected, showing that the abnormal returns occurred after an unexpected environmental hazard are not statistically significant. In other words, a na-tech occurrence does not seem to affect investors' psychology given they tend to keep an unchangeable strategic investment plan when an unexpected environmental disaster occurs.

Additionally, as examined by the forth hypothesis, we have proven that although there is a change in systematic risk after the occurrence of an event, in comparison with the one before the occurrence, this change is not significant; thus the question whether a potential disaster may affect systematic risk remains debatable. What is also crucial to mention is that the avoidance of diagnostic tests may under/overestimate systematic risk which is differentiated when there are violations of the basic hypotheses in OLS specifications with no adequate corrections in the final estimations.

The final part of the analysis was based on the macroeconomic influence on investors' behavior. With the use of pooled OLS regressions, we examined the third and fourth hypotheses of research proving that there are several macroeconomic factors, like GDP growth, tourism factors, inflation, and imports that may affect abnormal returns after an event occurrence. The fifth hypothesis has been accepted indicating that macroeconomic factors, influencing the investors' point of view, exist. More specifically, the abnormal returns after the occurrence of an unexpected events tend to decrease if the country of examination records an increase in tourism, both arrivals and expenditures. On the other hand, if the inflation and/or the imports of the suffered country increase then the abnormality recorded will also increase, due to the positive sign of their coefficients. Probably, the increased inflation and/or imports may settle the country in a needy condition, making it even riskier and probably unable to cope with investors' requirements. The fourth hypothesis was examined with the inclusion of GDP/c and GDP growth. The GDP/c in our research gives statistically insignificant coefficients indicating a non-affectionate behavior, however, the GDP growth coefficient is statistically significant and has a negative sign. This sign indicates that a possible increase in GDP growth will lead to a decrease in the abnormal returns when an unexpected environmental disaster occurs. This reaction may likely be influenced by a country's trustworthiness. In other words, increased economic growth influences the reliability of a country which therefore influences investors in a positive way. Generally, it is stated in the literature that investors tend to support a country, which has faced a natural disaster, while at the same time they tend to "punish" a corporation that caused a technological disaster, which may have led to economic losses and adverse impacts on flora, fauna, and the environment in general. What should raise more attention though is the fact that the oil companies that caused huge environmental disasters after the occurrence of the oil spills reached lower values of systematic risk. In other words, investors tended to support those companies and the answer may be hidden in the great profit those companies recorded. Finally, the last hypothesis regarding the religion and its affection to the abnormalities, we have shown that the

Islamic World tend to be more in target of the terrorist attacks over the last century, if we exclude the latest years with the ISIL rebellion.

With all this information beforehand, we believe that governments may have the opportunity to create better security and rescuing plans, as well as preparedness systems, while at the same time be able to cover possible damages with emergency payments from their annual budgets. Investment advisors, as we have already mentioned, may help their clients to diversify or hedge in a way that will minimize potential risk, without avoiding investment on specific corporations or countries. Furthermore, our paper provides evidence that some macroeconomic factors may have an effect on investors' psychology regarding their investment decisions after the occurrence of an unexpected environmental disaster. We can infer that the reputation of a country or corporation may be a decisive factor.

Supplementary research could be done by including events from other categories of unexpected events such as transport accidents, meteorological hazards, etc., or by expanding the time span of the event analysis. Although we would like to include cases such as Chernobyl nuclear accident or Three Mile Island, the lack of available information reduced our sample. Moreover, further research could be carried out with inclusion of more macroeconomic factors or with the use of other advanced econometric methods on modeling such issues. Inclusion of other explanatory variables like governmental announcements, such as bankruptcy, or the rise of an extremist political party may also be useful. Likewise, announcements of the downgrade/upgrade of countries or corporations from credit rating agencies may lead to useful knowledge on how investors may weight their risk based on available information.

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Appendix I

Table I: Descriptive Statistics of Na-tech Events (120 days estimation window)

	Event_01		Event_02		Event_03		Event_04		Event_05		Event_06		Event_07		Event_08		Event_09		Event_10	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	-0.00119	0.00048	-0.00122	-0.00050	0.00517	-0.00077	-0.00178	-0.00079	0.00017	-0.00127	-0.00012	-0.00116	-0.00020	0.00021	0.00088	0.00009	-0.00252	-0.00026	-0.00304	0.00093
St. Deviation	0.01567	0.01115	0.01017	0.01091	0.07075	0.00784	0.02516	0.01625	0.02026	0.01151	0.01203	0.01171	0.02190	0.01448	0.01101	0.01193	0.01810	0.01187	0.02099	0.02053
Skewness	0.3738	0.0226	0.6525	0.5489	0.5343	-0.0990	0.1218	0.2880	-0.3182	-0.0757	0.4915	-0.1611	0.3469	0.4326	-0.0972	0.1766	0.5242	0.3400	0.0935	1.1505
Kurtosis	2.9502	4.7837	4.3578	4.4865	4.3112	2.9848	3.9772	4.3605	4.3948	3.2516	3.5239	3.2967	6.9813	3.0468	2.8743	3.2883	3.8303	3.2813	3.4034	7.5449
J.B	2.7830	15.7859	17.5842	16.9308	14.1852	0.1957	5.0293	10.8231	11.6545	0.4275	6.1527	0.9515	80.9821	3.7229	0.2657	1.0303	8.8684	2.6845	0.9802	128.6759
Prob(JB)	0.2487	0.0004	0.0002	0.0002	0.0008	0.9068	0.0809	0.0045	0.0029	0.8076	0.0461	0.6214	0.0000	0.1554	0.8756	0.5974	0.0119	0.2613	0.6126	0.0000
Correlation	0.4070		0.7638		-0.0961		0.6656		0.5464		0.6511		0.5565		0.5574		0.4099		0.5750	
A.D.F	-11.3116	-13.6621	-12.2694	-11.3881	-18.9257	-9.4172	-14.6738	-11.1813	-10.6146	-11.7835	-10.1980	-12.0764	-9.3299	-12.1697	-11.7885	-11.7923	-12.4087	-11.3066	-11.0720	-12.2933
prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	Event_11		Event_12		Event_13		Event_14		Event_15		Event_16		Event_17		Event_18		Event_19		Event_20	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00029	-0.00033	0.00103	-0.00053	-0.00018	-0.00063	0.00208	-0.00262	-0.00140	-0.00071	0.00059	-0.00074	-0.00003	0.00036	0.00058	0.00087	0.00116	0.00040	0.00010	0.00105
St. Deviation	0.00954	0.01589	0.01777	0.00760	0.02149	0.01518	0.06176	0.01980	0.02275	0.02262	0.01656	0.01087	0.01216	0.00945	0.01021	0.00790	0.02303	0.01195	0.01234	0.01395
Skewness	-0.1081	2.0117	-0.4454	0.0922	0.1601	0.2945	3.1733	0.1327	-0.2006	-0.1279	0.7993	0.1273	0.2344	0.1375	0.2356	0.0827	-0.2752	-0.5179	-0.2893	2.7673
Kurtosis	4.7974	15.1261	3.8328	3.3857	2.6137	4.9665	25.0196	5.3379	2.8103	2.4692	6.4068	3.9635	3.2384	4.2971	3.5793	4.5457	5.1141	5.4261	3.2047	24.0912
J.B	16.2505	809.3543	7.3732	0.9064	1.2483	20.8951	2603.8360	27.4509	0.9769	1.7211	70.2187	4.9244	1.3719	8.7174	2.7654	11.9826	23.6632	34.5044	1.8679	2357.5430
Prob(JB)	0.0003	0.0000	0.0251	0.6356	0.5357	0.0000	0.0000	0.0000	0.6136	0.4229	0.0000	0.0852	0.5036	0.0128	0.2509	0.0025	0.0000	0.0000	0.3930	0.0000
Correlation	0.5182		0.3344		0.3742		0.2233		0.9159		0.5419		0.4637		0.6635		0.6817		0.5875	
A.D.F	-10.0694	-9.7970	-9.6873	-11.6734	-10.6474	-10.7053	-11.0430	-12.1138	-8.7775	-9.0136	-12.1507	-10.5884	-11.0726	-12.6408	-9.9076	-10.5891	-10.1903	-12.9183	-12.0263	-12.3568
prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	Event_21		Event_22		Event_23		Event_24		Event_25	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	-0.00257	-0.00120	-0.00174	-0.00123	0.00037	0.00016	0.00062	0.00146	-0.00225	-0.00127
St. Deviation	0.01494	0.01301	0.01765	0.01338	0.01641	0.01334	0.01086	0.01000	0.01656	0.01151
Skewness	-0.0376	-0.5021	0.0033	0.0031	0.1364	-0.3431	-0.4563	-0.1971	-1.4767	-0.0757
Kurtosis	5.9704	3.7034	2.2929	2.9675	4.7090	4.4588	4.0138	3.2606	10.9384	3.2516
J.B	43.7764	7.4533	2.4795	0.0054	14.8514	12.8856	9.2257	1.1074	355.7132	0.4275
Prob(JB)	0.0000	0.0241	0.2895	0.9973	0.0006	0.0016	0.0099	0.5748	0.0000	0.8076
Correlation	0.7364		0.8146		0.8216		0.9098		0.6733	
A.D.F	-10.7963	-13.4840	-12.7186	-12.2041	-12.6653	-14.4364	-10.6760	-10.7001	-9.8247	-11.7835
prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table II: Descriptive Statistics of Na-tech Events (70 days ex-ante estimation window)

