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Airline Stock Abnormal Returns

Market Reaction to Public Events

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Abstract

With the progress seen in recent years, and especially since the beginning of the decade towards a more globalized world, airlines have gained special relevance as key players in this new game field. Then role they play is fundamental to guarantee that industries and individuals can move freely around the world, enabling many economic processes to succeed. Academics have studied, among other things, the role that airlines play in the economy or their stock price evolution, yet few studies have covered how do airlines get affected by disasters of any kind, including here human or natural disasters, let alone in recent years during which the industry has experienced significant changes. This study aims to perform an event study about the abnormal returns that certain public events have caused in the airline industry in the last 25 years. The study also analyses if these abnormal returns are similar at a global level or if, on the contrary, significant differences are depending on the geographical region.

The study results indicate different behaviour of the airline industry stocks with respect to distinct events, as well as a change of behaviour over time of the whole industry with respect to the market for certain kind of events.

Keywords: Airline Industry, Event Study, Market Model, Adjusted Patell Test, Dummy Variable.

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List of Abbreviations

Abbreviation	Definition
AAR	Average Abnormal Return
AR	Abnormal Return
CAAR	Cumulative Average Abnormal Return
CAPM	Capital Asset Pricing Model
CAR	Cumulative Abnormal Return
COVID-19	Coronavirus Disease 2019
COW MID Dataset	Correlates of War Militarized Interstate Dispute Dataset
EM-DAT	Emergency Events Database
EMH	Efficient Market Hypothesis
GARCH	Generalized Autoregressive Conditional Heteroskedasticity Model
H0	Null Hypothesis
H1	Alternative Hypothesis
IATA	International Air Transport Association
ICB Project	International Crisis Behaviour Project
MVRM	Multivariate Regression Model
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
UCDP/PRIO Armed Conflict Dataset	Uppsala Conflict Data Program/ Peace Research Institute Oslo Armed Conflict Dataset

1 Introduction

"The threats of terrorism create risks and airlines have to pay for expensive safety measures and insurance costs. Economic recessions, terrorist activities, and war threats have adverse effects on business travels and the tourism industry. All the factors contribute to the continuous deterioration of financials for the airline industry" (Wang, 2011, p. 1206)

The 20th century was the beginning of a trend characterized by a decline in transportation costs as well as an equalization of commodity prices worldwide. This was the beginning of an acceleration in the globalization process, with a first wave before World War I, and a second and deeper one right after World War II and which continued until the 2000s (O'Rourke and Williamson, 2002).

After World War II, the World started a new stage characterized by a prominent economic growth, increased cultural, social and economic interconnections between most countries around the world, as well as the rise of the middle class in most of the developed economies. The combination of the mentioned three factors was decisive in the consolidation of travelling as something accessible for a big group of population. Tourism started to boom and with it, the airline industry.

The airline industry has helped shape the world in recent years. Its ability to provide fast connections between cities all over the world has empowered companies to grow and establish industries around the globe, as well as enabled travellers to reach places that seemed beyond reach just some decades ago. With this, airlines do undoubtedly play a main role in today's globalized world, creating value for both, customers and the economy.

However, airlines, as major players in today's reality, are affected by public events. Among the most relevant ones, it is possible to mention financial events (mainly economic cycles and changes in the fuel price), natural disasters (such as tsunamis, earthquakes or hurricanes), and human-made disasters such as wars, terror attacks, pandemics, flight accidents or even political tensions between countries.

The mentioned public events either have a positive or negative impact on the airline stocks, which induces volatility of different magnitudes in different markets and sometimes might even provoke counter-intuition return variations. Moreover, on a historical basis, the airline stocks have frequently shown higher volatility than the market index in the post-event period.

An example of this could be seen, for example, in the stock market reaction after the 9/11 terror attack in New York. A terror attack of such magnitude resulted in consequences in the economy at all levels, but one can arguably say that the commercial airlines industry was among the most affected by the incident. Right after the attack, during September 2001 the number of scheduled flights declined by 17% worldwide compared to the previous year (Drakos, 2004, p. 436). Additionally, the number of passengers carried by airlines in October fell by 33% in the North American region, as well as a fall ranging from 20% to 25% in the rest of the world. With this, IATA estimates that the losses recorded by airlines in 2001 amounted to more than USD 15 billion just in the United States (Drakos, 2004, p. 437).

As it may be expectable the investors also reacted to the events in the stock market. American Airlines, Inc. lost 39% of its market value in the aftermath of the attack compared to its previous closing price, whereas, in the case of United Airlines, Inc. its market value loss rose a 42% decline compared to its previous closing price. At the same time, on the first opening day after the incident, the Dow Jones was down more than 1,370 points, a loss of more than 14% (Yahoo Finance, 2020)

Consequently, in this thesis, historical data in the last 25 years is used to perform various statistical analyses in order to disclose the potential pattern of airline industry towards different impacts in different regions. Additionally, it is analyzed the evolution of the airline's stock returns over the last 25 years, as well as evaluated how much do the specific industry stock returns differ with respect to the market ones.

1.1 Purpose

The main purpose of this paper is contributing to the current literature available on the event studies area by implementing a series of test to see the significance that a bounded list of events has had on the main airlines stock returns during the last 25 years. The three main categories of events considered are natural disasters, financial disasters and human-made disasters. To see results not only at an individual level, but also at a regional level, the data has additionally been grouped in different portfolios that have been formed based on the geographical area in which each airline is based. In order to see the significance of the events previously mentioned, it has been performed a calculation of the abnormal returns for each of the events, with the market model as the underlying model for this event study. With the aim to see if the abnormal returns differ significantly from zero, hypothesis testing is performed by making use of two parametric tests, the original Patell test (1976) and the Adjusted Patell test (2010). Both of them have been widely used in previous event studies, with the Adjusted Patell test (2010) being a natural evolution of the Patell test that adds immunity to cross-sectional correlation.

As mentioned, the Adjusted Patell test is a relatively new form of parametric test; this, combined with the evolution that the airline industry has been experiencing in recent years, makes this paper a complement to the current event study literature, adding a new view on how airlines, at an industry level, are affected by certain events that probably will take place again in the future.

1.2 Research Questions

As it has already been mentioned, this research is performed on a sample containing a diversity of airlines from five main geographical regions and on a period between 1995 and 2019, evaluating the effects on their stock price of 67 events. In consequence, the first research question in this paper will be analysing if there is any specific sort of event from those studied that have a more obvious impact towards airlines, compared to how it affects the whole market. The hypothesis considered for the first research question is that, by common sense, the disasters that are associated with planes and or travelling in general, will mean higher abnormal returns in the airline industry compared to other industries. However, beforehand, other events that are not directly associated to the airline industry, would not necessarily need to affect the airline industry more than others in the market. In order to test this assumption, we will make use of the event study methodology. On the first step of the event study, regressions will be run using Global Market Portfolio as our independent variable and Continental Stock Portfolio as our dependent variable in order to get the AR values for each of the events. The aim is to observe the CAARs, see if they are significantly different from zero for each category of events and, based on that, draw some conclusions that can provide an answer to the question mentioned.

The second research question consists on analysing if a specific event can have a different scale of influence towards different continents. Our hypotheses for this question, based on our pre-study research, is that it will have a different scale of influence depending in where the event happened, being more relevant and causing higher abnormal returns if the event took place in European or North American territory, compared to, for example, Middle East. With the aim to test this assumption, the event study methodology will be used. Consequently, the first step of the study will consist of running different regressions using a Continental Market Portfolio as independent variable and a Continental Stock Portfolio for each of the geographical regions as the dependent variable. The purpose of this is to obtain the AR and CAR values of each continent and, once gotten them, doing a t-test to test their significance. On the basis of them, it will be possible to answer this research question.

Lastly, the third research question focuses on offering an answer to if there is some kind of event that has experienced a change of significance over time (e.g. used to matter in the past, but it does not matter anymore). Here, it will be analyzed thus if the investors and the market in general have become more used to certain events such as terror attacks, that used to cause a big panic in the market, but it does not anymore. The hypothesis considered here is that, it is true that the market does not react as much as it used to when certain kind of events occur. In the specific case of terror attacks, it may have to do with the fact that at some point, in this new decade, they have become something more frequent in the western countries so the whole society is more used to them and don’t overreact as it used to do. Here again, in order to test this assumption, it will be run a regression using Global Market Portfolio as the independent variable and Continental Stock Portfolio as the dependent variable with the purpose of getting the AR values for each of the events. Out of that, the CAARs for each event are calculated and, it is analysed if these follow any pattern over time. Based on these results, an answer to the research question can be provided.

1.3 Outline

In this paper, the first section outlines the reasons that have been considered and have led to the performance of an event study of the airline industry. Moreover, it is provided a theoretical background and review of event studies that show relative similarities to the one performed along this paper. Subsequently, it is presented an explanation of what event studies consist of and the various methods implemented to achieve results. In this area it is outlined the criteria that has been followed to select events that may be significant to the study, as well as it is exposed the design that the event study will take. In the forthcoming section, a description of the data chosen is provided, as well as the form that it will adopt in order to implement the event study. Following this part, the results from the different tests is presented. The final section, the conclusion, provides a summary of the results obtained, and compares them with the results that could have been expected from the testing.

2 Literature/Theoretical Review

Many authors have already studied the impact that disasters of all kinds have had in the economy, as well as the stock markets. It is clear that nowadays news, especially bad news spread fast along the investors, leading to abrupt decreases in the stock markets prices worldwide (quite notably in cases of bad news such as terror attacks). Fama (1969) found that if the market is efficient, the security prices will immediately fully reflect the new available information. This idea was further developed later on in Fama (1970) and formed into the Efficient Market Hypothesis, which most traditional finance theories followed. Under the EMH, abnormal returns should not continue after an event takes place and neither market information leakage should exist.

Opposed to the EMH, it has been developed the behavioural finance theory, whose father can be considered to be Richard Thaler (Hammond, 2015). Under this alternative theory, psychology and the mind in general have effects on the decisions taken by investors, analysts and the market in general (Shelfrin, 2000). Even though the EMH is widely accepted, some scholars found that behavior finance may also be a notable factor towards stock return volatility. According to Shiller (2003), observers tend to under- or overreact to new information "because of such things as 'sunspots', 'animal spirits' or just mass psychology" (p. 84). The main difference between the EMH and behavioural finance theory is not the availability of information for everyone at the same time, which both assume, but rather the different interpretation that investors give to that information, and thus the difference in their reactions (Szyszka, 2007).

Besides, some previous studies have conducted diverse financial models to explain the relationship between events and the returns of airline stocks, and showed that events can prominently impact the return of airline stocks. Borenstein and Zimmerman (1988) focused on the influence of airline accidents in the US to American airline industry during 1960-1985. They used the Capital Asset Pricing Model (CAPM) to analyse and figured out that the air accidents significantly and negatively influenced the returns of airline stocks. Wang (2011) studied the impact of crisis events on the volatility of 16 international airlines based on four major events by conducting Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model with dummy variables, and the results showed that major events increased the return volatility if airlines, especially the correlation with the returns of the previous period are concerned. Carter and Simkins (2004) used the multivariate regression model (MVRM) to examine the reaction of air-transport stock prices after the September 11th attacks. The result indicated that the American airlines suffered more than international carriers or airfreight, and airlines with lower levels of cash and equivalents were penalized more.

Moreover, to study the influence of bad news, another dimension is the choice of disasters. Previous papers always included detailed event studies but didn't focus on the airline industry. Chen and Siems (2004) found evidence that even though volatility and abnormal negative returns exist when military/terror attacks take place, the market is showing more resilience with time as compared with previous attacks. This position is partially shared by Abadie and Gardezabal (2007) who considers that terrorism affects the financial markets, and the whole of the economy, reaching the conclusion that the intensity of the effects of a terror attack in the economy are defined by the intensity of the terrorism. Certain studies only focused on the impact of one particular sort of events towards airline industry. Noronha and Singal (2004) whose research focus on the relation between plane accidents and airlines' financial health, make use of a Hausman implementation of the Poisson process. The results obtained show that only 2-3% of the aviation crashes that take place are severe enough as for causing financial damage to the airline. Nonetheless, it also concludes that a severe accident could have enough damaging financial power as for causing a whole letter change in the affected airline investment bond credit rating. Kaplanski and Levi (2009) research also go in the same direction. In their case, they make use of a modified version of the Fama and French model, find that there is a high volatility in the market after a severe aviation accident happens, especially in riskier stocks and less stable industries; however, in a short period a price reversal generally occurs.

However, all these studies only choose one category of events or picked several typical events to investigate the influence towards airline stocks, mainly on American stock market. Thus, study from a more comprehensive angle is in absence in the airline stock field, with special emphasis on how those events have affected and affect nowadays to the industry, as well as possible different reactions between continents.