	Event_01		**Event_02**		**Event_03**		**Event_04**		**Event_05**		**Event_06**		**Event_07**		**Event_08**		**Event_09**		**Event_10**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	-0.00143	-0.00017	-0.00117	-0.00146	0.00325	-0.00181	-0.00034	0.00027	0.00036	-0.00068	0.00065	-0.00041	-0.00125	-0.00124	0.00106	0.00118	-0.00347	-0.00112	-0.00019	0.00207
St. Deviation	0.01663	0.01054	0.01007	0.01052	0.06543	0.00784	0.02286	0.01683	0.01566	0.00964	0.01199	0.01015	0.02037	0.01270	0.01008	0.01069	0.01554	0.01003	0.02102	0.02235
Skewness	0.4660	-0.5541	0.9014	1.1008	0.5404	-0.2375	0.3380	0.5692	0.5204	0.2429	0.6657	0.3333	0.8361	1.1188	-0.1097	-0.1762	-0.4725	0.3582	-0.2036	1.2827
Kurtosis	2.9192	4.1984	4.7939	7.1953	5.5816	3.1565	3.9775	4.4074	3.6010	3.1710	3.6426	3.3958	7.2208	4.5933	3.2615	3.0682	3.4399	3.4052	3.0077	7.7925
J.B	2.5161	7.6603	18.5956	64.5359	22.5193	0.7189	4.0610	9.4206	4.1529	0.7625	6.2828	1.7282	59.2571	21.6926	0.3350	0.3703	3.1240	1.9474	0.4770	84.9531
Prob(JB)	0.2842	0.0217	0.0001	0.0000	0.0000	0.6981	0.1313	0.0090	0.1254	0.6830	0.0432	0.4214	0.0000	0.0000	0.8458	0.8310	0.2097	0.3777	0.7878	0.0000
Correlation	0.3819		0.7136		0.0493		0.7249		0.4208		0.7031		0.5279		0.4499		0.3574		0.5375	
A.D.F	-9.6454	-11.9436	-7.8993	-7.9740	-3.8672	-7.3720	-9.6646	-7.9630	-8.7537	-8.1495	-7.6999	-7.5830	-7.5663	-9.1302	-7.0845	-9.0233	-10.0305	-9.5504	-4.7572	-4.4632
prob (A.D.F)	0.0000	0.0001	0.0000	0.0000	0.0039	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0002	0.0006
	Event_11		**Event_12**		**Event_13**		**Event_14**		**Event_15**		**Event_16**		**Event_17**		**Event_18**		**Event_19**		**Event_20**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00110	-0.00092	0.00593	-0.00026	-0.00037	-0.00114	-0.00338	-0.00214	-0.00088	0.00044	-0.00049	-0.00081	0.00106	0.00086	0.00071	0.00147	0.00452	0.00103	0.00202	0.00220
St. Deviation	0.00952	0.01261	0.02037	0.00909	0.02015	0.01305	0.03333	0.01785	0.01445	0.01388	0.01321	0.01090	0.01295	0.00873	0.00957	0.00766	0.01975	0.00992	0.01162	0.01531
Skewness	0.5059	0.3120	0.3954	0.0137	-0.0713	-0.1494	-0.2298	-0.0416	0.4941	0.5764	0.1397	0.7109	0.2133	-0.0872	0.1669	-0.2489	0.9002	0.2076	-0.0054	3.8178
Kurtosis	4.4357	2.8017	4.3067	4.6485	2.8020	2.7375	6.8853	9.6130	3.2621	4.3911	4.0635	3.5724	3.1457	2.3583	2.5145	3.7115	4.0855	4.3110	3.1078	26.5702
J.B	8.8689	1.2325	6.7072	7.8155	0.1711	0.4546	44.0064	125.7481	3.0056	9.3845	3.4761	6.7545	0.5842	1.2712	0.9981	2.1678	12.7059	5.4374	0.0337	1764.8320
Prob(JB)	0.0119	0.5400	0.0350	0.0201	0.9180	0.7967	0.0000	0.0000	0.2225	0.0092	0.1759	0.0341	0.7467	0.5296	0.6071	0.3383	0.0017	0.0660	0.9833	0.0000
Correlation	0.6301		0.2163		0.5332		0.2989		0.7763		0.6274		0.3542		0.5536		0.5882		0.4515	
A.D.F	-7.1072	-7.0487	-6.1437	-7.2300	-8.3240	-6.8119	-7.9673	-11.7005	-7.7462	-7.9799	-7.4915	-7.3857	-7.8667	-8.6397	-7.7061	-9.8624	-7.4709	-10.0893	-9.3755	-7.9928
prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0000

	Event_21		**Event_22**		**Event_23**		**Event_24**		**Event_25**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	-0.00066	-0.00073	-0.00250	-0.00132	0.00045	0.00044	0.00111	0.00224	0.00132	-0.00068
St. Deviation	0.01365	0.01181	0.01812	0.01458	0.01388	0.01064	0.01106	0.01024	0.01125	0.00964
Skewness	0.0921	-0.0445	-0.0388	-0.0099	-0.6373	-0.0493	-0.1654	-0.1655	0.3785	0.2429
Kurtosis	3.8471	2.4994	2.2025	2.8745	4.1806	2.6509	3.0427	3.2779	3.0319	3.1710
J.B	2.1606	0.7431	1.8458	0.0464	8.6779	0.3783	0.3197	0.5371	1.6503	0.7625
Prob(JB)	0.3395	0.6897	0.3974	0.9771	0.0131	0.8277	0.8523	0.7645	0.4382	0.6830
Correlation	0.7616		0.8479		0.0001		0.8998		0.5747	
A.D.F	-8.0622	-8.9881	-10.4486	-10.4040	-8.9757	-9.5412	-9.1836	-9.7339	-8.3699	-8.1495
prob (A.D.F)	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table III: Descriptive Statistics of Na-tech Events (70 days ex post estimations window)

	Event_01		**Event_02**		**Event_03**		**Event_04**		**Event_05**		**Event_06**		**Event_07**		**Event_08**		**Event_09**		**Event_10**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	-0.00213	-0.00103	-0.00074	0.00056	-0.00235	-0.00207	0.00358	0.00118	-0.00228	-0.00042	-0.00251	-0.00061	-0.00001	0.00188	0.00039	0.00059	0.00281	-0.00134	0.00042	-0.00044
St. Deviation	0.01633	0.01284	0.01246	0.00902	0.01120	0.01245	0.02164	0.01443	0.01365	0.01147	0.00966	0.01112	0.01877	0.01261	0.01138	0.01059	0.02981	0.01192	0.01718	0.01367
Skewness	0.2955	0.1600	0.0163	-0.0283	0.0669	-0.1701	0.4276	0.0526	0.7019	0.2889	-0.6549	0.2781	0.0568	-0.0981	0.0399	0.2644	0.7998	0.9061	0.4726	0.8856
Kurtosis	2.8573	2.4038	4.8892	3.7705	3.0569	2.6800	3.2028	2.6971	4.5183	3.1229	3.9905	3.2273	2.6767	3.1968	2.9343	4.3579	3.9914	4.6765	3.2749	4.5314
J.B	1.0624	1.3162	10.2640	1.7161	0.0608	0.6270	2.2208	0.2955	12.2932	1.0034	7.7526	1.0383	0.3376	0.2219	0.0308	6.1049	10.1825	17.5228	2.7862	15.7626
Prob(JB)	0.5879	0.5178	0.0059	0.4240	0.9700	0.7309	0.3294	0.8626	0.0021	0.6055	0.0207	0.5950	0.8447	0.8950	0.9847	0.0472	0.0062	0.0002	0.2483	0.0004
Correlation	0.5374		0.6014		0.8773		0.5982		0.3958		0.4811		0.6839		0.6030		0.3605		0.6816	
A.D.F	-8.2679	-9.0869	-9.9412	-7.2180	-8.1892	-7.7799	-9.0918	-7.0179	-8.1577	-8.7327	-8.4637	-8.2027	-8.4055	-10.6500	-4.4244	-9.4810	-8.6588	-9.5893	-9.0212	-7.0398
prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Event_11		**Event_12**		**Event_13**		**Event_14**		**Event_15**		**Event_16**		**Event_17**		**Event_18**		**Event_19**		**Event_20**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	-0.00002	0.00131	0.00024	-0.00049	0.00210	0.00309	-0.00006	-0.00100	-0.00435	-0.00075	-0.00138	-0.00142	0.00059	0.00120	-0.00470	0.00077	-0.00227	-0.00033	0.00112	0.00060
St. Deviation	0.00771	0.00930	0.01775	0.00820	0.03275	0.02457	0.03230	0.01376	0.01137	0.01115	0.01766	0.01416	0.02044	0.01683	0.02273	0.01121	0.01229	0.00862	0.00928	0.01354
Skewness	-0.0158	0.0592	0.2995	0.3817	-0.4684	-1.1006	1.9775	0.0884	-0.0703	0.3121	0.9880	0.8061	1.3298	2.8482	-1.0513	-0.1902	-0.3236	0.3339	0.0495	0.2178
Kurtosis	3.4930	2.7808	2.9460	4.6451	4.4348	5.4540	13.9206	2.7335	2.3268	2.8255	5.6051	5.9317	7.1158	16.6833	4.8932	2.8225	3.6020	3.0208	3.2308	2.8675
J.B	0.7017	0.1785	1.0397	9.4567	8.4423	31.2429	387.8409	0.2940	1.3598	1.2076	30.7373	32.1842	69.0390	631.5833	23.0152	0.5066	2.2464	1.2835	0.1813	0.5961
Prob(JB)	0.7041	0.9146	0.5946	0.0088	0.0147	0.0000	0.0000	0.8633	0.5067	0.5467	0.0000	0.0000	0.0000	0.0000	0.0000	0.7762	0.3252	0.5264	0.9133	0.7423
Correlation	0.4576		0.3063		0.5435		0.2223		0.6855		0.5914		0.7840		0.4288		0.7206		0.6020	
A.D.F	-10.0254	-8.6195	-6.4363	-12.3657	-9.7215	-6.8150	-8.4347	-9.1531	-7.1120	-7.4548	-6.4412	-8.8196	-7.9469	-7.6190	-8.2344	-9.9313	-6.8552	-9.0795	-9.8249	-8.2999
prob (A.D.F)	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000