3 Methodology

3.1 Data Description

International Air Transport Association (IATA) has 299 airline members worldwide (IATA, 2020a), however, the number of tradable listed airlines worldwide at the same day were only between 90-140 from 1995 to 2019. Thus, we chose top 50 airline companies ranked by market capital value to represent the whole airline industry. For every five years, we re-ranked all listed airlines back then based on the last date of that period to always include those stocks that could indicate airline industry. If market capitalization for certain equities on that day was not available, then replaced it with the latest valid data. We left out airlines which was delisted during the period and substituted them with latter ones in order so that we got 50 airlines to form the portfolios. The daily share prices, numbers of outstanding shares and market capitalization of these airlines in according period were recorded as the fundamental data.

Then data of daily market capitalization of the certain country's stock markets where these 50 airline stocks are listed and traded in the last 25 years was downloaded too. If an airline stock is listed on several stock markets, only the prime listed stock exchange counts. There are only two special cases. The first one is that two companies, AVIANCA HOLDINGS SA and COPA HOLDINGS SA-CLASS A, belong to Panama which does not have its stock exchange and are traded on American stock exchanges. Thus, these two companies are included in North America market. The other special case is that in the Top 50 market capitalization airline list for last 25 years, there was only one airline, 1 Time Holdings Ltd., in Africa in period 1995-1999. Also, the passenger-countries ranking for Africa is not among the significant top in 2018 either (IATA, 2020b). Based on these facts, we substituted 1 Time Holdings Ltd. with the 51st largest airline in the portfolio. In the end, portfolios are formed only for five areas: Asia and Pacific, Europe, Latin America and Caribbean, Middle East, and North America. All data above were collected on Bloomberg and DataStream, and both market and stock data were converted into US dollar based on the history daily exchange to ensure they are comparable.

These airline stocks and country market capitalization are divided into several groups according to the areas that they are in and formed airline portfolios and market portfolios for each area based on NYSE Indices calculation (NYSE, 2018b). The reason why we decided to from portfolios rather than do cross-sectional study in each area are:

- Firstly, in the long time period, every area renewed its top-market-value airlines list every 5 years, which means that the stocks within the list changed throughout the time. And that change is a disturbing factor to the return calculation, especially when estimating the possible effects of events that happened near the end of a specific 5 years period. Also, there were many invalid values because of suspension, listing and delisting of securities and different holidays in different countries. Most available methods to handle these two problems, like using the last valid data for invalid days, are either complicated or new-bias-causing.

- Secondly, since the data is from airline stocks all over the world, it is hard to find unbiased, typical and consistent indices to represent the market because of the differences of the financial system in different countries.
- Thirdly, the data set is quite large since these airlines were listed on various stock exchanges in many countries. We needed to simplify and extract the core information from the large sample into comparable and unified series of data.

The portfolio forming method from NYSE is an index calculation approach. The main idea is to use market capitalization to form securities into one index, and the index level can be treated as the price of the new portfolio. Also, by changing the divisor, the interfering influences of suspension, listing and delisting of single security and different holidays in different countries can be excluded from the change of index level. Thus, forming new portfolios based on the data we had is the optimal choice.

The portfolio forming method is stated below (NYSE, 2018a):

The Index Level is only calculated on a weekday. For the first day to start the calculation, the initial assumption is that the initial Index Level (Base Level) was set as 1000 at the starting point (on the Base date). The general formula for divisor is:

$$Divisor = \frac{\sum_i P_i Q_i}{Index\ Level} \tag{1}$$

Where:

- $Divisor$ means the Price Return Index Divisor. It is the key variable to determine the Index Level and keep the Index Level from disturbing information;
- P_i means the Price (in the Index Base Currency) of Index Constituent i on the first day;
- Q_i means the number of Shares of Index Constituent i on the first day;
- $\sum_i P_i Q_i$ means Index Market Capitalization on the first day.

For the stock portfolio forming, we deleted the stocks as components that didn't have a valid price on that date because of suspension, delisting or holidays from the portfolio. The reason is that if a stock didn't have a valid value on a certain day, it could not reflect the impact of the event. When we form the portfolios for the market, the problem doesn't exist for the market capitalization for the whole stock exchange is always valid.

If the components for the portfolio maintains the same as the previous day, then:

$$Divisor_t = Divisor_{t-1} \tag{2}$$

The formula for the Price Return of the index on Date t is:

$$Index(PR)_t = \frac{\sum_i P_{i,t} Q_{i,t}}{Divisor_t} \tag{3}$$

Where:

- t means Index Calculation Date t;
- $Divisor_t$ means the Price Return Index Divisor on Index Calculation Date t;
- $P_{i,t}$ means the Price (in the Index Base Currency) of Index Constituent i on Index Calculation Date t;
- $Q_{i,t}$ means the number of Shares of Index Constituent i on Index Calculation Date t.

If the components for the portfolio changed compared to the previous day, Divisor may be adjusted for suspension, listing and delisting of single security and different holidays in different countries in the index constituents:

$$D_t = \frac{\sum_i APC_{i,t} Q_{i,t}}{Index(PR)_{t-1}} \tag{4}$$

Where:

- D_t means the Index Divisor on Index Calculation Date t;
- $Index(PR)_{t-1}$ means the Price Return Index Level from Date t-1;
- $APC_{i,t}$ means the Adjusted Previous Close Price of Index Constituent i on Index Calculation Date t. The way to calculate APC is that if the price of Index Constituent i was invalid on Date t-1 but was valid on Date t, then the invalid numbers on Date t-1 are substituted with valid numbers on Date t. And if the price was valid on Date t-1 but was invalid on Date t, then substitute valid number on Date t-1 with invalid number on Date t. Otherwise, keep the original number on Date t-1;
- $Q_{i,t}$ means the number of Shares of Index Constituent i on Index Calculation Date t.

Then the Index Level on Date t can be calculated according to the formula (2).

Additionally, the value of Divisor, Index Market Capitalization and Index Level on the previous day will be assigned to those on the current day in the situation where all components were unavailable on certain dates because of common public holidays.

Finally, to process the mass data and do the complicated Index Level calculation throughout 25 years, Matlab program was used here.

3.2 Research Design

3.2.1 Event Selection

Since the main goal of this project is analyzing the market reaction of the airline industry to public events, and comparing it to the whole market reacts, the first step would be defining which events are we going to analyze. As may be understandable, the main focus should be on substantial events that have the capacity to affect the financial markets at a regional or global level. In order to select the events for the event study, we need to establish some criteria first. The main focus should be events that are big enough as for affecting one or more countries' economies, or that at least have received enough attention from the media as for having effects in the stock markets.

The selected events can be categorized into two main groups: expected events and unexpected. Inside of this wide categorization, the event can be classified into three sub-groups: natural disasters, financial disasters and human-made disasters. And all the events are listed in Appendix A: Event List.

The categorization of the events in either expected or unexpected events has been done taking into consideration the possibility of those certain events to be predicted by the market, allowing investors to take decisions before the event has officially taken place. Furthermore, the already mentioned sub-grouping of events in natural, financial and human-made disasters have the goal of easing reaching compelling conclusions.

The first sub-group is formed by natural disasters. Natural disasters can be always grouped as unexpected events. This sub-group includes natural catastrophes such as tsunamis, earthquakes or hurricanes. To perform the analysis, it has been done a selection of what could be considered the 23 most serious natural disasters that have taken place during the last 25 years, out of a sample of 94 events registered at the natural disasters EM-DAT database. At first, when performed a selection of events, 30 of them had been chosen to be included; however, for 7 of the events, no valid data satisfied the criteria that there should not be more than continuous 8 suspension days during the estimation window and should not be more than continuous 2 suspension days during the event window and thus, they were additionally excluded. Furthermore, the mentioned selection has been done attending to the estimated cost of each of the disasters. No geographical discrimination has been done in the selection, and only one event has been excluded, the great famine that took place in the Democratic People's Republic of Korea due to obvious difficulties to measure the economic consequences of such event. An example of an event of this category is the 2011 Japan's Earthquake and Tsunami that took place in the Fukushima area.

A second sub-group is formed by financial events, selecting the 10 most serious financial disasters that have occurred in the last 25 years. Financial disasters are always classified as expected events in this study, as it is supposed that before they take place, some signs that could be interpreted by investors will be given in the market. In order to define what kind of events are included, it has been performed an analysis of the biggest fall in stock returns during the last 25 years and suffered by three major stock indexes: the S&P 500 (North America), the EUROSTOCK 1000 (Europe) and the NIKKEI 225 (Asia) as an approximation of the three major geographical areas of interest. The selection has been performed based on the data available at Yahoo Finance. It is important to mention that only drops due to financial and economic decisions (such as bankruptcies or changes in monetary policies) have been taken into consideration to avoid overlapping with the other categories. Additionally, some of the drops performed by the mentioned indexes are due to the same event, whereas some others are due to national or regional events that don't have, at least, such a big influence in the international markets.

Finally, a third sub-group includes all kinds of human-made disasters such as wars, terror attacks, pandemics, flight accidents or political tensions between countries. The events included in this sub-group can either belong to the category of expected events (political events and wars) or unexpected events (plane crashes and terror attacks). The selection of events for this category can be considered among the most complex ones. This is due to the difficulties to measure above the obvious economic damage that the event causes; for example, lost investment opportunities or impact that a certain event such a terror attack can have over-tourism. However, a list of the 40 most relevant human-made disasters that have taken place in the last 25 years has been created by unifying data from different databases, as well as making a subjective selection of the hundreds of events registered to pick those that can be considered the most relevant ones. In addition, for 6 of the events, no valid data satisfied the criteria of quality defined for the selection, so it was excluded. Some of the sources used for the selection of the events categorized in this group are the ICB (International Crisis Behaviour) Project, the COW MID Dataset, the UCDP/PRIO Armed Conflict Dataset as well as some encyclopaedias.

3.2.2 Event Study Design

The performance of event studies is a relatively powerful tool in order to acknowledge the market reaction to a certain event. The first-ever recorded event study took place more than 80 years ago, with James Dolley (1933) being its author. In this very first event study, the author analysed the price effects of stock splits, focusing on the nominal price changes at the time of a certain split. Since then, the event studies have evolved, with additions in the number of test statistics available, which has led to improvements in its reliability.

To measure the effect of different categories of public events on the value of airline stocks, the event study methodology is conducted.

The traditional event study, as developed by Fama, Fisher, Jensen and Roll (1969) involves making use of a timeline with two main clearly defined periods. An estimation window that goes from t0 to t1 and that provides the required information in order to specify the so-called 'normal return'. An event window which contains the event date and that goes from t1 to t2. During the mentioned event window, it will be calculated the abnormal returns; these abnormal returns will depend on both, the actual returns during the event window and the forecasted 'normal returns'. However, according to more recent Campbell et al (1997), the event study divides the time horizon of an event into three windows: estimation window, event window and post-event window. This study mainly operated the data of estimation window and event window of events to research the impact magnitude, thus, post-event window information was not used here.

Then, one of the first decisions that should be made in an event study is to decide the length of the estimation window and event window. While there are plentiful works of literature and a long history of event studies, there is no consensus that how long these windows should be.

There are many different choices of length of the estimation window. E. Boehmer et al. (1991) used an estimation window of 239 days (-249, -11) in their study. A.R.Cowen et al. (1996) used 255 days of estimation window (-255, -1). MacKinlay (1997) advocated two different ideas, one is 250 days (-270, -21) and the other is 120 days. Considering to avoid overlap and variation of stocks during a long period, we choose 120 days / 17 weeks / 85 weekdays as the length of the estimation window.

As for the length of the event window, Hillmer and Yu (1979) found that event impact towards stocks should end within only several hours after the initial announcement, which means that the event window should only last for one day. However, Chang and Chen(1989) claimed that the market would keep responding to the impact for several days. Based on the assumption of event study that the abnormal returns all happened during the event window and three rules proposed by D. Krivin et al. (2003) to decide the appropriate event window length, we tried to determine an event window length that suits the data we used the most.

We have performed some tests to find the most suitable event window for each kind of event. The tests have consisted of performing the Adjusted Patell Test(see below for detail) on AARs calculated from different lengths of event windows, analysing the results provided and thus choosing a length that can be in equilibrium between having a reasonable number of days that include all significant related abnormal returns but, at the same time, trying to minimize the effect that other social events could have on the results by excluding other event dates, even they're not on our event list.

As a result, for the expected events, in which we include wars, financial events and political events, the chosen length is 8 workdays starting on -2 and finishing on +5. For the unexpected events, in which we include natural disasters, terror attacks and plane crashes, the chosen length is 12 workdays starting on -1 and finishing on +10.

To sum up, the default time for the estimation window is 85 working days. In the case of the event window, it lasts 12 working days for unexpected events and 8 working days for the expected events. Considered time differences and potential information leakage, the event date is determined as one day before the event date. A special case to take into consideration is when a certain event takes place during a non-working day (including weekends or national holidays). In those cases, it would be considered that the event day (day 0) in the event window would be the next working day, and the last working day before the event took place, would be considered to be day -1 in the event window.

Another initial is deciding on which model shall be used to measure the normal performance. As per MacKinley (1997), it is possible to distinguish two main approaches. The first one, a statistical approach based solely on statistical assumptions, and secondly, an economic approach that combines the mentioned statistical approach with some economic arguments and restrictions. The major difference between them, apart from the economic restrictions imposed, is the assumption in the statistical models that asset returns are independently and identically distributed through time (MacKinley, 1997). This assumption is enough for the statistical models to be "correctly specified", not making necessary in most cases the use of economic models.

Once selected a statistical approach model, the next step is choosing which statistical model could be the most suitable for our event study. Two models were considered, the constant mean return model and the market model. In this case, it has been chosen a modified market model to which it has been added dummy variables for reasons explained later on. The market model, even though less simple and straightforward than the constant mean return model, controls for the correlation between the market and the company's return, unless the constant mean return model (MacKinley, 1997). In addition, the market model also removes the part of the return that is related to the variation in the market returns, leading to a reduction in the variance of the abnormal return (MacKinley, 1997). The reasons mentioned make the market model widely accepted as the standard model for an event study.

Thus, under the assumption that the relation between the market return and the stock return is stable, and that the risk-free interest rate in the factor is constant, we can use Market Model to measure securities' normal performance based on the concept of Ordinary Least Squares (OLS). Market Model can decrease the variance of abnormal return by excluding the portion of the securities that are influenced by the market return, and increase the possibility of detecting the event's effect.

The first step would be proceeding to calculate the daily returns of both market and airline portfolios:

$$R_{it} = \frac{P_{it} - P_{i,t-1}}{P_{i,t-1},} \tag{5}$$

Where P_{it} is the Index Level for market portfolio and airline portfolio at time t.

Market Model is performed to get the relation between the return of the market portfolio and airline portfolios during the estimation window:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it},\ E[\varepsilon_{it}] = 0,\ Var[\varepsilon_{it}] = \sigma^2_{\varepsilon_i} \tag{6}$$

where:

- R_{it} means the return of the airline portfolio i on date t;
- R_{mt} means the return of the reference market portfolio on date t;
- α_i , β_i are the estimated parameters in the linear regression model α_i is the intercept and β_i is a measure of the sensitivity of R_{it} on the reference market;
- ε_{it} means the error term (a random variable) with expectation zero and finite variance.

However, in practice, using the Market Model directly can lead to biased results. This is because some event dates are quite close to each other, and estimation windows of these events include one or even more event windows of other events. Considering that event window may encompass significant abnormal returns, running regression based on these data will certainly interfere, no matter how little, the results of estimated parameters. To exclude the disturbance of the overlap between the estimation window and event window, dummy variables were introduced into the Market Model. In this paper, 67 specific events were chosen to be studied in total. Thus, 67 dummy variables were formed and listed chronologically according to the event dates.

$$D_{nt} = \begin{cases} 0, & if\ date\ t\ is\ NOT\ included\ in\ the\ event\ window\ for\ event\ n \\ 1, & if\ date\ t\ is\ included\ in\ the\ event\ window\ for\ event\ n \end{cases} \quad (7)$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + [D_{1t}\ D_{2t}\ D_{3t} \dots D_{nt}][\beta_{1i}\ \beta_{2i}\ \beta_{3i} \dots \beta_{ni}]' + \varepsilon_{it} \quad (8)$$

$$E[\varepsilon_{it}] = 0, Var[\varepsilon_{it}] = \sigma^2_{\varepsilon_i}$$

where:

- R_{it} , R_{mt} , α_i , β_i, ε_{it} still stand for the same meaning as they are in the normal Market Model;
- D_{nt} means the value of the n-th dummy variable on date t;
- β_{ni} are estimated parameters of the n-th dummy variable D_n in the linear regression model for airline portfolio i.

During the event window, the expected normal return in the case where there was no impact of the event can be estimated by using the two parameters α_i , β_i above:

$$E[R^*_{it} \mid \Omega_{it}] = \alpha_i + \beta_i R_{mt} \quad (9)$$

where:

- $E[R^*_{it} \mid \Omega_{it}]$means the expected return if there was no event happened based on the information of the airline portfolio i on date t;
- α_i , β_i are the parameters obtained during the estimation window;
- R_{mt} means the actual return of the reference market portfolio on date t.

The abnormal return of the airline stocks during the event window can be calculated as:

$$AR_{it} = R_{it} - E[R^*_{it} \mid \Omega_{it}] \quad (10)$$

where:

- AR_{it}means the abnormal return of the airline portfolio i on date t;
- R_{it} means the actual return of the airline portfolio i on date t during the event window.

During the performed study, one of the problems encountered has been events overlapping. This is due to the closeness with which some of the events took place in the study.

Once every period has been clearly defined, the next step is the aggregation of abnormal return observations with the purpose to draw inferences for the analysed event. During the mentioned event window, it will be calculated the abnormal returns; these abnormal returns will depend on both, the actual returns during the event window and the forecasted 'normal returns'. This aggregation is performed in two dimensions, through time and across securities. $CAR_i\ (t1, t2)$ can be defined as the sample cumulative abnormal return (CAR) from t1 to t2, where $T1 < t1 \leq t2 \leq T2$. Thus, the CAR from t1 to t2 is the sum of the included abnormal returns in the mentioned period (MacKinlay, 1997).

$$CAR_i\ (t1, t2)\ =\ \sum_{t=T_1+\,1}^{T_2} AR_{i,t} \tag{11}$$

To test the significance of CAR for single stock, t-test was performed according to Brown and Warner(1985) test method. The hypotheses for the test are:

$$H_0\colon CAR_i = 0$$

$$H_1\colon CAR_i \neq 0$$

The t statistic under null hypothesis is:

$$t\ =\ \frac{CAR_i}{S_{CAR}} \tag{12}$$

and test statistics obeys t-distribution. S_{CAR} stands for the standard deviation of CAR, and can be derived from the following equation:

$$S_{CAR}^2 = L_2 * \frac{1}{M_i - 2} * \sum_{t=T_0}^{T_1} (AR_{i,t})^2 \tag{13}$$

where Mi stands for the number of observations during the estimation window for airline portfolio i, and L2 stands for the number of abnormal returns, etc, the number of dates for the event window.

Furthermore, the cumulative abnormal returns follow a normal distribution.

After performing those calculations, then the abnormal returns and the cumulative abnormal returns are "averaged" for each day in the event window, forming the "AAR" and "CAAR" respectively. Given N markets, the sample aggregated abnormal returns for period t would be:

$$AAR_t\ =\ \frac{1}{N} \sum_{i=1}^{N} AR_{i,t} \tag{14}$$

$$CAAR\ =\ \frac{1}{N} \sum_{i=1}^{N} CAR_{i,t} \tag{15}$$

Under the null hypothesis, both the average abnormal returns and the cumulative average abnormal returns follow a normal distribution.

Notwithstanding, another common reason to perform event studies is to specify if the abnormal effects belonging to certain events are significantly different from zero. This is determined by executing hypothesis testing (Schrimmer et al., 2014).

In hypothesis testing, there is a Null hypothesis (H0) that in the case of event studies sets that there are no abnormal returns within the event window. On the other hand, there is an Alternative hypothesis (H1) which establishes that there are abnormal returns within the event window.

To perform an event study, there are several kinds of significance tests available, which can be grouped in parametric and non-parametric tests. The most common parametric test is the "typical" classic t-test. However, the classic t-test has some widely known problems, among them, its tendency to cross-sectional correlation and volatility changes (Schrimmer et al., 2014).

Different approaches have been taken by a diversity of authors to address the statistical issues of the t-test.

As it is widely known, in the case of the stock-return based studies, event-date clustering, which can be understood as gathering of many events in close dates and can cause certain impact on each other's results, supposes a serious threat that can lead to cross-sectional correlation of abnormal returns as well as produce distortions from event-induced volatility changes (Schrimmer et al., 2014). Different solutions could be proposed to address this problem.

On the one hand, a possible solution to cope with the mentioned event-date clustering problem could be the addition of all abnormal returns into a portfolio. The point on this method is aggregating in order to draw overall differences for the event of interest as per Campbell, Lo and MacKinlay (1997). Under this method, firstly it would be created an average weighted portfolio that includes all the analyzed airline stocks for, after that, deriving the abnormal return for the newly created portfolio.

Another possible solution is the approach suggested by Kolari and Pynnönen (2010); their proposed method consists on making use of scaled or standardized abnormal returns and, at the same time, using a new test statistic that takes into consideration both, cross-correlation and inflation of the event date variance. The mentioned test statistics is based on the ideas already developed by Patell (1976) and Boehmer, Musumeci and Poulsen (1991).

As demonstrated by Kolari and Pynnönen (2010), this method proofs that scaled returns successfully reduce the implied cross-correlation problem into the single number of average correlations.

In this thesis, an application of the second solution is performed in order to deal with the event-date clustering.

The Adjusted Patell test, as proposed by Kolari and Pynnönen, is an extensively used test statistic in event studies, and evolution of the original Patell test proposed by Patell (1976, 1979). The Adjusted Patell test manages to deal successfully with all the problems that the original Patell was already solving, keeping its immunity to the way in which abnormal returns are distributed across the event window, but adding the already mentioned immunity to cross-sectional correlation.

In addition to performing the Adjusted Patell test, in this project, it is performed a similar parametric test, the original Patell Test (1976, 1979) in order to perform a comparison between their results.

a) Patell test

As proposed by Patell (1976, 1979) the first step in the test would be proceeding to standardize each abnormal return. In order to do this, the following formula would be used;

$$SAR_{it} = \frac{AR_{it}}{S_{AR_{it}}} \tag{16}$$

In which $S_{AR_{it}}$ stands for the standard deviation of the abnormal return.

The $S_{AR_{it}}$ can be derived from the following equation;

$$S^2_{AR_{it}} = S^2_{AR_i} \left(1 + \frac{1}{Q} + \frac{(R_{mt} - \underline{R}_m)^2}{\sum_{t=T_0}^{T_1}(R_{mt} - \underline{R}_m)^2}\right) \tag{17}$$

$$\underline{R}_m = \frac{1}{Q}\sum_{t=1}^{T} R_{mt} \tag{18}$$

$$S^2_{AR_i} = \frac{\sum_{t=T_0}^{T_1} SSR}{Q-2} \tag{19}$$

In the equation above, R_m is the market return, $\underline{R}_m$ stands for the average market return in the estimation period and Q is the number of days in estimation period. The $S_{AR_{it}}$ is distributed as a t-distribution with $Q - 2$ degrees of freedom under the Null hypothesis.

The test statistic for testing the null hypothesis, $H_0: AAR = 0$, is given by the following equation:

$$Z_{Patell,t} = \frac{ASAR_t}{S_{ASAR}} \tag{20}$$

In which $ASAR_t$ means the sum of the standardized abnormal returns;

$$ASAR_t = \sum_{i=1}^{N} SAR_{it} \tag{21}$$

With expectation equal to zero and variance equal to:

$$S^2_{ASAR} = \sum_{i=1}^{N} \frac{Q_i - 2}{Q_i - 4} \tag{22}$$

When it comes to testing the Null hypothesis that $H_0: CAAR = 0$, we use an analogous approach to get the test statistic;

$$Z_{Patell} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \frac{CSAR_i}{S_{CSAR_i}} \tag{23}$$

In which $CSAR_i$ stands for cumulative standardized abnormal returns

$$CSAR_i = \sum_{t=T_1+1}^{T_2} SAR_{it} \tag{24}$$

And with expectation equal to zero and variance equal to;

$$S^2_{CSAR_i} = N * \frac{Q_i - 2}{Q_i - 4} \tag{25}$$

With Q as the number of returns in the estimation window and N as the number of different markets.

Under the assumption of cross-sectional independence and other conditions, Z_{Patell} follows a standard normal distribution.

b) Adjusted Patell test

In the modification of the Patell test proposed by Kolari and Pynnönen (2010), it is used the standardized abnormal returns (SAR_{it}) as previously defined, as well as the defined $\underline{r}$ as the average cross-correlation of the abnormal returns in the estimation period (Schrimmer et al., 2014).

With this the test statistic for $H_0: AAR = 0$ in the adjusted Patell-test would be the following

$$Z_{Patell,t\ ADJUSTED} = Z_{Patell,t} \sqrt{\frac{1}{1 + (N-1)\underline{r}}} \tag{26}$$

With $Z_{Patell,t}$ as the Patell test statistic. It is possible to see that if the average cross-correlation of the abnormal returns in the estimation period ($\underline{r}$) is zero, then the adjusted Patell test statistic is basically equal to the original Patell test statistic.