	Event_21		Event_22		Event_23		Event_24		Event_25	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	-0.00256	-0.00053	-0.00226	-0.00199	-0.00609	-0.00142	0.00373	0.00411	-0.01865	-0.00042
St. Deviation	0.01137	0.00750	0.02109	0.01934	0.03880	0.01706	0.01937	0.01918	0.10808	0.01147
Skewness	-0.4859	-0.2299	0.9913	1.0870	-0.1411	0.0291	0.7974	1.0545	0.5528	0.2889
Kurtosis	3.0821	3.2107	5.6198	6.2576	4.3751	3.4109	5.0519	5.1128	4.4837	3.1229
J.B	2.7350	0.7356	31.0333	44.0963	5.6651	0.4951	19.4161	25.6210	9.8429	1.0034
Prob(JB)	0.2547	0.6923	0.0000	0.0000	0.0589	0.7807	0.0001	0.0000	0.0073	0.6055
Correlation	0.5481		0.9242		0.3217		0.9598		0.1384	
A.D.F	-6.5671	-9.8372	-9.8296	-10.2844	-7.5434	-8.4491	-9.2786	-9.3826	-5.8528	-8.7327
prob (A.D.F)	0.0000	0.0001	0.0000	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table IV: Descriptive Statistics of Terrorist Attacks (120 days estimation window)

	Event_01		Event_02		Event_03		Event_04		Event_05		Event_06		Event_07		Event_08		Event_09		Event_10	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	-0.00007	-0.00069	-0.00062	-0.00183	-0.00015	0.00023	-0.00078	0.00090	-0.00174	0.00231	-0.00310	-0.00243	0.00067	-0.00375	-0.00174	-0.00125	-0.00142	-0.00097	-0.00029	0.00091
St. Deviation	0.01226	0.02732	0.01148	0.01435	0.04786	0.01563	0.01312	0.01282	0.01073	0.01474	0.01913	0.01713	0.02488	0.03744	0.01319	0.02059	0.02141	0.01304	0.01043	0.00911
Skewness	-0.6282	0.5127	0.3267	0.0602	2.8360	0.2110	0.5795	0.2900	-1.7123	0.7349	0.2220	-0.5335	-1.0813	-0.1770	0.1953	0.2300	4.0256	-0.0136	-0.1893	-0.3576
Kurtosis	5.7101	3.7514	3.9634	3.6406	48.1162	3.2461	4.6532	3.0661	9.5903	4.5881	7.4996	3.5003	5.3716	3.4249	4.0379	4.7827	33.7441	2.7400	4.4208	3.9846
J.B	44.2428	8.0123	6.7193	2.1064	10252.0500	1.1830	20.2111	1.6897	273.5017	23.2153	101.3661	6.8862	51.0767	1.5167	6.0971	16.8073	5008.0280	0.3388	10.7205	7.3424
Prob(JB)	0.0000	0.0182	0.0347	0.3488	0.0000	0.5535	0.0000	0.4296	0.0000	0.0000	0.0000	0.0320	0.0000	0.4684	0.0474	0.0002	0.0000	0.8442	0.0047	0.0254
Correlation	0.3709		0.5813		0.0207		0.7214		0.4049		0.4449		0.4550		0.6991		0.2071		0.7441	
A.D.F	-11.1720	-10.9760	-12.3720	-11.8220	-17.0100	-11.2530	-11.6950	-12.1150	-9.3739	-10.4560	-11.9940	-9.8815	-9.8385	-9.3970	-12.4030	-12.1250	-10.1350	-10.7770	-11.6860	-10.4680
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Event_11		**Event_12**		**Event_13**		**Event_14**		**Event_15**		**Event_16**		**Event_17**		**Event_18**		**Event_19**		**Event_20**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00118	0.00132	0.00314	0.00056	0.00082	0.00125	-0.00015	0.00016	0.00022	-0.00027	-0.00163	0.00021	-0.00103	-0.00011	0.00001	0.00114	0.00268	-0.00101	-0.00052	0.00082
St. Deviation	0.01710	0.01068	0.02940	0.02593	0.01341	0.01380	0.01203	0.01362	0.01153	0.01221	0.01377	0.01169	0.01032	0.01090	0.01089	0.01236	0.01990	0.01515	0.01695	0.01608
Skewness	-0.2174	-0.1236	0.1704	0.5032	-0.2375	-0.1278	0.0980	0.0175	-0.1022	0.1374	0.2712	0.2043	-0.5182	0.0567	-1.2534	-0.3108	3.4893	0.0612	-0.2662	-0.3749
Kurtosis	3.2940	2.8694	4.2531	5.5451	4.0782	3.8110	4.1162	3.5586	3.5789	3.0895	3.3085	3.1131	4.2766	4.7264	9.5786	4.3504	33.7576	4.0696	4.9042	3.5816
J.B	1.3660	0.3876	8.3612	37.1385	6.8822	3.5849	6.3683	1.5531	1.8688	0.4140	1.9302	0.8914	13.4066	14.8417	245.7452	10.9576	4932.2070	5.7466	19.3835	4.4650
Prob(JB)	0.5051	0.8238	0.0153	0.0000	0.0320	0.1666	0.0414	0.4600	0.3928	0.8130	0.3809	0.6404	0.0012	0.0006	0.0000	0.0042	0.0000	0.0565	0.0001	0.1073
Correlation	0.7038		0.2103		0.7762		0.6937		0.6376		0.4513		0.4985		0.6388		0.2822		0.3354	
A.D.F	-10.8570	-11.1880	-9.3849	-10.6080	11.9650	-12.6460	-11.8540	-12.0190	12.6070	-11.0130	9.8372	-10.8820	-10.5030	-9.9867	-12.3050	-11.1030	-12.5540	-7.5076	-10.3830	-11.3540
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	Event_21		Event_22		Event_23		Event_24		Event_25		Event_26		Event_27		Event_28		Event_29		Event_30	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00062	0.00014	0.00024	0.00039	0.00070	0.00101	0.00163	-0.00027	0.00087	-0.00046	0.00056	0.00053	0.00041	0.00106	-0.00202	-0.00045	-0.00215	-0.00132	-0.00357	-0.00137
St. Deviation	0.01491	0.01220	0.01875	0.01962	0.01621	0.01574	0.01416	0.01643	0.00978	0.01747	0.02406	0.01917	0.01574	0.01495	0.03029	0.01726	0.01741	0.01729	0.01919	0.01454
Skewness	0.1996	0.1203	-0.3195	0.3629	-1.0460	1.7867	-0.0233	-0.2872	0.4332	0.1482	0.3485	-0.0118	0.1049	0.2987	0.2376	0.2475	-0.1974	-1.1158	-0.2881	-0.1403
Kurtosis	4.6508	3.8753	4.6082	7.6530	6.2587	11.5312	2.9520	2.8144	5.9177	5.8526	4.0685	2.8059	2.5093	3.3116	3.4164	3.2572	2.5775	6.1528	4.1586	2.6062
J.B	14.3016	4.0859	14.8486	109.9601	74.3536	424.1924	0.0222	1.8071	45.9323	40.7839	8.0698	0.1896	1.4123	2.2515	1.9792	1.5425	1.6579	73.9803	8.3021	1.1595
Prob(JB)	0.0008	0.1296	0.0006	0.0000	0.0000	0.0000	0.9890	0.4051	0.0000	0.0000	0.0177	0.9095	0.4936	0.3244	0.3717	0.4624	0.4365	0.0000	0.0157	0.5600
Correlation	0.6348		0.2303		0.0776		0.2781		0.3943		0.1242		0.3311		0.0619		0.4157		0.3943	
A.D.F	-14.9290	-11.1910	-13.4290	-7.6834	-13.0560	-7.5661	-10.2730	-11.3470	-9.5905	-10.1790	-10.2520	-10.2900	-10.0910	-10.3490	-11.6590	-9.7556	-11.9980	-11.5530	-13.5800	-11.1730
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	31		Event_32		Event_33		Event_34		Event_35		Event_36		Event_37		Event_38		Event_39		Event_40	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00035	-0.00160	0.01158	0.00271	0.00325	0.00120	0.00084	0.00094	-0.00150	0.00036	-0.00131	0.00041	-0.00042	-0.00060	-0.00021	0.00008	-0.00003	0.00020	-0.00119	0.00058
St. Deviation	0.01577	0.01892	0.06786	0.01413	0.01602	0.01771	0.02488	0.01292	0.02073	0.01173	0.01955	0.01455	0.02586	0.01487	0.02283	0.01776	0.01840	0.01681	0.01787	0.01844
Skewness	-0.1720	-0.0439	0.1693	0.2076	0.6062	-0.6916	-0.0112	0.1929	0.3763	0.1169	0.6647	0.2822	0.2688	0.4816	0.5397	0.6512	0.2875	0.1825	-0.3389	0.0640
Kurtosis	3.8883	3.5752	4.0627	4.0213	5.4091	5.8896	4.4410	6.2905	3.8217	8.4035	4.7611	4.3624	5.3473	4.6061	3.8083	3.8757	3.2460	3.7770	4.4474	3.9025
J.B	4.4991	1.6789	6.1679	6.0261	36.0642	50.8892	10.2977	54.4223	6.1569	145.0410	24.1409	10.7826	28.7520	17.3887	9.0157	12.2123	1.9398	3.6543	12.6653	4.1198
Prob(JB)	0.1054	0.4320	0.0458	0.0491	0.0000	0.0000	0.0058	0.0000	0.0460	0.0000	0.0000	0.0046	0.0000	0.0002	0.0110	0.0022	0.3791	0.1609	0.0018	0.1275
Correlation	0.3923		0.1583		0.4043		0.3674		0.4123		0.5538		0.6075		0.7127		0.7809		0.8202	
A.D.F	-10.3480	-8.3259	-10.6120	-10.6050	-10.3050	-10.6520	-12.1070	-12.4180	-11.9230	-13.9320	-11.9900	-12.6430	-14.0300	-15.9990	-13.1230	-15.1350	-13.0150	-16.7680	-14.3770	-13.8700
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table V: Descriptive Statistics of Terrorist Attacks (70 days ex-ante estimation window)