In addition, if assumed that that the square root rule stands for the standard deviation, it is possible to make use of this test when considering Cumulative Abnormal Returns (Schrimmer et al., 2014), as it is shown

$$Z_{Patell\ ADJUSTED} = Z_{Patell} \sqrt{\frac{1}{1 + (N-1)\underline{r}}} \tag{27}$$

3.3 Limitations

In this study, we realized that several issues will influence the quality of the study, and we tried to alleviate them by all means. The main three limitations are stated below.

Firstly, we accept the fact that part of the event list is subjective. We tried to get criteria for selection of every category of event, nevertheless, two aspects of event choosing can cause further biases. One is that we discarded several events because of no valid data that satisfies the criteria that there should not be more than continuous 8 suspension days during the estimation window and should not be more than continuous 2 suspension days during the event window. The other is that for terror attacks, wars and global political tensions, it is difficult to set selection criteria. Thus, we performed a selection of the most impactful events and those which are repetitive in several databases consequently. In the end, there are 67 events for the last 25 years, and for each category, there are still more than five events, which helped to relieve the possible influence.

In addition, we abandoned the conventional fixed length of the event window and decided flexible event window time for two main categories, expected event and unexpected event, which may be unbefitting with other event studies. This method is based on previous widely accepted studies (Hillmer and Yu, 1979; D. Krivin et al., 2003), therefore it is credible to produce reliable results.

Finally, to study the differences of continental responses towards the same events, we chose to use the continental stock portfolios rather than individual stocks to estimate parameters, and to apply t-test to test significance. The reason is that for those continents with relative less global airline giants like the Middle East and Latin America and Caribbean, it is quite common that there are no valid stock data that satisfy the valid data criteria. Using individual stocks needs to exclude more than 10 events from the event list that are without valid data during the estimation window or event window, and hence may cause more severe uncontrollable biases. However, using continental stock portfolios and running one-to-one regression means we can only get CAR and can only perform t-test, and t-test is prone to cross-sectional correlation and volatility changes. In the methodology part, portfolio forming and tailor-made event window length can alleviate these biases.

4 Results and Analysis

In this chapter, the empirical results obtained are presented and each of the previously outlined hypothesis are discussed. In order to obtain the presented results, as explained before, the data is grouped in different portfolios to obtain as much information as possible from its historical evolution and to test the different hypotheses already presented.

It is important to remark that the main purpose of this project is analysing the possible abnormal returns that certain events have produced in the airlines industry. This means that this study will mainly detect if a specific event has produced a different reaction in the airlines stock values compared to the one that the market as a whole has experienced. This reaction could be more positive than the one experienced by the whole market, which means that the airline industry is less affected by a specific event, or more negative, in which case the airline industry could be considered more affected by a specific event. However, the lack of significant abnormal returns would not mean that the airline industry is not affected by a certain event, but simply that it is affected similarly to how the market on average is.

4.1 Is there any specific sort of event, from those studied, that have a more obvious impact towards airlines, compared to how it affects the whole market?

In order to test the hypothesis for this research question, a series of regressions are run using Global Market Portfolio as our independent variable and Continental Stock Portfolios as our dependent variables, with the purpose to get the AR values for each of the events. More specifically, 67 regressions had to be run for each category of event, which are five, making in total 335 the number of regressions run. The aim is to observe the CAARs, see if they are significantly different from zero for each category of events and, based on that, draw some conclusions that can provide an answer to the question mentioned. In addition, the events are classified into two major groups based on the chances that information leakage could occur before the event was officially announced or took place: expected events and unexpected events. The results of the test can be seen in Appendix B: Patell Test and Adjusted Patell Test of CAAR. Some test result description is shown in Table 1.

Category	Number of Events	Number of Significant Events	Significant Percentage	Mean of CAARs
Financial	10	2	20.00%	-0.0290
Natural Disasters	23	5	21.74%	0.0066
War	5	1	20.00%	0.0064
Terror Attacks	13	5	38.46%	-0.0184
Political	6	1	16.67%	-0.0159
Plane Crashes	10	1	10.00%	-0.0037

Table 1. Description of Test Results

4.1.1 Unexpected Events

a) Natural disasters

Natural disasters are always considered to be unexpected. Based on that, at a 90% confidence level, only 2 out of 23 natural events show significant negative cumulative abnormal returns in the industry at a global level when performing an Adjusted Patell test. The two events which cause significant negative cumulative abnormal returns are Japan's 2016 Earthquake that occurred in the Island of Kyushu, one of the most important manufacturing regions of Japan (Financial Times, 2016) and the Hurricane Irma, which widely affected to locations where major U.S. airlines have their hubs and causing more than 15,000 flights cancellations and hundreds of millions US. Dollars in profit losses (CNBC, 2017).

In addition, at a 90% confidence level, 3 out of 23 events show significant positive cumulative abnormal returns in the industry at a global level when performing an Adjusted Patell test. Of those 3 events, 2 of them correspond to hurricanes that took place in American soil, and one with an earthquake that occurred in Japan. Having a closer look at those events, it is possible to see that even though airlines were affected by those events, they were not among the worst affected industries for different reasons such as lacking hubs in the affected areas, low-season for travelling and other factors.

As an example, weeks before Hurricane Sandy made landfall in U.S. territory, there was a widespread degree of anxiety over its arrival in the American population (National Association of Insurance Commissioners, 2012). This restlessness, which most likely also affected to some extent to the investors operating in the market, may have occurred due to the expected affected area (East Coast, home to megalopolises such as New York or Boston) and the possible severe economic damage that such a strong hurricane could cause if it hit the coast during its peak of intensity, leading to expected huge insurance claims. However, for the mentioned period of time, the stock price of the three major U.S. airlines that operate in the affected region, American Airlines, United Airlines and Delta Airlines show a different pattern compared to the one followed by the S&P 500. This, altogether with what it seems like a lower level of disturbance, evidences the little impact that the hurricane was expected to have on the American airline industry. It may be relevant to mention that the main hubs of American Airlines, United Airlines and Delta Airlines are Dallas-Fort Worth (TX), Chicago-O'Hare (IL) and Atlanta (GA) respectively, none of them located directly in the path that the hurricane was expected to follow.

As an illustration, the difference in the pattern followed by the North American airlines stock index compared to the S&P 500 can be seen in Figure 1.

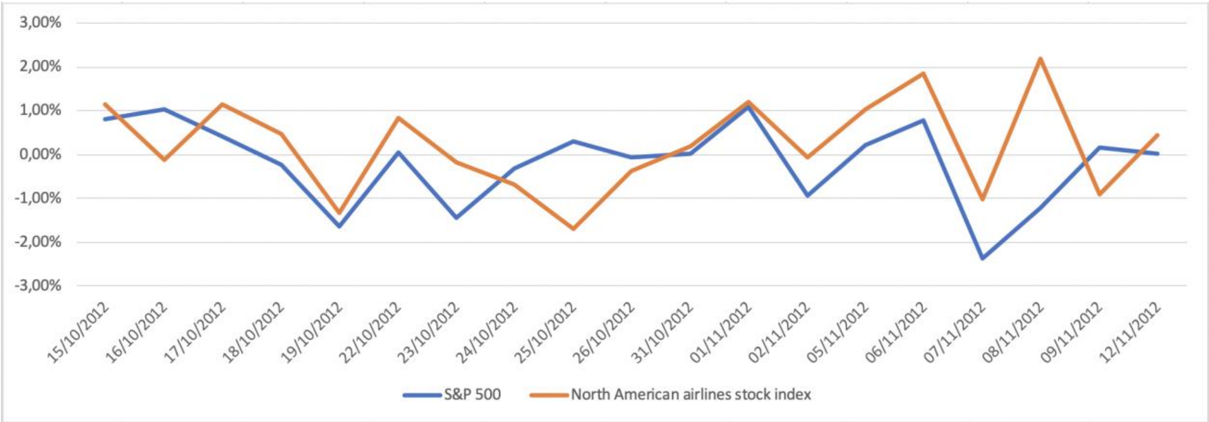

Figure 1. Difference in the daily stock returns between the S&P 500 and the three major U.S. airlines before, during and after Hurricane Sandy hit the East Coast.

The same argument applies for Hurricane Michael, which occurred in 2018 and was considered to be the strongest hurricane ever to hit Northern Florida by then.

On the day that the hurricane hit the U.S. coast, October 10th 2018, the S&P 500 plunged 3.29%. In the following day, losses further increased by another 2.06%. However, the North American airlines stock index shows a different behaviour during the days that Hurricane Michael was hitting North America, falling slightly less than the S&P 500 on the event date a 3.07% but registering gains the following day, increasing an 0.91%. In this case, again, none of the major airlines hubs was located in the path that the hurricane was expected to follow, and the event took place during low travelling season, which resulted in a lower number of delays and cancellations compared to if the event had taken place during the high travelling season.

With this, it is possible to say that, based on the data, natural events only show major influence in the evolution of the airline industry stock price in case that a certain event could have major direct consequences for airlines.

b) Human-made Disasters

In this thesis, four different subcategories of events are treated as human-made disasters. From those, only two can be considered unexpected events: plane crashes and terror attacks.

For those two subcategories of events, at a 90% confidence level, 4 out of 23 events show significant negative cumulative abnormal returns in the industry at a global level when performing an Adjusted Patell test. Of those four events, all of them correspond to terror attacks.

Historically, terror attacks have caused a lead to high volatility in the market due to the uncertainty and fear caused on investors (Scanlon, 2019). In the aftermath of a terror attack, the uncertainty is also shared by passengers and travellers in general, with some of them reconsidering their travelling plans or simply cancelling them, leading to a decrease in the revenue of airline companies. This is was widely reported by different airlines in, for example, the period after the 9/11 terror attack in New York, U.S. or after the series of coordinated attacks that occurred in Paris in November 2015 (Wall Street Journal, 2016). However, as analysed later, it may be possible that the trend is changing, with both, travellers and investors becoming more used to these events, and thus tempering their reaction.

Along with that, at a 90% confidence level, 2 out of 23 events show significant positive cumulative abnormal returns in the industry at a global level when performing a Patell and an Adjusted Patell test. One of the events was a terror attack that occurred in 2002 in Kuta, Bali, whereas the other one was a mid-air collision plane crash between a Saudi Airlines flight and a Kazakhstan Airlines flight that occurred in 1996.

A possible explanation on why during the period that those events occurred, the airline industry records positive cumulative abnormal returns, is the irrelevance of both events in an international context. On the one hand, the terror attack happened in Bali, Indonesia, a very touristic place but that is not located in the so-called ‘First World’ and, at the same time, it was performed by a local terrorist group; on the other hand, in this event study, no plane crashes have shown to cause significant cumulative negative returns, which can be interpreted as that if that specific kind of event is not powerful enough as to cause a generalized plunge of the airline industry stock index. With this, it can be said that the significant positive cumulative abnormal returns recorded during those events are, most probably, related to a positive trend in the industry (CNN, 1996) during the period that both events happened rather than having any relation to the previously mentioned events.

Thus, based on the figures, the airline industry has always been among the most affected by terror attacks, exhibiting a high sensitivity to these kinds of events as long as they were severe and occurred in a country that is part of the ‘First World’. With this, the airline industry has been showing, until recently and in response to severe attacks, highly negative cumulative abnormal returns in the study performed.

4.1.2 Expected Events

a) Financial disasters

Financial disasters are considered to be expected as it is assumed that in a majority of cases, there is information leakage so investors start reacting before public announcements are made.

At a 90% confidence level, 2 out of 10 financial events show significant negative cumulative abnormal returns in the industry at a global level when conducting an Adjusted Patell test.

The first event, the Asia contagion that occurred in 1997, caused a really significant drop in the number of passengers of airlines that operated in the south-east part of Asia and merged the industry in a crisis from which took them years to recover. At the same time, the industry was experiencing additional problems as a whole due to the several months delay of Boeing aircraft deliveries (which, by that time, had just merged with McDonnell Douglas). Thus, the causes for the negative abnormal returns can be understood as a mix of both, the financial crisis in Asia and the very own crisis that the industry was already experiencing due to the Boeing aircrafts delays (FlightGlobal, 1997).

In consequence, it is possible to say that financial disasters only show a higher degree of influence in the evolution of the airline industry stock price, compared to the market one, in case that the event could have major direct consequences for airlines.

No financial disasters events show significant positive cumulative abnormal returns in the industry.

b) Human-made disasters

As mentioned previously, four different subcategories of events are treated as human-made disasters. From those, in this case, only two can be considered expected events: political decisions and wars.

For these remaining subcategories of events, at a 90% confidence level, only 1 out of 11 events shows significant negative cumulative abnormal returns. This event was a political event, the date on which the Brexit referendum results were announced, and with no wars as a subcategory of the event showing significant negative cumulative abnormal returns.

A reason that could explain why these specific political events affected the airline industry more severely than other previous ones, is an uncertainty that an exit of the United Kingdom from the European Union would cause at all levels but with a main focus in the aviation sector and the tourism. It could be assumed that an exit of the UK from the EU could also mean the UK leaving the EU Open Skies agreement, that currently makes easier to British and European airlines to operate with no restrictions in both sides of the Channel. In addition, it can be mentioned the great exposure that most European airlines have to the UK market and vice versa, or the assumption that a UK outside of the EU could simply mean a decrease in the air traffic between both parts, affecting to the airlines revenues.

In addition, for these two subcategories of events, at a 90% confidence level, there is also 1 event out of 11 that shows significant positive cumulative abnormal returns. This event corresponds to the announcement of the starting of the Iraq War in 2003.

Even though it may sound a bit shocking at first to see positive news for airlines at the beginning of a war, in this case, it may not have been the war, but rather a direct consequence of it, what made the airline industry obtain those positive abnormal returns; a sharp decrease in the oil price. Right after the beginning of the war, the oil price plunged. As proven by previous studies (C Hsu, 2017), there is a statistically significant negative relationship between the airlines stock returns and shocks in the fuel price. Thus, it is highly possible that the positive cumulative abnormal returns registered during this event, are a consequence of the decrease in the oil price.

In consequence, as previously said for financial events, it is possible to say that expected human-made disasters only show a higher degree of influence in the evolution of the airline industry stock price, compared to the market one, in case that the event could have major direct consequences for airlines.

Based on the previous analysis it is not possible to accept the hypothesis that disasters that are associated with planes or travelling in general, will mean higher significant abnormal returns in the airline industry compared to other industries. With this, events from most categories can be related to both, higher significant abnormal returns but only in these cases in which, for a specific reason, airlines find themselves particularly affected by an individual event, being difficult to generalize. However, there is an exception: terror attacks. As it has been shown previously, terror attacks can historically be related to higher negative abnormal returns for the airline industry, even in cases in which airlines, airport or aircrafts were not directly involved in the attack.

4.2 Does the same event have different scale of influence towards different continents?

To compare the reactions of different continents towards the same event, the abnormal returns of every continent need to be tested individually. The dataset used here is market returns, which are calculated on continental market portfolios, and the stock returns, which are from continental airline stock portfolios. Also, the test method changed too. The two-tail t-test is used to test the significance of AR and CAR of each continent since t-test is the only applicative test for these two indicators. The test results are shown in Appendix C: Test Results of Global and Continental Data.

From the test results, the most distinct conclusion is that even though some events were significant at a global level, not all airline industries from different areas showed the same trend. Take the September 11th attacks as an example. After this world-shaking terror attack, even the global market showed significant abnormal returns, only airlines from Latin America and

Caribbean, Europe and Asia Pacific also showed significant abnormal returns. But for airlines from Middle East and North America, they still maintained the normal risk relation with the local market, although, from the raw data, the local markets experienced a sharp decline, i.e. the airlines and their local markets suffered the same impact at the same extent.

Another discovery from the test is that, in certain cases, some airlines showed the same feedbacks towards specific categories of events. Firstly, airlines globally displayed no negative abnormal returns towards wars for the last 25 years. On contrast, wars could even bring significant positive influence to airline stocks, especially for those from North America (See Table 2). Besides, political issues imposed no extra effect for air transportation except for airlines based in Europe (See Table 3).

Date	**Event**	**LAC**		**ME**		**EU**		**AP**		**NA**	
		t stat	p value	t stat	p value	t stat	p value	t stat	p value	t stat	p value
1996-04-22	Kosovo War	1,2061	26,22%	-0,6442	53,75%	-1,1339	28,97%	0,2342	82,07%	-1,2944	23,16%
2001-10-07	Afghanistan War	-0,7708	46,30%	0,1224	90,56%	-0,2593	80,19%	-0,4763	64,66%	-1,7942	11,05%
2003-03-20	Iraq War	1,3467	21,50%	-0,0160	98,76%	1,3338	21,90%	-1,1768	27,31%	0,9244	38,23%
2006-06-15	Lebanon War	0,2286	82,49%	0,9688	36,10%	0,4726	64,91%	-0,3095	76,48%	**2,1288**	**6,59%**
2008-08-08	Russia-Georgia War	-0,4780	64,54%	-0,0623	95,18%	-0,1685	87,04%	-0,1312	89,89%	-0,2931	77,69%

Table 2. Test results for War Events

Date	Event	LAC		ME		EU		AP		NA	
		t stat	p value	t stat	p value	t stat	p value	t stat	p value	t stat	p value
2010-09-08	Japan-China: Diaoyu Islands	0,4926	63,55%	-0,5175	61,88%	-0,5912	57,07%	-0,1523	88,27%	0,3370	74,48%
2013-10-21	Euromaidan	1,6183	14,43%	-1,1904	26,80%	-0,4262	68,12%	-0,0786	93,93%	0,7534	47,28%
2014-04-26	Russian Annexation of Crimea	-0,5395	60,42%	-0,3487	73,63%	**-2,6713**	**2,83%**	-1,1124	29,83%	0,6001	56,50%
2016-06-24	Brexit referendum	-1,3944	20,07%	-0,4398	67,17%	**-4,9024**	**0,12%**	-0,6334	54,42%	-0,6080	56,00%
2018-03-22	America-China: trade war	0,0938	92,76%	0,8217	43,51%	-1,2402	25,00%	-0,9373	37,60%	-0,5230	61,51%
2019-08-09	HK Airport Storming	-1,1651	27,75%	0,6493	53,44%	-0,9848	35,36%	1,0816	31,10%	-1,0969	30,46%

Table 3. Test results for Political Events

Also, the location of the events seems to have little influence on the performance of the airlines. It is quite counter-intuitive, however, solely from the test results, the data shows no pattern between the location of the event and the airline reaction. Two possible reasons for the phenomenon are: firstly, there could be some missing market information, such as a certain non-disaster event that occurred during that period or a case in which certain information influenced the regional market. However, this information is difficult to both obtain and corroborate. The second possible reason could be that we missed some specialized airline industry information that is difficult to obtained by outsiders. For instance, main sources of customers, the price fluctuation of oil or the main destinations of air routes of airline companies can be the unseen reasons for the ARs. Nevertheless, the second possible cause is not the main research direction of this study and thus, it is only briefly mentioned and shared, in case there are people interested in performing research in this direction.

4.3 Is there any kind of event, from those studied, that has experienced a change of significance over time?

In order to answer this question, it is necessary to analyse the evolution of the abnormal returns that each kind of event has produced whenever it has occurred, taking into consideration the direct consequences that the event has had such as economic damages or casualties in order to compare one with another and observe possible differences in the market reaction. The results of the test can be seen in Appendix B: Patell Test and Adjusted Patell Test of CAAR.

a) *Natural disasters*

In the time period considered for this study, a total of 23 natural disasters of different magnitude took place. Analysing the cumulative abnormal returns that occurred in the airline industry on the date that those events happened, it is possible to see what seems to be an increase of the significance of the abnormal returns.

Making further analysis on each of the 23 events that took place during the studied event period, the following can be inferred: first of all, the fact that a certain event affects to heavily populated areas or zones in which airlines have major hubs, can be considered as a decisive factor related to highly negative abnormal returns on the airline industry. This was the case, for example, of Hurricane Irma, which or Hurricane Katrina. In addition, the definition of natural event is quite wide, including many different kinds of events that vary in the capacity to provoke disruptions in the air traffic or damages to airline's assets, another important factor. Furthermore, since the beginning of the century and until this year (The World Bank, 2020), the airline industry has experienced an almost continuous increase in the number of passengers carried, as well as the revenue per kilometre flown (International Civil Aviation Organization, 2018). This has led to an expansion on the industry, as well as an opening of numerous new routes. That said, it is not unreasonable to see a possible relation between an industry expansion, that means more areas covered by the industry but, at the same time, more risk of being affected by a certain natural disaster.

The higher significant abnormal returns experienced in recent years have either taken a positive or a negative form, depending on the event and the consequences for the industry. On the one hand, the higher significant abnormal returns observed in recent years may be the result of the combination of the three factors. Whereas the two first factors mentioned previously, the events location and the specific kind of natural event, are more or less a matter of 'luck' and do not follow any specific pattern over time as they are unpredictable. However, due to the climate change and based on scientific research, it may be wise to think that the situation has not only no sights of improve, but rather to get worse with time. Thus, more and more severe natural disasters can be expected to occur in the upcoming years. In addition, with an increase in number of passengers and further air routes expected to be open in the next years, the exposure of the airline industry to natural events can be expected to increase too.

On the other hand, the events occurred more recently, the 2018 Hurricane Michael and 2018 Camp Fire (CA) show a positive trend, which may sound contradictory. A possible explanation for the positive CAARs registered on the industry could be that, these events, even though catastrophic, did not have direct effects on airlines apart from some possible flight cancelations, as explained on question 1. This is because, among others, no major airline hub was located in the area where the events occurred. However, surely these events had severe consequences for other industries such as the insurance one, causing the stock market to drop in the aftermath of those events, and leading to fictitious positive abnormal returns for airlines.

This said, in summary, the extreme weather is a factor that contributes to an increase in the market volatility. With this, it is reasonable to expect that due to climate change, extremely destructive natural events may become a cause for highly significant abnormal returns in the industry on a more constant basis in the upcoming years.

Date	**Event Description**	**CAAR**	**CAAR Adjusted Patell Test**	
			Z value	p value
1998-07-01	China - 1998 Flooding	-0.0202	-0,4389	66,08%
1999-08-17	Turkey's 1999 earthquake	-0.0177	0,0981	92,19%
2004-08-13	USA - Charley Tropical cyclone	0.0088	0,5836	55,95%
2004-09-15	USA - Tropical cyclone Ivan	-0.0060	-0,3835	70,13%
2004-10-23	Japan's 2004 earthquake	0.0121	1,4890	13,65%
2005-08-29	USA - Katrina Cyclone	-0.0123	-0,3717	71,01%
2005-09-23	USA - Rita Tropical cyclone	0.0324	1,4629	14,35%
2005-10-24	USA - Hurricane Wilma	0.0402	1,5706	11,63%
2008-01-01	China - 2008 Extreme winter	0.0068	-0,0158	98,74%
2008-05-12	China's 2008 earthquake	-0.0576	-1,3975	16,23%
2010-02-27	Chile - 2010 earthquake and tsunami	-0.0104	-0,5308	59,55%
2010-05-29	China - 2010 Floods	0.0275	1,0139	31,06%
2011-02-22	New Zealand's 2011 earthquake	-0.0010	0,0457	96,35%
2011-03-11	Japan's 2011 tsunami	0.0179	0,5290	59,68%
2012-05-20	Italy's 2012 earthquake	0.0023	0,2713	78,61%
2012-06-15	USA - 2012 Droughts	0.0320	1,2861	19,84%
2012-10-28	USA - Hurricane Sandy	0.0400	1,7754	7,58%
2014-09-01	India - 2014 floods	0.0180	0,9076	36,41%
2016-04-16	Japan's 2016 earthquake	-0.0663	-2,3881	1,69%
2017-09-10	USA - Hurricane Irma	-0.0579	-2,5244	1,16%
2018-10-10	USA - Hurricane Michael	0.0748	2,4093	1,60%
2018-11-08	USA - 2018 Camp Fire	0.0737	2,0265	4,27%
2019-10-10	USA - Forest Saddleridge fire and Sandalwood fire	0.0146	0,5334	59,38%

Table 4. CAARs and test results for natural disasters

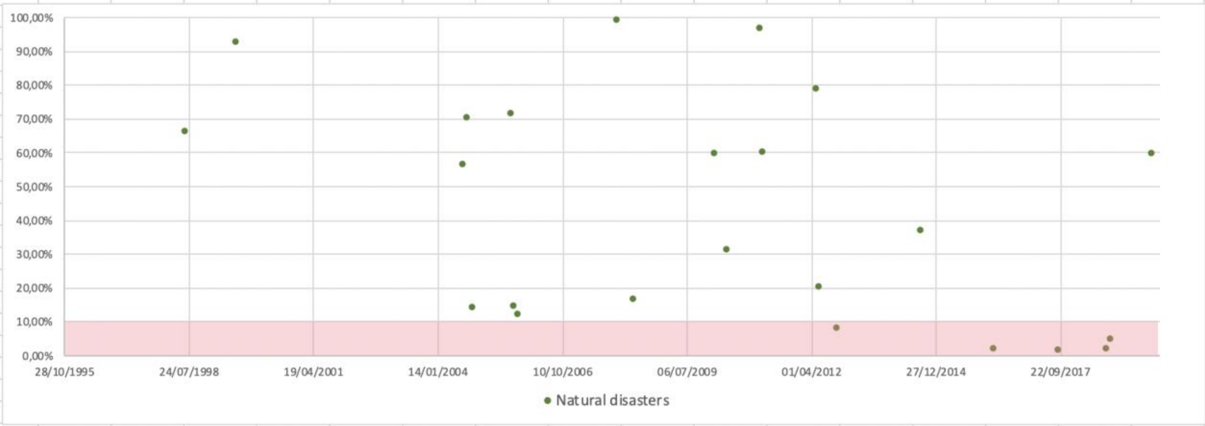

Figure 2. Test Result for the evolution of the airline industry's CAARs when natural disasters have occurred.

b) Financial disasters

When it comes to financial events, in total 10 events are considered during the study period. Using the data from the cumulative average abnormal returns for the airlines global stock portfolio, it is not possible to see any trend that indicates a change of significance of these abnormal returns due to time reasons, as shown by the graph.