	Event_01		**Event_02**		**Event_03**		**Event_04**		**Event_05**		**Event_06**		**Event_07**		**Event_08**		**Event_09**		**Event_10**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	-0.00104	-0.00363	-0.00121	-0.00040	0.00000	0.00026	-0.00126	0.00176	-0.00397	0.00306	-0.00184	-0.00389	-0.00322	-0.00764	-0.00273	-0.00229	-0.00060	-0.00198	0.00115	0.00221
St. Deviation	0.01123	0.02202	0.01203	0.01344	0.02171	0.01495	0.01347	0.01175	0.01220	0.01345	0.01729	0.01760	0.02946	0.04207	0.01356	0.02293	0.02376	0.01390	0.00895	0.00942
Skewness	0.3140	0.2296	0.1718	0.4341	1.9490	0.0353	0.1558	0.0979	-1.7648	0.0369	0.6044	-0.6745	-1.0602	-0.0590	-0.0469	0.2025	5.1180	-0.1212	0.4270	-0.0809
Kurtosis	3.4325	3.2645	3.9823	3.7858	24.0680	3.3445	3.8634	3.3920	8.0157	3.9402	5.0207	3.4270	3.7538	3.1480	4.0813	4.5004	37.1563	2.5146	2.7860	3.4504
J.B	1.6716	0.8075	3.1137	3.9425	1319.7820	0.3556	2.4222	0.5522	108.1438	2.5570	15.9400	5.7567	14.5591	0.1030	3.3866	6.9434	3655.3540	0.8465	2.2282	0.6583
Prob(JB)	0.4335	0.6678	0.2108	0.1393	0.0000	0.8371	0.2979	0.7587	0.0000	0.2784	0.0003	0.0562	0.0007	0.9498	0.1839	0.0311	0.0000	0.6549	0.3282	0.7195
Correlation	0.5456		0.6191		0.3316		0.7625		0.3613		0.4829		0.4341		0.6906		0.4021		0.7364	
A.D.F	-8.7987	-8.6000	-10.3970	-8.4146	-12.7040	-9.8056	-8.6742	11.1760	-6.7934	-6.7535	-7.7610	-6.8106	-7.2531	-6.7765	-10.2580	-9.6944	-8.2807	-8.0048	-8.3297	-7.5895
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	Event_11		**Event_12**		**Event_13**		**Event_14**		**Event_15**		**Event_16**		**Event_17**		**Event_18**		**Event_19**		**Event_20**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00115	0.00251	0.00257	-0.00127	0.00055	-0.00075	-0.00090	-0.00242	-0.00046	-0.00167	-0.00093	0.00111	-0.00145	0.00173	-0.00078	0.00159	0.00367	-0.00202	-0.00451	-0.00108
St. Deviation	0.01685	0.01162	0.02915	0.02640	0.01193	0.01342	0.01061	0.01369	0.00921	0.01249	0.01445	0.01079	0.01075	0.01068	0.01233	0.01172	0.02561	0.01896	0.01912	0.01978
Skewness	-0.3966	0.3635	0.0562	0.3371	0.4175	0.3509	0.8811	0.5342	-0.1403	0.0830	0.1385	0.1011	-0.6447	0.0609	-1.6680	-0.4532	2.7434	0.2178	-1.2871	-0.2847
Kurtosis	3.7618	4.0328	4.6314	4.7343	4.3187	4.0838	5.8719	4.1021	2.5327	2.8932	3.2460	2.5866	5.1204	6.4044	8.4792	3.7480	21.0639	2.9021	5.8084	2.8811
J.B	3.4777	4.5866	7.6882	9.9535	7.0037	4.7930	32.6401	6.7740	0.8540	0.1119	0.3945	0.6087	17.7054	33.3637	118.3069	3.9706	1024.6760	0.5731	41.7277	0.9729
Prob(JB)	0.1757	0.1009	0.0214	0.0069	0.0301	0.0910	0.0000	0.0338	0.6525	0.9456	0.8210	0.7376	0.0001	0.0000	0.0000	0.1373	0.0000	0.7509	0.0000	0.6148
Correlation	0.7568		0.1002		0.6828		0.6488		0.5943		0.3327		0.5531		0.7452		0.2684		0.4417	
A.D.F	-8.8147	-9.7605	-6.4183	-7.4487	-9.3185	-8.7553	-9.1495	-8.5803	-9.0007	-7.9428	-7.6027	-8.1019	-7.0462	-7.4741	-9.1688	-8.9887	-9.5134	-5.5843	-6.1895	-8.0813
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	Event_21		Event_22		Event_23		Event_24		Event_25		Event_26		Event_27		Event_28		Event_29		Event_30	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00022	0.00059	-0.00116	0.00254	0.00183	-0.00094	0.00115	-0.00044	-0.00070	-0.00066	0.00055	-0.00044	0.00058	0.00271	-0.00770	-0.00275	-0.00136	0.00043	-0.00353	-0.00072
St. Deviation	0.01420	0.01188	0.01838	0.01755	0.01334	0.01285	0.01489	0.01551	0.00970	0.01734	0.02471	0.02039	0.01448	0.01566	0.03117	0.02052	0.01658	0.01432	0.01799	0.01270
Skewness	0.1547	0.6335	-0.8493	2.1592	-0.5383	0.3439	-0.1337	-0.0668	-0.2369	-0.7189	0.0294	0.0396	0.2811	0.4859	-0.1090	0.3926	-0.0965	-0.0569	0.0696	0.1118
Kurtosis	4.4303	4.5592	4.8501	12.7431	3.3348	2.5393	2.6294	2.6936	3.4152	4.4009	3.3371	2.8116	2.4787	3.1866	3.1772	2.8768	2.1449	2.8505	3.9232	2.1695
J.B	6.1569	11.6048	18.1367	326.5313	3.6551	1.9702	0.6003	0.3212	1.1408	11.5859	0.3366	0.1201	1.6898	2.8154	0.2271	1.8161	2.2094	0.1015	2.5061	2.1266
Prob(JB)	0.0460	0.0030	0.0001	0.0000	0.1608	0.3734	0.7407	0.8516	0.5653	0.0030	0.8451	0.9417	0.4296	0.2447	0.8927	0.4033	0.3313	0.9505	0.2856	0.3453
Correlation	0.6489		0.0927		0.2870		0.1434		0.4613		0.1878		0.3358		0.0524		0.5122		0.5324	
A.D.F	-9.8529	-8.4034	-10.7630	-6.0866	-8.8541	-6.0588	-7.9036	-9.7723	-7.3420	-7.1732	-7.3502	-9.5288	-6.9050	-9.9100	-9.7641	-7.8092	-8.8077	-7.4414	-8.4758	-7.1654
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	31		**Event_32**		**Event_33**		**Event_34**		**Event_35**		**Event_36**		**Event_37**		**Event_38**		**Event_39**		**Event_40**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00241	0.00115	0.01593	0.00326	0.00436	0.00231	-0.00198	-0.00047	-0.00107	0.00018	-0.00120	-0.00107	0.00053	-0.00150	-0.00055	-0.00042	-0.00018	0.00023	-0.00096	0.00075
St. Deviation	0.01349	0.01674	0.05881	0.01621	0.01496	0.01433	0.02434	0.01216	0.01970	0.01197	0.01976	0.01514	0.02599	0.01673	0.02275	0.01874	0.02024	0.01900	0.01971	0.02125
Skewness	-0.2873	0.0912	0.3783	0.2141	0.1634	0.3274	-0.2734	-0.6558	-0.2264	0.7261	0.2610	-0.1282	0.5418	0.3644	0.4828	0.5417	0.3409	0.3711	-0.3004	0.1911
Kurtosis	3.8037	3.5948	2.6086	3.7347	4.1514	5.0310	5.7978	7.9915	4.0681	8.7877	3.4705	3.0864	3.6626	4.0580	3.5894	3.0990	3.1600	3.3262	4.0015	3.6086
J.B	2.8068	1.1128	2.0864	2.0791	4.1184	13.0920	23.3641	76.5756	3.8695	102.3695	1.4197	0.2105	4.6386	4.7448	3.6797	3.4033	1.4104	1.8896	3.9215	1.4847
Prob(JB)	0.2458	0.5733	0.3523	0.3536	0.1276	0.0014	0.0000	0.0000	0.1445	0.0000	0.4917	0.9001	0.0983	0.0933	0.1588	0.1824	0.4940	0.3888	0.1408	0.4760
Correlation	0.4378		0.3103		0.3844		0.5595		0.4301		0.5904		0.5950		0.7983		0.8239		0.8713	
A.D.F	-8.4812	-6.6582	-8.5972	-8.4603	-7.9656	-8.0699	-9.0523	-10.6370	-8.1924	-9.3847	-8.9718	-10.5400	-8.2081	-11.4410	-10.1890	-11.3840	-10.0050	-11.8720	-11.9300	-10.4800
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table VI: Descriptive Statistics of Terrorist Attacks (70 days ex-post estimation window)