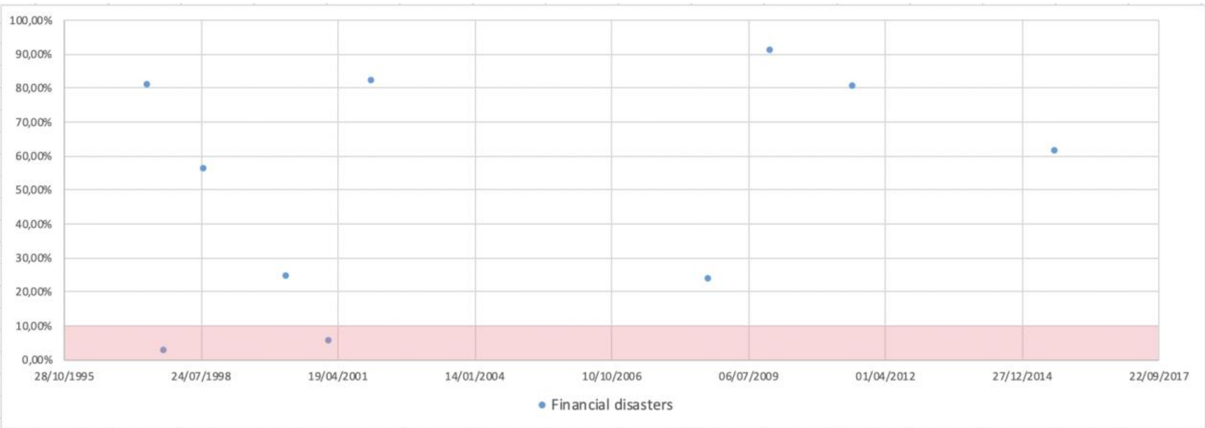

Figure 3. Test Result for the Evolution of the airline industry's CAARs when financial disasters have occurred.

c) Human-made disasters

Finally, the largest category, human-made events includes a total of 34 events. In this heterogeneous group of events, it is included plane crashes with 10 events, political events with 6 events in total, terror attacks with 13 events, and lastly, wars with 5 events.

In order to reach a conclusion to if the hypothesis can be accepted or rejected, again, the evolution over time of the cumulative abnormal returns are analysed. For the first sub-category, plane crashes, it is not possible to find a trend over time that hints that plane crashes have become more or less significant for the airline's stock price with time. Instead, based on the information, it is highly possible that an increase on the negative abnormal returns is caused by the relevance that a specific crash is given by the media and also, the specific circumstances involving the accident.

Date	Event Description	CAAR	CAAR Adjusted Patell Test	
			Z value	p value
2001-09-11	09/11 Attack	-0.2262	-8,6524	0,00%
2002-10-14	Bali Attack	0.1202	3,2714	0,11%
2004-03-11	Madrid train attack	-0.0158	-0,5318	59,49%
2005-07-07	London terror attack	0.0358	1,4960	13,46%
2013-03-18	Boston Marathon Bombings	-0.0329	-1,6728	9,44%
2015-01-07	Charlie Hebdo terror attack (Paris, France)	-0.0756	-2,0746	3,80%
2015-06-26	Sousse Attack	0.0080	0,2804	77,92%
2015-11-13	Paris terror attacks	-0.0775	-3,0747	0,21%
2016-06-07	Bastille Day terror attack in Nice, France	-0.0067	-0,3964	69,18%
2017-03-22	Westminster Bridge attack in London, UK	0.0026	0,1962	84,44%
2017-04-07	Stockholm attack	0.0180	0,9053	36,53%
2017-05-22	Manchester Arena bombing	0.0143	1,1647	24,41%
2017-08-17	Barcelona Terror Attacks	-0.0039	-0,3297	74,16%

Table 5. CAARs and test results for terror attacks

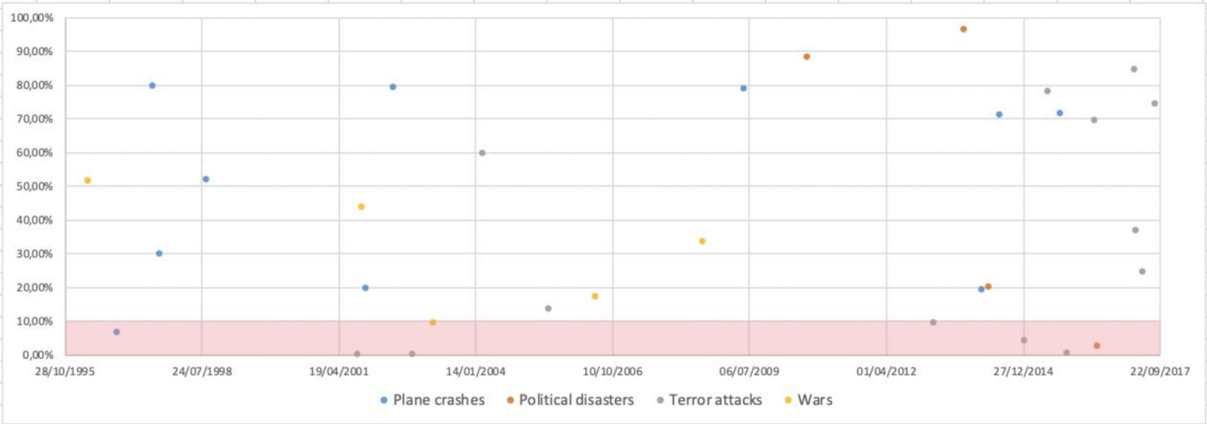

Figure 4. Test Result for the Evolution of the airline industry's CAARs when human made disasters have occurred.

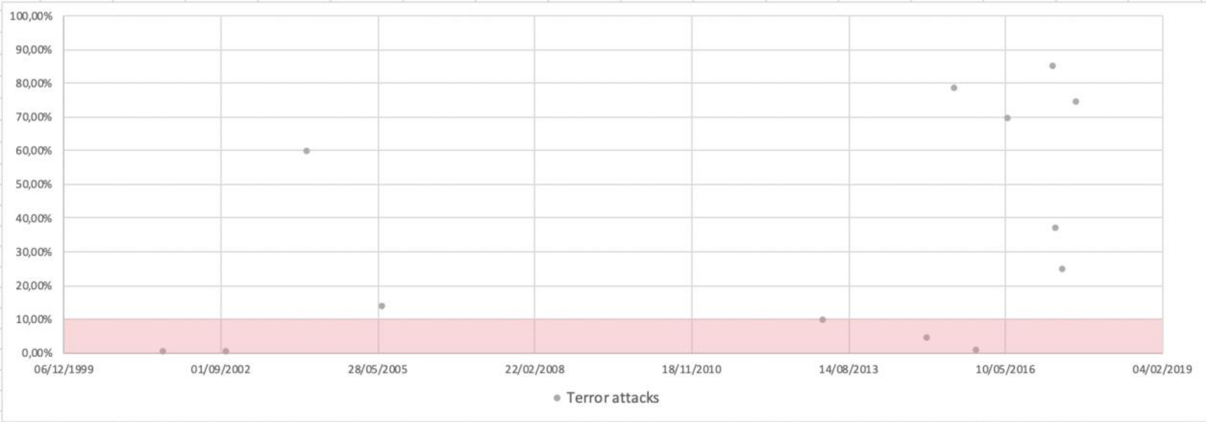

Figure 5. Test Result for the Evolution of the airline industry's CAARs when terror attacks have occurred.

When it comes to political disasters or wars, it is not possible either to identify a pattern or trend on the abnormal returns that took place when those events occurred. However, when analyzing the pattern drawn by the abnormal returns caused by terror attacks, it seems to be possible to find a certain pattern with time.

As it is possible to observe in Figures 4 and 5, the event that has ever caused the highest negative abnormal returns is the 9/11 terror attack that occurred in New York, in the United States. Among the reasons for this, it is possible to mention the strong questioning of the safety measures on board aircraft, as well as at airports, as a group of terrorists managed to get four planes hijacked almost at the same time. This terror attack led to an unprecedented crisis in the industry, that required to get a Federal bailout in the US in order to guarantee its survival (CNN, 2001). It took years for the industry to recover the number of passengers previously seen before the attack.

After this event, no major terror attacks occurred for a certain period of years. However, on March 18th 2013, the first terror attack in US soil after 9/11 took place, causing a huge panic along with the industry and in the market in general.

At the same time, in Europe, a relative period of calm happened between 2006 and 2015, with no major terror attacks reported and with most terrorist incidents affiliated with separatist movements or anarchist attacks. The mentioned period of calm was broken in January 2015, with the Islamic terror attack against the editorial offices of the Charlie Hebdo magazine in Paris, France. After this, in November 2015 it took place also in Paris, France, a series of coordinated Islamic terror attacks carried out by the terrorist group Daesh. Both attacks, and with special emphasis the last mentioned one due to the high number of fatalities and complexity, caused strong volatility in the stock market and high negative abnormal returns in the airline industry.

Notwithstanding, even though these mentioned terror attacks were only the beginning of a series of major attacks that have taken place all over Europe during the recent years when running an event study, it is possible to perceive that, with time, the significance of the subsequent abnormal returns decline consistently.

The mentioned hypothesis can be observed in the cumulative average abnormal returns of the airline industry in the aftermaths of the wave of terror attacks that followed those that took place in Paris. Here it can be included, among others, by the UK terror attacks in 2016 and 2017, the Stockholm one of the Barcelona attack in 2017. As shown in the graph, the significance of the cumulative average abnormal returns seems to decrease constantly over time. In addition, even though the magnitude of the attack seems to play a significant role in the significance of the negative abnormal returns registered after an attack, the decrease of the significance of the abnormal returns seems to be more a continuous trend rather than isolated events. This can be seen after the Boston Marathon Bombings (2013) or the Charlie Hebdo Attack in Paris (2015), which caused only 3 and 12 fatalities respectively but produced in both cases negative cumulative average abnormal returns. However, in 2017 it took place a series of bombing during an Ariana Grande concert in Manchester; it caused 23 fatalities, mostly children, but still, it didn’t cause significant negative cumulative abnormal returns.

With this, it could be accepted the hypothesis that terror attacks are a kind of event that used to be more significant in the past for the airline industry, normally causing huge negative cumulative abnormal returns in the industry, but with time, it has decreased its significance. This goes in compliance with the results from Chen and Siems (2004) study, as the market seems to be showing a higher level of resilience when terror attacks take place.

A possible reason for this change could be that, as attacks have become more frequent in recent years, the importance given to them by both travellers and investors decreases with time, not affecting as much as they used to the decisions they make.

5 Conclusion

The airline industry is being, at the moment of writing this thesis, among the most badly hit industries by the current travel restrictions due to the COVID-19 pandemic. The current measures to contain the spread of the virus have sunken the industry into the worst crisis ever experienced. This is proof of how some events that are not directly related to the industry can, not only affect it, but event conditions its economic viability for some time.

In this paper, it has been performed an analysis of events that have taken place in the last 25 years, in order to understand the mechanisms under which the industry works, and how it has reacted to disasters of all kinds that have occurred in the analysed period. This could be useful in order to find patterns that could be taken into consideration by investors in the market.

In addition, in this paper it has been assumed at all moment that information leakage may occur for certain kind of events, and also, the influence of events lasted more than one day. That said, on that instances, the assumption of the EMH that the security prices fully reflect the information can at some point be considered as utopic. That is the main reason why the events were classified in two broad categories, expected and unexpected events, both of them with different event window length.

The first study question analysed in this paper tested the hypothesis of if there is any specific sort of event, from those studied, that has a more obvious impact towards airlines, compared to how it affects the whole market. This paper found that, with respect to unexpected events, for natural disasters, negative cumulative abnormal returns only occurred in case that the industry was affected directly by the specific event, because of damages, stops in the air traffic or other direct relation. However, for a specific kind of human-made disasters, terror attacks, the airline industry has historically shown a higher degree of sensitivity when compared to other industries, even in cases where no airlines or aircrafts were involved in the incident. Furthermore, with respect to the findings of Noronha and Singal (2004) and Kaplanski and Levi (2009), who concluded that certain aviation crashes may get to affect severely to the financial situation of an airline, the main goal of this paper was not analyzing how events affected to a specific airline, but rather to the whole airline industry. That said, it has not possible to find evidence of any aviation crash that has been the source of significant negative cumulative abnormal returns for the airline industry globally. With regards to expected events, for financial disasters and all human-made disasters included in this category (political disasters and wars), the conclusion is similar to the one already outlined for natural disasters, showing a higher impact for the airline industry only in the cases that these events have affected in a direct way to airlines. With this, the hypothesis can only be accepted for the events considered as terror attacks.

With regards to the second study question, which analysed the hypothesis of if the same event can have a different scale of influence towards different continents, based on the study performed it can be concluded that, regardless some events being significant at a global level, not all airlines from different areas showed the same trend. However, during this study, it has been found out that for wars, as a category of event, did not impact the airline industry in an extra negative way during the period analysed. The same can be said about political events but with the exception of airlines that are based in Europe.

Finally, the third study question evaluated if there is any kind of event, from those studies, that used to matter in the past but it does not anymore. In regards to this question, natural events show an increase in significant abnormal returns in recent years. This increase in the significance may be related to an increase in the destructive power of natural disasters, which depending on if it affects directly to an area of great importance for airlines, may cause positive or negative significant abnormal returns for the industry. In addition, for a specific kind of human-made disasters, terror attacks, it is possible to find a pattern in the evolution over time of abnormal returns that indicates a decrease of the importance of this category of events over time for the airline industry. This goes in line with evidence previously found by Chen and Siems (2004) who concluded that, with time, the market is showing more resilience as compared with previous attacks when military/terror attacks take place. In addition, that change of behavior and reaction of investors towards terror attacks, goes in line with the behavioral finance theory, which assumes that investors may interpret information in different ways, and thus, some of them may consider terror attacks less relevant now than before. Financial events did not show yet any specific pattern over time that could indicate an increase or decrease of their significance over time.

Overall, as already developed, the airline industry is not vulnerable for all disasters, but showed some patterns towards certain specific categories of events in the past 25 years.

Moreover, it could also be interesting performing an analysis of the consequences that the current COVID-19 pandemic is having for the airline industry. In addition, another possible line of research could be expanding this analysis of the airline industry to companies that offer other means of transportations such as train operators or bus operator companies. That could be of special interest due to the different pattern followed by the users of the different means of transportation. This is a kind of event could be categorized as a natural disaster; however, its magnitude cannot be compared to any other event ever happened before. Thus, with current data, it is possible to say that some of the current airlines may not survive if the situation does not improve anytime soon, and if the travel restrictions are not lifted. In addition, other researchers with a deeper understanding of the industry dynamics could find interest on performing further developing of the research question number 2, which analysed the different reactions that airlines from different geographic have towards the same category of events.

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Appendix A: Event List

Date	Category	Subcategory	Event
1996-04-22	Expected	War	Start of Kosovo War
1996-11-12	Unexpected	Plane Crashes	Charkhi Dadri colission (Saudia 763 - Kazakhstan 1997)
1997-07-02	Expected	Financial	Start of the East Asian financial crisis
1997-08-06	Unexpected	Plane Crashes	Korean Air 801 crashed on approach to Guam
1997-09-26	Unexpected	Plane Crashes	Garuda Indonesia 152 Jakarta - Sumatra
1997-10-27	Expected	Financial	October 27, 1997, economic crisis in Asia, the "Asian contagion"
1998-07-01	Unexpected	Natural Disasters	China - 1998 Flooding
1998-08-17	Expected	Financial	Russian financial crisis
1998-09-02	Unexpected	Plane Crashes	Swissair 111 crashed into Atlantic Ocean
1999-08-17	Unexpected	Natural Disasters	Turkey's 1999 earthquake
2000-04-10	Expected	Financial	Dot-com bubble crisis
2001-02-16	Expected	Financial	Turkish economic crisis.
2001-09-11	Unexpected	Terror Attacks	09/11 Attack
2001-10-07	Expected	War	Afghanistan War starts
2001-11-12	Unexpected	Plane Crashes	American Airlines 587 crashed in Queens, NY
2001-12-26	Expected	Financial	Argentina defaulted US$93 billion of its external debt
2002-05-25	Unexpected	Plane Crashes	China Airlines 611 crashed into Taiwan Strait while flying to HK
2002-10-14	Unexpected	Terror Attacks	Bali Attack
2003-03-20	Expected	War	Iraq War starts
2004-03-11	Unexpected	Terror Attacks	Madrid train attack
2004-08-13	Unexpected	Natural Disasters	USA - Charley Tropical cyclone

Date	Category	Subcategory	Event
2004-09-15	Unexpected	Natural Disasters	USA - Tropical cyclone Ivan
2004-10-23	Unexpected	Natural Disasters	Japan's 2004 earthquake
2005-07-07	Unexpected	Terror Attacks	London terror attack
2005-08-29	Unexpected	Natural Disasters	USA - Katrina Cyclone
2005-09-23	Unexpected	Natural Disasters	USA - Rita Tropical cyclone
2005-10-24	Unexpected	Natural Disasters	USA - Hurricane Wilma
2006-06-15	Expected	War	Lebanon War starts
2008-01-01	Unexpected	Natural Disasters	China - 2008 Extreme winter
2008-05-12	Unexpected	Natural Disasters	China's 2008 earthquake
2008-08-08	Expected	War	Russia-Georgia War Starts
2008-09-15	Expected	Financial	Lehman Brothers files for brankupcy.
2009-06-01	Unexpected	Plane Crashes	Air France 447 crashed into Atlantic Ocean (Rio - Paris)
2009-12-14	Expected	Financial	Greek sovereign debt crisis. PM of Greece addresses the Nation over serious situation.
2010-02-27	Unexpected	Natural Disasters	Chile - 2010 earthquake and tsunami
2010-05-29	Unexpected	Natural Disasters	China - 2010 Floods
2010-09-08	Expected	Political	Political crash Japan-China: Diaoyu Islands.
2011-02-22	Unexpected	Natural Disasters	New Zealand's 2011 eartquake
2011-03-11	Unexpected	Natural Disasters	Japan's 2011 tsunami
2011-08-08	Expected	Financial	USA - Black Monday.
2012-05-20	Unexpected	Natural Disasters	Italy's 2012 earthquake
2012-06-15	Unexpected	Natural Disasters	USA - 2012 Droughts
2012-10-28	Unexpected	Natural Disasters	USA - Hurricane Sandy
2013-03-18	Unexpected	Terror Attacks	Boston Marathon Bombings

Date	Category	Subcategory	Event
2013-10-21	Expected	Political	Start of Euromaidan (pro-EU protests in Kyiv, Ukraine. Fall of Ukrainian government).
2014-03-08	Unexpected	Plane Crashes	Malaysia Airlines MH370 Kuala-Beijing dissapeared in Indian Ocean
2014-04-26	Expected	Political	Russian Annexation of Crimea
2014-07-17	Unexpected	Plane Crashes	Malaysia Airlines MH17 shot down in Ukraine
2014-09-01	Unexpected	Natural Disasters	India - 2014 floods
2015-01-07	Unexpected	Terror Attacks	Charlie Hebdo terror attack (Paris, France)
2015-06-26	Unexpected	Terror Attacks	Sousse Attack. – A gunman attacked a hotel targeting the European tourists staying there.
2015-08-24	Expected	Financial	China's Black Monday.
2015-09-30	Unexpected	Plane Crashes	Metrojet 9268 crashed in Sinai Peninsula due to bomb inside. ISIS claimed responsability.
2015-11-13	Unexpected	Terror Attacks	Paris terror attacks. Series of attacks including shootings and suicide bombings.
2016-04-16	Unexpected	Natural Disasters	Japan's 2016 earthquake
2016-06-07	Unexpected	Terror Attacks	Bastille Day terror attack in Nice, France
2016-06-24	Expected	Political	First day after Brexit referendum occured
2017-03-22	Unexpected	Terror Attacks	Westminster Bridge attack in London, UK. Man drove a car into pedestrians.
2017-04-07	Unexpected	Terror Attacks	Stockholm attack.
2017-05-22	Unexpected	Terror Attacks	Manchester Arena bombing during Ariana Grande's concert.
2017-08-17	Unexpected	Terror Attacks	Barcelona Terror Attacks. Three separate attacks in Barcelona.
2017-09-10	Unexpected	Natural Disasters	USA - Hurricane Irma
2018-03-22	Expected	Political	Political crash America-China: trade war.
2018-10-10	Unexpected	Natural Disasters	USA - Hurricane Michael
2018-11-08	Unexpected	Natural Disasters	USA - 2018 Camp Fire
2019-08-09	Expected	Political	HK Airport occupation by protesters
2019-10-10	Unexpected	Natural Disasters	USA - Forest Saddleridge fire & Sandalwood fire

Appendix B: Patell Test and Adjusted Patell Test of CAAR

Date	CAAR	Patell Test		Adjusted Patell Test	
		z value	p value	z value	p value
1996-04-22	-0.0228	-0.6346	54.34%	-0.6556	51.21%
1996-11-12	0.0572	1.8601	8.75%	1.8580	6.32%
1997-07-02	-0.0067	0.2546	80.55%	0.2428	80.82%
1997-08-06	-0.0463	-0.2922	77.51%	-0.2594	79.53%
1997-09-26	-0.0310	-1.1795	26.11%	-1.0450	29.60%
1997-10-27	-0.0878	-2.3026	5.03%	-2.1979	2.80%
1998-07-01	-0.0202	-0.4550	65.73%	-0.4389	66.08%
1998-08-17	-0.0277	-0.5919	57.03%	-0.5786	56.29%
1998-09-02	-0.0482	-0.6726	51.39%	-0.6477	51.72%
1999-08-17	-0.0177	0.0983	92.33%	0.0981	92.19%
2000-04-10	-0.0278	-1.1283	29.19%	-1.1624	24.51%
2001-02-16	-0.0668	-2.4116	4.24%	-1.8964	5.79%
2001-09-11	-0.2262	-8.8030	0.00%	-8.6524	0.00%
2001-10-07	-0.0041	-0.8840	40.25%	-0.7779	43.66%
2001-11-12	0.0527	1.5811	13.98%	1.2992	19.39%
2001-12-26	-0.0043	-0.2854	78.26%	-0.2232	82.34%
2002-05-25	-0.0124	-0.2698	79.19%	-0.2676	78.90%
2002-10-14	0.1202	4.0188	0.17%	3.2714	0.11%
2003-03-20	0.0651	1.8870	9.59%	1.6745	9.40%
2004-03-11	-0.0158	-0.5505	59.21%	-0.5318	59.49%
2004-08-13	0.0088	0.5836	57.03%	0.5836	55.95%
2004-09-15	-0.0060	-0.3896	70.37%	-0.3835	70.13%

Date	CAAR	Patell Test		Adjusted Patell Test	
		z value	p value	z value	p value
2004-10-23	0.0121	1.6534	12.42%	1.4890	13.65%
2005-07-07	0.0358	1.6362	12.77%	1.4960	13.46%
2005-08-29	-0.0123	-0.4314	67.38%	-0.3717	71.01%
2005-09-23	0.0324	1.7949	9.79%	1.4629	14.35%
2005-10-24	0.0402	2.0059	6.79%	1.5706	11.63%
2006-06-15	0.0340	1.3578	21.16%	1.3731	16.97%
2008-01-01	0.0068	-0.0165	98.71%	-0.0158	98.74%
2008-05-12	-0.0576	-1.4636	16.90%	-1.3975	16.23%
2008-08-08	-0.0402	-1.1837	27.05%	-0.9694	33.24%
2008-09-15	-0.0708	-1.5405	16.20%	-1.1776	23.90%
2009-06-01	0.0012	-0.3053	76.54%	-0.2729	78.49%
2009-12-14	-0.0026	-0.1149	91.14%	-0.1112	91.14%
2010-02-27	-0.0104	-0.5686	58.01%	-0.5308	59.55%
2010-05-29	0.0275	0.9961	33.88%	1.0139	31.06%
2010-09-08	-0.0023	-0.1408	89.15%	-0.1494	88.12%
2011-02-22	-0.0010	0.0484	96.22%	0.0457	96.35%
2011-03-11	0.0179	0.5722	57.77%	0.5290	59.68%
2011-08-08	-0.0143	-0.3047	76.84%	-0.2461	80.56%
2012-05-20	0.0023	0.3237	75.17%	0.2713	78.61%
2012-06-15	0.0320	1.4067	18.49%	1.2861	19.84%
2012-10-28	0.0400	2.1486	5.28%	1.7754	7.58%
2013-03-18	-0.0329	-1.9251	7.82%	-1.6728	9.44%
2013-10-21	-0.0014	0.0583	95.49%	0.0506	95.97%
2014-03-08	-0.0317	-1.3373	20.59%	-1.3094	19.04%
2014-04-26	-0.0170	-1.3347	21.87%	-1.2875	19.79%