	Event_01		Event_02		Event_03		Event_04		Event_05		Event_06		Event_07		Event_08		Event_09		Event_10	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00098	0.00411	-0.00264	0.00011	0.00157	0.00096	0.00073	0.00019	-0.00175	0.00198	0.00189	0.00235	-0.00126	-0.00140	-0.00219	-0.00033	-0.00259	-0.00218	0.00267	0.00392
St. Deviation	0.01652	0.02285	0.00865	0.01215	0.01362	0.01613	0.01264	0.01512	0.01537	0.02157	0.01887	0.02104	0.03010	0.02966	0.01749	0.01510	0.03939	0.03173	0.01510	0.01729
Skewness	-0.1055	0.2388	0.1784	0.0430	0.8158	0.4914	0.6759	-0.4371	-0.2980	-0.3510	0.8167	0.2605	1.0776	0.0062	0.2420	0.4574	0.4778	0.0093	3.4280	1.5993
Kurtosis	4.6518	3.3193	2.6778	2.4086	3.0164	3.5018	2.9606	4.1839	5.6610	4.1916	4.1601	4.0690	6.8537	2.1971	2.5180	2.6591	3.0390	3.5902	20.6568	11.2947
J.B	7.9727	0.9490	0.6644	1.0268	7.6540	3.5004	5.2578	6.2264	21.3791	5.4992	11.5400	4.0661	56.0526	1.8537	1.3416	2.7399	2.6298	1.0025	1031.4580	227.2214
Prob(JB)	0.0186	0.6222	0.7173	0.5985	0.0218	0.1737	0.0722	0.0445	0.0000	0.0640	0.0031	0.1309	0.0000	0.3958	0.5113	0.2541	0.2685	0.6058	0.0000	0.0000
Correlation	0.1738		0.5527		0.0001		0.6563		0.1152		0.7014		0.3313		0.5936		0.6236		0.8659	
A.D.F	-6.8399	-7.2710	-9.6460	-8.1750	-6.4129	-7.4391	-7.0790	-10.6496	-8.7223	-6.7020	-6.5489	-7.1031	-7.0934	-7.9132	-7.6506	-8.5468	-3.9692	-8.3253	-7.2159	-7.9442
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0028	0.0000	0.0000	0.0000
	Event_11		**Event_12**		**Event_13**		**Event_14**		**Event_15**		**Event_16**		**Event_17**		**Event_18**		**Event_19**		**Event_20**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00380	0.00179	0.00135	0.00053	-0.00038	0.00150	-0.00058	0.00242	-0.00143	0.00124	-0.00266	0.00019	0.00139	-0.00126	-0.00178	-0.00024	-0.00024	0.00175	-0.00517	0.00284
St. Deviation	0.02291	0.01666	0.01743	0.01436	0.00960	0.01112	0.01010	0.01018	0.00935	0.01003	0.01459	0.00991	0.00764	0.00937	0.01921	0.01314	0.02233	0.02153	0.02951	0.01100
Skewness	0.5537	0.6389	-0.1438	-0.4112	-0.2140	0.0442	-0.3898	-0.0596	-0.7498	0.6607	-0.1054	-0.2625	0.2087	-0.3055	-0.0397	-0.1216	-0.7782	1.2649	-1.0111	-0.3172
Kurtosis	3.2243	4.5785	2.6675	3.5169	3.3062	2.8589	3.9489	3.6373	5.9897	4.5103	2.7210	4.4111	2.8617	3.3954	3.0582	3.4888	4.8543	8.0667	5.4006	2.6539
J.B	3.6702	11.8573	0.5555	2.7122	0.7963	0.0796	4.3360	1.2085	32.1627	11.5777	0.3516	6.5176	0.5557	1.5227	0.0278	0.8568	16.8502	92.2053	28.3258	1.5015
Prob(JB)	0.1596	0.0027	0.7575	0.2577	0.6716	0.9610	0.1144	0.5465	0.0000	0.0031	0.8388	0.0384	0.7574	0.4670	0.9862	0.6516	0.0002	0.0000	0.0000	0.4720
Correlation	0.6627		0.5426		0.5205		0.5812		0.4840		0.4129		0.5019		0.1595		0.3189		0.4207	
A.D.F	-9.0353	-9.5671	-8.0961	-8.1095	-9.7265	-7.0345	-9.0619	-6.6203	-7.4873	-6.2111	-8.8805	-6.8288	-8.4150	-7.5355	-10.1106	-7.0955	-10.4999	-5.8043	-5.6337	-8.0271
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0000	0.0000

	Event_21		**Event_22**		**Event_23**		**Event_24**		**Event_25**		**Event_26**		**Event_27**		**Event_28**		**Event_29**		**Event_30**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	0.00031	-0.00101	0.00124	0.00390	-0.00368	-0.00114	0.00189	-0.00068	-0.00071	-0.00386	-0.00331	-0.00358	-0.00478	-0.00333	-0.00391	-0.00136	-0.00140	0.00099	-0.00277	0.00178
St. Deviation	0.01441	0.01045	0.01616	0.01681	0.02509	0.01450	0.01309	0.01730	0.01006	0.02290	0.02340	0.02182	0.02072	0.01844	0.03113	0.01642	0.01894	0.01531	0.04235	0.01582
Skewness	-0.3959	0.1505	0.0618	0.3141	-0.5596	0.4923	-0.0078	0.8327	-0.4657	-0.7837	0.3836	0.2213	-0.7286	-0.3923	0.1449	-0.9103	-0.2065	-2.8608	-0.9503	-1.6848
Kurtosis	3.9990	3.9015	2.1436	2.5771	5.8324	4.2446	2.9946	4.9566	3.9457	3.8569	3.9587	2.8540	4.5054	2.6671	3.1851	4.5314	3.1781	17.7233	5.9767	10.9801
J.B	4.6716	2.5973	2.1526	1.6484	26.6661	7.2403	0.0008	18.9807	5.0654	9.1750	4.3345	0.6244	12.6194	2.0879	0.3399	16.2722	0.5818	717.3525	35.8593	215.7277
Prob(JB)	0.0967	0.2729	0.3409	0.4386	0.0000	0.0268	0.9996	0.0001	0.0794	0.0102	0.1145	0.7318	0.0018	0.3521	0.8437	0.0003	0.7476	0.0000	0.0000	0.0000
Correlation	0.6674		0.8216		0.3516		0.2966		0.4358		0.1439		0.3998		0.2507		0.1746		0.3381	
A.D.F	-7.0707	-9.3862	-9.3862	-7.6049	-7.9299	-7.8119	-8.0432	-7.0067	-9.6672	-7.7504	-7.6316	-8.3729	-10.0099	-9.4201	-8.8300	-6.0658	-7.7985	-6.2469	-6.4846	-6.9130
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	31		**Event_32**		**Event_33**		**Event_34**		**Event_35**		**Event_36**		**Event_37**		**Event_38**		**Event_39**		**Event_40**	
	RA	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*	*RA*	*RM*
Mean	-0.00060	-0.00102	0.00195	-0.00063	-0.00166	0.00144	-0.00079	-0.00002	0.00017	-0.00074	-0.00012	-0.00070	-0.00162	0.00085	-0.00101	-0.00037	-0.00062	-0.00029	-0.00210	0.00161
St. Deviation	0.01506	0.01440	0.03659	0.01139	0.01551	0.01349	0.02557	0.01458	0.02612	0.01445	0.02370	0.01892	0.02610	0.01911	0.02454	0.02082	0.02548	0.02598	0.02361	0.02407
Skewness	-1.5271	-0.5880	0.2187	-1.3648	-0.7973	0.0319	0.4518	0.6457	-0.1740	0.1080	0.2203	0.2324	0.2477	-0.0657	0.0620	-0.0883	-0.0148	-0.3552	-0.0034	-0.5065
Kurtosis	8.2929	6.9656	2.4283	10.0288	6.0767	4.3935	4.0397	6.1002	3.0269	3.9861	3.5577	2.8126	2.8219	3.0891	2.8878	3.0366	2.2380	3.1360	2.2861	2.7424
J.B	107.3635	49.1876	1.4897	163.4576	34.5249	5.5944	5.4555	32.4265	0.3501	2.9297	1.4521	0.7223	0.7970	0.0725	0.0804	0.0936	1.6717	1.5040	1.4653	3.1415
Prob(JB)	0.0000	0.0000	0.4748	0.0000	0.0000	0.0610	0.0654	0.0000	0.8394	0.2311	0.4838	0.6969	0.6713	0.9644	0.9606	0.9543	0.4335	0.4714	0.4806	0.2079
Correlation	0.5787		0.3420		0.2934		0.6410		0.6073		0.7342		0.6819		0.6972		0.8238		0.8823	
A.D.F	-7.6669	-6.7192	-7.4304	-9.6385	-9.1450	-10.3339	-12.1973	-11.3880	-10.3233	-11.5194	-9.5319	-11.7811	-10.6618	-12.3306	-9.6537	-13.7338	-10.9947	-9.2740	-12.2982	-11.1663
Prob (A.D.F)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001	0.0000	0.0001	0.0001	0.0000	0.0001	0.0001

Table VII: Beta estimations of Na-tech Events (120 days estimation window)

	(1)					(2)				
	β	R^2	Breusch -Gofrey lm test	ARCH lm test	Jarque Bera test	β	R^2	Breusch -Gofrey lm test	ARCH lm test	Jarque Bera test
Event_01	0.566306 (4.77) [0.0000]	0.1568	[0.6864]	[0.2231]	6.125573 [0.0457]					
Event_02	0.716023 (12.823) [0.0000]	0.5761	[1.0000]	[0.2935]	66.193960 [0.0000]					
Event_03	-0.923018 (-1.119) [0.2653]	0.0052	[0.0000]	[0.0002]	9.635179 [0.0080]	0.948602 (5.160086) [0.0000]	-0.038252		[0.8041]	7.411470 [0.0245]
Event_04	1.033715 (9.713) [0.0000]	0.4415	[0.0001]	[0.0009]	8.063520 [0.0177]	0.852833 (170.56) [0.0000]	0.4278		[0.1902]	0.008157 [0.9959]
Event_05	0.948716 (7.009) [0.0000]	0.2939	[1.0000]	[0.0443]	31.612030 [0.0000]	0.878074 (7.850) [0.0000]	0.2922		[0.8520]	0.876908 [0.6450]
Event_06	0.663717 (9.264) [0.0000]	0.4210	[0.0323]	[0.4505]	0.063877 [0.9385]	0.670526 (9.984) [0.0000]	0.4579	[1.0000]	[0.7950]	0.172649 [0.9172]
Event_07	0.841452 (7.272) [0.0000]	0.3094	[0.1643]	[0.3429]	70.845710 [0.0000]					
Event_08	0.514983 (7.269) [0.0000]	0.3049	[1.0000]	[0.8173]	7.932357 [0.0189]					
Event_09	0.629387 (4.866) [0.0000]	0.1509	[1.0000]	[0.3813]	4.552755 [0.1026]					
Event_10	0.579811 (7.378) [0.0000]	0.3012	[1.0000]	[0.2888]	4.384949 [0.1116]					
Event_11	0.310581 (6.565) [0.0000]	0.2669	[0.7176]	[0.8722]	21.469250 [0.0000]					
Event_12	0.768107 (3.782) [0.0000]	0.1051	[0.5110]	[0.0055]	2.532925 [0.2818]	0.601126 (30.66) [0.0000]	0.0999		[0.6091]	0.560280 [0.7556]
Event_13	0.529411 (4.383) [0.0000]	0.1399	[0.5665]	[0.3449]	1.023537 [0.5994]					
Event_14	0.670650 (2.411) [0.0174]	0.0459	[1.0000]	[0.8634]	24.58208 [0.0000]					
Event_15	0.922181 (24.736) [0.0000]	0.8377	[1.0000]	[0.2722]	0.038119 [0.981121]					
Event_16	0.818089 (6.929) [0.0000]	0.2883	[1.0000]	[0.2354]	136.8950 [0.0000]					

Event_17	0.595667 (5.679) [0.0000]	0.2146	[1.0000]	[0.7961]	51.47385 [0.0000]					
Event_18	0.855654 (9.661) [0.0000]	0.4399	[0.5770]	[0.8506]	22.40908 [0.0000]					
Event_19	1.315889 (10.134) [0.0000]	0.4640	[0.0174]	[0.5010]	10.03947 [0.0000]	1.311919 (11.012) [0.0000]	0.5059	1.0000	[0.3912]	10.94580 [0.0000]
Event_20	0.517310 (7.865) [0.0000]	0.3439	[1.0000]	[0.8409]	65.27417 [0.0000]					
Event_21	0.856874 (11.889) [0.0000]	0.5314	[0.4533]	[0.4863]	13.79099 [0.0010]					
Event_22	1.077069 (15.344) [0.0000]	0.6629	[0.7361]	[0.9733]	0.322768 [0.8510]					
Event_23	1.010974 (15.654) [0.0000]	0.6748	[1.0000]	[0.9610]	407.2559 [0.0000]					
Event_24	0.975986 (23.390) [0.0000]	0.8220	[1.0000]	[0.1760]	8.539876 [0.0139]					
Event_25	0.978716 (10.018) [0.0000]	0.4496	[0.0628]	[0.0888]	176.0476 [0.0000]	0.830885 (27.762) [0.0000]	0.4389		[0.6290]	20.6789 [0.0000]

Table VIII: Beta estimations of Terrorist Attacks (120 days estimation window)

	(1)					(2)				
	β	R2	Breush-Godfrey lm test	ARCH lm test	Jarque Bera test	β	R2	Breush-Godfrey lm test	ARCH lm test	Jarque Bera test
Event 01	0.166364 (4.337943) [0.0000]	0.137514	0.6004	0.6523	75.84128 [0.0000]					
Event 02	0.462977 (7.787347) [0.0000]	0.337527	0.4706	0.1194	5.310068 [0.070296]					
Event 03	0.063344 (0.224731) [0.8226]	0.000418	0.0000	0.0000	10413.8 [0.0000]	0.458113 9.866229 [0.0000]	- 0.016198		0.1877	148.7495 [0.0000]
Event 04	0.729994 (11.08382) [0.0000]	0.508326	1.0000	0.9973	8.482277 [0.014391]					
Event 05	0.269536 (4.324414) [0.0000]	0.114041	0.9273	0.0713	423.6048 [0.0000]	0.224304 (5.366465) [0.0000]	0.110087		0.7648	5.892425 [0.052538]
Event 06	0.512321 (5.588195) [0.0000]	0.18827	1.0000	0.0005	277.8741 [0.0000]	0.57245 (7.615479) [0.0000]	0.185311		0.8553	21.34837 [0.000023]
Event 07	0.297527 (5.47141) [0.0000]	0.201777	1.0000	0.1782	4.767607 [0.092199]					
Event 08	0.451396 (10.64108) [0.0000]	0.480712	1.0000	0.0855	1.780817 [0.410488]	0.398751 (10.9416) [0.0000]	0.473934		0.6787	1.317355 [0.517535]
Event 09	0.346441 (2.345642) [0.0207]	0.040314	0.4132	0.9832	5019.669 [0.0000]					
Event 10	0.840522 (11.85804) [0.0000]	0.543369	1.0000	0.3365	20.70419 [0.000032]					
Event 11	1.123071 (10.8075) [0.0000]	0.495052	0.4315	0.4056	16.51436 [0.000259]					
Event 12	0.240952 (2.348373) [0.0205]	0.033641	0.0202	0.6076	14.22125 [0.000816]	0.948395 (29.79304) [0.0000]	0.882264	0.3706	0.6851	11.65269 [0.002949]

Event 13	0.753626 (13.41504) [0.0000]	0.602474	0.8153	0.1479	17.80416 [0.000136]					
Event 14	0.612709 (10.45514) [0.0000]	0.480806	1.0000	0.1716	5.350699 [0.068883]					
Event 15	0.601808 (8.974499) [0.0000]	0.40545	0.0746	0.1349	15.10097 [0.000526]	0.59074 (9.032007) [0.0000]	0.408458	1.0000	0.1604	7.925821 [0.019008]
Event 16	0.528947 (5.413034) [0.0000]	0.187636	1.0000	0.9097	5.226807 [0.073285]					
Event 17	0.472835 (6.222914) [0.0000]	0.239559	1.0000	0.002	54.17713 [0.0000]	0.535828 (7.469612) [0.0000]	0.235129		0.3848	0.987429 [0.610355]
Event 18	0.55812 (8.957084) [0.0000]	0.404729	0.484	0.9164	144.5372 [0.0000]					
Event 19	0.357279 (3.047643) [0.0028]	0.05606	1.0000	0.8275	7529.917 [0.0000]					
Event 20	0.351014 (3.83964) [0.0002]	0.110229	0.5259	0.1114	6.474332 [0.032156]					
Event 21	0.776381 (8.92138) [0.0000]	0.401759	0.0000	0.0000	73.72415 [0.0000]	0.721573 (18.56485) [0.0000]	0.399748		0.124	72.68325 [0.0000]
Event 22	0.220221 (2.572918) [0.0113]	0.052964	0.0446	0.4632	40.24331 [0.0000]	0.178545 (2.301594) [0.0231]	0.042773	0.7156	0.8894	35.43809 [0.0000]
Event 23	0.08243 (0.87314) [0.3844]	0.004538	0.1121	0.8674	105.3563 [0.0000]					
Event 24	0.237973 (3.099368) [0.0024]	0.062977	1.0000	0.4393	0.253557 [0.880929]					
Event 25	0.219257 (4.604166) [0.0000]	0.145463	0.0122	0.1744	79.9074 [0.0000]	0.248114 (5.479852) [0.0000]	0.199264	1.0000	0.9733	70.36219 [0.0000]
Event 26	0.15663 (1.366215) [0.1745]	0.015039	0.5224	0.4168	15.61651 [0.000406]					

Event 27	0.348807 (3.824156) [0.0002]	0.109651	0.2583	0.5051	2.275732 [0.320502]					
Event 28	0.124452 (0.770638) [0.4425]	0.000528	1.0000	0.5521	2.297607 [0.317016]					
Event 29	0.425786 (5.038693) [0.0000]	0.164467	0.096	0.6552	0.453076 [0.797289]	0.45435 (5.520449) [0.0000]	0.18822	1.0000	0.4523	0.315517 [0.854056]
Event 30	0.538836 (4.78615) [0.0000]	0.133405	0.2613	0.9253	14.16085 [0.000841]					
Event 31	0.322972 (4.585884) [0.0000]	0.150833	0.0822	0.0003	11.46834 [0.003234]	0.424715 (8.095455) [0.0000]	0.135814		0.6699	3.126942 [0.209408]
Event 32	0.885698 (2.046627) [0.0429]	0.005904	1.0000	0.038	7.940177 [0.018872]	0.918576 (2.883708) [0.0039]	0.005856		0.4471	0.812171 [0.666253]
Event 33	0.376427 (4.865134) [0.0000]	0.132577	1.0000	0.8945	68.7836 [0.0000]					
Event 34	0.708659 (4.308792) [0.0000]	0.134961	0.3741	0.9513	3.818741 [0.148174]					
Event 35	0.723893 (4.865663) [0.0000]	0.162722	0.4557	0.881	1.460956 [0.481679]					
Event 36	0.741097 (7.161609) [0.0000]	0.29982	1.0000	0.4314	6.060506 [0.048303]					
Event 37	1.055975 (8.310085) [0.0000]	0.369013	0.1533	0.0269	15.69229 [0.000391]	1.002006 (12.12488) [0.0000]	0.368048		0.8557	9.069253 [0.010731]
Event 38	0.916175 (11.03472) [0.0000]	0.50781	0.2005	0.1433	3.221296 [0.199758]					
Event 39	0.854387 (13.57528) [0.0000]	0.609643	0.7346	0.4389	23.58575 [0.000008]					
Event 40	0.792062 (15.32848) [0.0000]	0.664198	1.0000	0.6299	316.0297 [0.0000]					

Table IX:Na-tech Events ARCH specification

Na-tech Events		
120 days estimation window		
	ARCH specification	**A.I.C**
Event 03	*EGARCH(3,2)*	*-3.379545*
Event 04	*GARCH(1,1)*	*-5.240263*
Event 05	*GARCH(1,1)*	*-5.559473*
Event 12	*GARCH(1,2)*	*-5.524545*
Event 25	*EGARCH(3,3)*	*-6.143567*
70 days ex-ante estimation window		
Event 02	*EGARCH(2,2)*	*-7.373550*
Event 03	*EGARCH(3,3)*	*-4.698165*
Event 06	*EGARCH(2,3)*	*-6.881292*
Event 12	*EGARCH(2,2)*	*-5.285149*
Event 13	*GARCH(2,3)*	*-5.376315*
70 days ex-post estimation window		
Event 02	*EGARCH(3,3)*	*-6.852977*
Event 04	*PARCH(1,3)*	*-5.444653*
Event 11	*EGARCH(3,3)*	*-7.379666*
Event 18	*EGARCH(3,2)*	*-5.588135*
Event 21	*EGARCH(3,2)*	*-6.567307*
Event 25	*PARCH(2,2)*	*-2.059220*

Table X: Terrorist Attacks ARCH specification

Terrorist Attacks		
120 days estimation window		
	ARCH specification	**A.I.C**
Event 3	*EGARCH(2,2)*	*-4.952435*
Event 5	*EGARCH(2,3)*	*-6.918033*
Event 6	*GARCH(3,1)*	*-5.543121*
Event 8	*GARCH(3,3)*	*-6.505962*
Event 17	*GARCH(2,1)*	*-6.679309*
Event 21	*GARCH(2,2)*	*-6.478978*
Event 31	*EGARCH(2,3)*	*-5.820242*
Event 32	*GARCH(2,1)*	*-2.631706*
Event 37	*ARCH(3)*	*-4.994758*
70 days ex-ante estimation window		
Event 3	*EGARCH(3,3)*	*-6.286376*
Event 17	*GARCH(2,1)*	*-6.771176*
Event 21	*ARCH(2)*	*-6.680048*
Event 32	*EGARCH(2,2)*	*-2.967361*
70 days ex-post estimation window		
Event 3	*GARCH(1,3)*	*-6.251403*
Event 4	*GARCH(3,2)*	*-6.692648*
Event 15	*GARCH(2,3)*	*-7.039217*
Event 17	*EGARCH(1,1)*	*-7.323477*
Event 20	*ARCH(3)*	*-4.443783*
Event 29	*ARCH(1)*	*-5.164277*
Event 31	*GARCH(1,2)*	*-6.244766*
Event 33	*GARCH(2,2)*	*-5.772407*
Event 34	*GARCH(2,1)*	*-5.270770*
Event 35	*ARCH(3)*	*-5.060556*
Event 36	*GARCH(2,1)*	*-5.644532*

Table XI: Systematic Risk Comparison of Na-tech Events (ex-ante and ex-post analysis)

Event	Ex-ante	Ex-post	Δ(β)
1	0.604627	0.692331	0.087704
2	0.627643	0.850764	0.223121
3	0.995803	0.798632	-0.197171
4	0.954242	0.831756	-0.122486
5	0.677096	0.477908	-0.199188
6	0.663115	0.428907	-0.234208
7	0.848343	0.995659	0.147316
8	0.429804	0.648179	0.218375
9	0.585545	0.863526	0.277981
10	0.500411	0.85447	0.354059
11	0.466809	0.19399	-0.272819
12	1.209781	0.658889	-0.550892
13	0.732459	0.69544	-0.037019
14	0.572725	0.519378	-0.053347
15	0.805822	0.721883	-0.083939
16	0.759383	0.731661	-0.027722
17	0.532475	0.949284	0.416809
18	0.683732	0.908994	0.225262
19	1.206142	1.035517	-0.170625
20	0.354545	0.415583	0.061038
21	0.880564	0.589922	-0.290642
22	1.060922	1.009471	-0.051451
23	0.975651	0.756432	-0.219219
24	0.949111	0.966894	0.017783
25	0.657127	3.078681	2.421554

Table XII: Systematic Risk Comparison of Terrorist Attacks (ex-ante and ex-post analysis)

Event	Ex-ante	Ex-post	Δ(β)
1	0.278441	0.129237	-0.149204
2	0.528811	0.388643	-0.140168
3	0.233074	0.47274	0.239666
4	0.838330	0.54966	-0.288670
5	0.246784	0.073867	-0.172917
6	0.474239	0.617766	0.143527
7	0.307713	0.337416	0.029703
8	0.416293	0.690755	0.274462
9	0.679822	0.745319	0.065497
10	0.689736	0.752306	0.062570
11	1.068372	0.925139	-0.143233
12	0.170821	0.730583	0.559762
13	0.602435	0.436677	-0.165758
14	0.499031	0.532555	0.033524
15	0.435533	0.557892	0.122359
16	0.432047	0.602749	0.170702
17	0.688756	0.49883	-0.189926
18	0.760941	0.235716	-0.525225
19	0.337605	0.32775	-0.009855
20	0.438237	0.382776	-0.055461
21	0.724177	0.897611	0.173434
22	0.085609	0.355435	0.269826
23	0.285819	0.624725	0.338906
24	0.135390	0.219733	0.084343
25	0.259248	0.191278	-0.067970
26	0.226983	0.174816	-0.052167
27	0.307532	0.480849	0.173317
28	0.128191	0.491711	0.363520
29	0.589654	0.354227	-0.235427
30	0.767588	0.873789	0.106201
31	0.36099	0.594923	0.233933
32	1.789615	1.085304	-0.704311
33	0.439623	0.337042	-0.102581
34	1.12949	1.007235	-0.122255
35	0.706127	1.074508	0.368381
36	0.772599	1.087809	0.315210
37	0.913995	0.925872	0.011877
38	0.969342	0.826967	-0.142375
39	0.877512	0.808216	-0.069296
40	0.805408	0.855715	0.050307

Appendix II

Figure I: Moment Magnitude and Intensity Scale for Earthquakes (Derived from https://earthquake.usgs.gov/learn/topics/mag_vs_int.php Accessed: 10 October 2018)

Magnitude	Description	Mercalli intensity	Average earthquake effects	Average frequency of occurrence (estimated)
1.0–1.9	Micro	I	Microearthquakes, not felt, or felt rarely. Recorded by seismographs.[28]	Continual/several million per year
2.0–2.9	Minor	I to II	Felt slightly by some people. No damage to buildings.	Over one million per year
3.0–3.9		III to IV	Often felt by people, but very rarely causes damage. Shaking of indoor objects can be noticeable.	Over 100,000 per year
4.0–4.9	Light	IV to VI	Noticeable shaking of indoor objects and rattling noises. Felt by most people in the affected area. Slightly felt outside. Generally causes none to minimal damage. Moderate to significant damage very unlikely. Some objects may fall off shelves or be knocked over.	10,000 to 15,000 per year
5.0–5.9	Moderate	VI to VII	Can cause damage of varying severity to poorly constructed buildings. At most, none to slight damage to all other buildings. Felt by everyone.	1,000 to 1,500 per year
6.0–6.9	Strong	VIII to X	Damage to a moderate number of well-built structures in populated areas. Earthquake-resistant structures survive with slight to moderate damage. Poorly designed structures receive moderate to severe damage. Felt in wider areas; up to hundreds of miles/kilometers from the epicenter. Strong to violent shaking in epicentral area.	100 to 150 per year
7.0–7.9	Major	X or greater[29]	Causes damage to most buildings, some to partially or completely collapse or receive severe damage. Well-designed structures are likely to receive damage. Felt across great distances with major damage mostly limited to 250 km from epicenter.	10 to 20 per year
8.0–8.9	Great		Major damage to buildings, structures likely to be destroyed. Will cause moderate to heavy damage to sturdy or earthquake-resistant buildings.	One per year

			Damaging in large areas. Felt in extremely large regions.	
9.0 and greater			At or near total destruction – severe damage or collapse to all buildings. Heavy damage and shaking extends to distant locations. Permanent changes in ground topography.	One per 10 to 50 years

Figure II: Volcanic Eruption Index (VEI) (Derived from https://volcanoes.usgs.gov/vsc/glossary/vei.html Accessed: 10 October 2018)

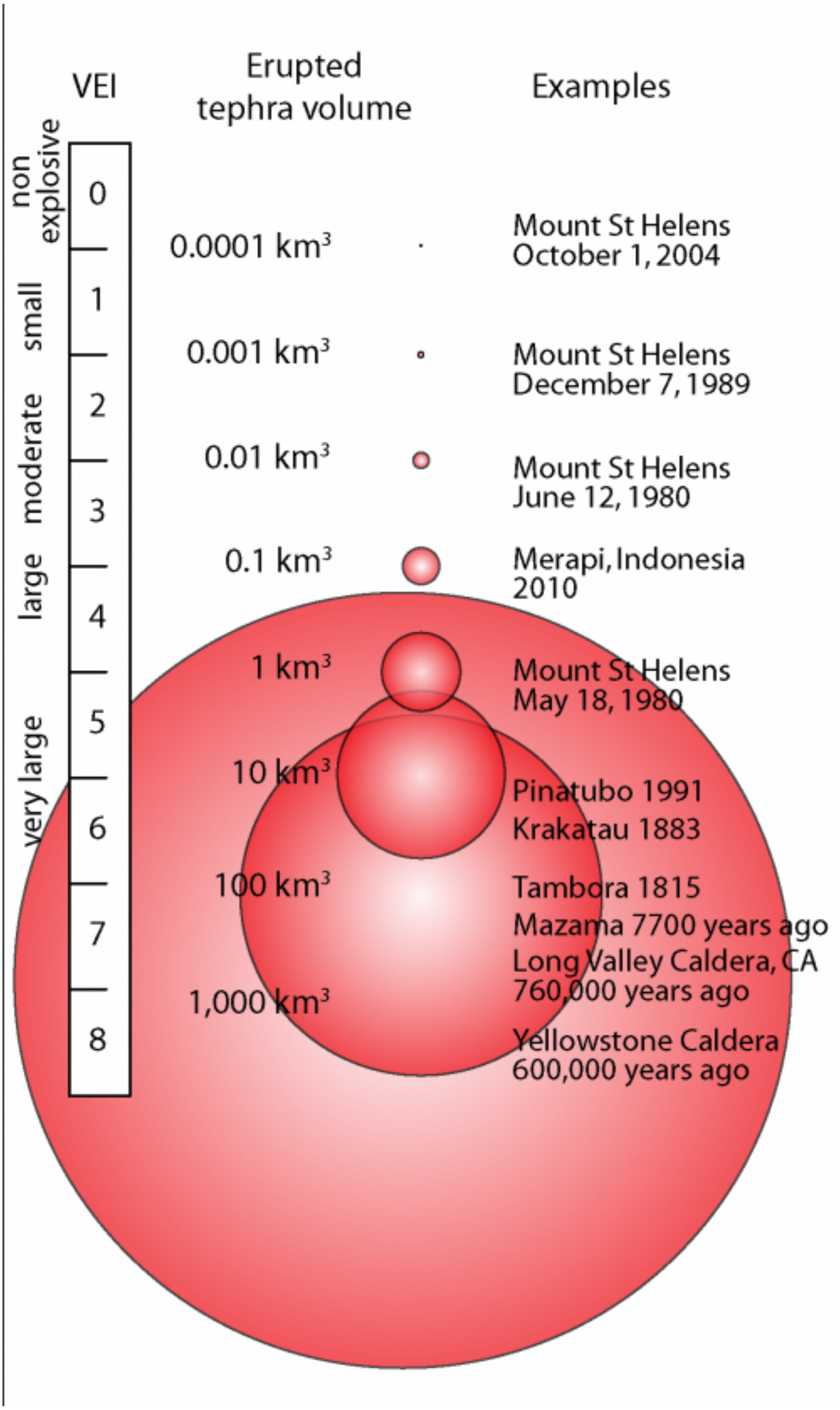

Figure III: International Nuclear and Radiological Event Scale – INES (Derived from https://www.iaea.org/topics/emergency-preparedness-and-response-epr/international-nuclear-radiological-event-scale-ines Accessed: 10 October 2018)