Date	CAAR	Patell Test		Adjusted Patell Test	
		z value	p value	z value	p value
2014-07-17	-0.0118	-0.4474	66.25%	-0.3745	70.80%
2014-09-01	0.0180	1.0598	31.01%	0.9076	36.41%
2015-01-07	-0.0756	-2.5327	2.63%	-2.0746	3.80%
2015-06-26	0.0080	0.2843	78.10%	0.2804	77.92%
2015-08-24	0.0189	0.5087	62.47%	0.5047	61.38%
2015-09-30	0.0335	0.3662	72.06%	0.3699	71.15%
2015-11-13	-0.0775	-2.9154	1.29%	-3.0747	0.21%
2016-04-16	-0.0663	-2.6025	2.31%	-2.3881	1.69%
2016-06-07	-0.0067	-0.4091	68.96%	-0.3964	69.18%
2016-06-24	-0.0455	-2.3157	4.92%	-2.2375	2.53%
2017-03-22	0.0026	0.1926	85.05%	0.1962	84.44%
2017-04-07	0.0180	0.8942	38.88%	0.9053	36.53%
2017-05-22	0.0143	1.1292	28.09%	1.1647	24.41%
2017-08-17	-0.0039	-0.3679	71.94%	-0.3297	74.16%
2017-09-10	-0.0579	-2.9219	1.28%	-2.5244	1.16%
2018-03-22	-0.0033	-0.5688	58.51%	-0.5086	61.10%
2018-10-10	0.0748	2.7641	1.71%	2.4093	1.60%
2018-11-08	0.0737	2.4121	3.28%	2.0265	4.27%
2019-08-09	-0.0261	-1.0700	31.58%	-1.0579	29.01%
2019-10-10	0.0146	0.5695	57.95%	0.5334	59.38%

Appendix C: Test Results of Global and Continental Data

Date	Global		LAC		ME		EU		AP		NA	
	Z value	p value	t stat	p value	t stat	p value	t stat	p value	t stat	p value	t stat	p value
1996-04-22	-0.6556	51.21%	1.2061	26.22%	-0.6442	53.75%	-1.1339	28.97%	0.2342	82.07%	-1.2944	23.16%
1996-11-12	1.8580	6.32%	0.9164	37.75%	0.6095	55.36%	-0.4044	69.30%	1.8249	9.30%	1.2333	24.11%
1997-07-02	0.2428	80.82%	-0.4141	68.97%	-1.1767	27.31%	-0.6750	51.87%	2.0298	7.69%	-0.0779	93.99%
1997-08-06	-0.2594	79.53%	-0.3456	73.56%	0.2179	83.12%	1.0368	32.03%	1.1503	27.24%	0.0963	92.49%
1997-09-26	-1.0450	29.60%	-0.7582	46.30%	-0.9073	38.21%	-0.5494	59.28%	-2.5200	2.69%	0.7639	45.97%
1997-10-27	-2.1979	2.80%	-1.6621	13.51%	-1.0735	31.44%	-0.4625	65.61%	1.3185	22.38%	-1.5851	15.16%
1998-07-01	-0.4389	66.08%	-0.8404	41.71%	-0.3863	70.60%	-0.1319	89.73%	0.2999	76.94%	-1.0654	30.77%
1998-08-17	-0.5786	56.29%	0.6197	55.27%	0.0175	98.64%	0.0888	93.14%	-0.3249	75.36%	-0.4037	69.70%
1998-09-02	-0.6477	51.72%	0.0652	94.91%	0.3341	74.40%	-0.8566	40.84%	2.9423	1.23%	-0.7858	44.72%
1999-08-17	0.0981	92.19%	-1.0301	32.33%	1.3443	20.37%	1.6744	11.99%	-0.1650	87.17%	-0.0491	96.16%
2000-04-10	-1.1624	24.51%	0.0232	98.21%	-0.1461	88.75%	-1.4588	18.27%	0.0344	97.34%	-1.2231	25.61%
2001-02-16	-1.8964	5.79%	-1.9210	9.10%	2.2641	5.34%	-0.6237	55.02%	-1.0577	32.11%	-0.8663	41.16%
2001-09-11	-8.6524	0.00%	-4.4257	0.08%	-1.2049	25.15%	-6.6310	0.00%	-8.4721	0.00%	1.1566	26.99%
2001-10-07	-0.7779	43.66%	-0.7708	46.30%	0.1224	90.56%	-0.2593	80.19%	-0.4763	64.66%	-1.7942	11.05%
2001-11-12	1.2992	19.39%	1.3603	19.87%	-1.7010	11.47%	1.4313	17.79%	0.7290	48.00%	0.7542	46.53%
2001-12-26	-0.2232	82.34%	0.1947	85.05%	-1.1975	26.54%	-0.6848	51.28%	-0.6052	56.18%	-0.3934	70.43%
2002-05-25	-0.2676	78.90%	-0.5688	58.00%	-0.1680	86.94%	0.4255	67.80%	-0.4317	67.36%	0.4970	62.82%
2002-10-14	3.2714	0.11%	2.0116	6.73%	-0.4022	69.46%	4.1141	0.14%	1.7066	11.36%	2.2175	4.67%
2003-03-20	1.6745	9.40%	1.3467	21.50%	-0.0160	98.76%	1.3338	21.90%	-1.1768	27.31%	0.9244	38.23%
2004-03-11	-0.5318	59.49%	0.0795	93.79%	-0.5953	56.27%	-1.1713	26.42%	-1.2809	22.44%	0.7093	49.17%
2004-08-13	0.5836	55.95%	0.0434	96.61%	-1.1422	27.56%	1.5125	15.63%	0.7705	45.59%	0.5180	61.39%
2004-09-15	-0.3835	70.13%	-0.2284	82.32%	0.7524	46.63%	-0.8604	40.65%	-0.0779	93.92%	-0.7989	43.99%

Date	Global		LAC		ME		EU		AP		NA	
	Z value	p value	t stat	p value	t stat	p value	t stat	p value	t stat	p value	t stat	p value
2004-10-23	1.4890	13.65%	0.9375	36.70%	-2.4224	3.22%	2.9749	1.16%	1.5439	14.86%	1.6213	13.09%
2005-07-07	1.4960	13.46%	1.2834	22.36%	2.3236	3.85%	-0.3890	70.41%	0.8044	43.68%	0.9685	35.19%
2005-08-29	-0.3717	71.01%	-0.9162	37.76%	-0.1920	85.10%	0.2753	78.78%	-0.3054	76.53%	-0.4498	66.09%
2005-09-23	1.4629	14.35%	1.0345	32.13%	-0.6806	50.91%	2.4282	3.18%	-0.2445	81.10%	2.3436	3.71%
2005-10-24	1.5706	11.63%	0.7804	45.03%	0.9158	37.78%	0.8550	40.93%	1.0878	29.81%	1.7923	9.83%
2006-06-15	1.3731	16.97%	0.2286	82.49%	0.9688	36.10%	0.4726	64.91%	-0.3095	76.48%	2.1288	6.59%
2008-01-01	-0.0158	98.74%	-0.9633	35.44%	-0.3682	71.91%	-1.3177	21.22%	-0.7472	46.93%	1.8164	9.44%
2008-05-12	-1.3975	16.23%	-1.0932	29.58%	-0.0911	92.89%	-1.6655	12.17%	-0.0857	93.32%	-1.1367	27.79%
2008-08-08	-0.9694	33.24%	-0.4780	64.54%	-0.0623	95.18%	-0.1685	87.04%	-0.1312	89.89%	-0.2931	77.69%
2008-09-15	-1.1776	23.90%	-0.7042	50.13%	-1.0309	33.27%	-1.1156	29.70%	-0.2853	78.27%	-0.3667	72.34%
2009-06-01	-0.2729	78.49%	0.8557	40.89%	-0.0594	95.36%	-1.5214	15.41%	-0.9408	36.53%	0.4362	67.04%
2009-12-14	-0.1112	91.14%	0.0345	97.33%	-2.3492	4.67%	-0.2998	77.20%	1.2279	25.44%	1.2075	26.17%
2010-02-27	-0.5308	59.55%	-0.7985	44.01%	-0.0736	94.25%	0.7622	46.07%	-1.1031	29.16%	-0.5977	56.11%
2010-05-29	1.0139	31.06%	0.1405	89.06%	1.6474	12.54%	0.7846	44.79%	-0.6302	54.04%	0.1047	91.84%
2010-09-08	-0.1494	88.12%	0.4926	63.55%	-0.5175	61.88%	-0.5912	57.07%	-0.1523	88.27%	0.3370	74.48%
2011-02-22	0.0457	96.35%	-1.3123	21.40%	-0.4925	63.13%	-0.5321	60.44%	-0.6083	55.43%	1.5888	13.81%
2011-03-11	0.5290	59.68%	-0.1117	91.29%	-1.9167	7.94%	-0.2360	81.74%	0.6018	55.85%	-0.1447	88.73%
2011-08-08	-0.2461	80.56%	0.6942	50.72%	-2.2631	5.35%	0.5305	61.02%	1.1642	27.79%	0.0326	97.48%
2012-05-20	0.2713	78.61%	0.0166	98.70%	-0.3215	75.33%	-0.3337	74.44%	1.1358	27.82%	-0.0929	92.75%
2012-06-15	1.2861	19.84%	-0.3752	71.40%	1.0334	32.18%	2.1781	5.01%	0.1832	85.77%	0.1189	90.74%
2012-10-28	1.7754	7.58%	0.1485	88.44%	0.1507	88.27%	2.8922	1.35%	-0.0354	97.23%	1.4033	18.59%
2013-03-18	-1.6728	9.44%	-2.4003	3.35%	-0.8683	40.23%	-0.9009	38.54%	-0.5114	61.83%	0.1369	89.34%
2013-10-21	0.0506	95.97%	1.6183	14.43%	-1.1904	26.80%	-0.4262	68.12%	-0.0786	93.93%	0.7534	47.28%
2014-03-08	-1.3094	19.04%	-1.4641	16.89%	-1.1085	28.94%	-0.8509	41.15%	-0.1603	87.53%	-1.0043	33.50%
2014-04-26	-1.2875	19.79%	-0.5395	60.42%	-0.3487	73.63%	-2.6713	2.83%	-1.1124	29.83%	0.6001	56.50%

Date	Global		LAC		ME		EU		AP		NA	
	Z value	p value	t stat	p value	t stat	p value	t stat	p value	t stat	p value	t stat	p value
2014-07-17	-0.3745	70.80%	-2.3132	3.92%	-0.8330	42.11%	1.0623	30.90%	0.4964	62.86%	-0.2040	84.18%
2014-09-01	0.9076	36.41%	0.8748	39.88%	-0.2757	78.75%	1.1001	29.29%	1.6270	12.97%	-1.1145	28.69%
2015-01-07	-2.0746	3.80%	-1.8820	8.43%	-2.4755	2.92%	-1.5841	13.92%	-0.9525	35.96%	-1.1310	28.02%
2015-06-26	0.2804	77.92%	-0.3092	76.25%	0.8913	39.03%	0.7249	48.24%	-1.5274	15.26%	0.0675	94.73%
2015-08-24	0.5047	61.38%	0.7588	46.98%	-0.1350	89.59%	0.1808	86.10%	-1.9379	8.86%	-0.3985	70.07%
2015-09-30	0.3699	71.15%	2.1166	5.59%	0.5467	59.46%	-2.3149	3.91%	-0.6491	52.85%	0.0655	94.89%
2015-11-13	-3.0747	0.21%	0.2441	81.13%	-1.9595	7.37%	-2.5006	2.79%	-1.4781	16.51%	-1.5554	14.58%
2016-04-16	-2.3881	1.69%	-0.8311	42.21%	-1.7850	9.95%	0.4283	67.60%	-1.1263	28.20%	-2.7910	1.63%
2016-06-07	-0.3964	69.18%	0.3240	75.15%	-1.2025	25.24%	-0.5301	60.57%	-0.1754	86.37%	-0.7054	49.40%
2016-06-24	-2.2375	2.53%	-1.3944	20.07%	-0.4398	67.17%	-4.9024	0.12%	-0.6334	54.42%	-0.6080	56.00%
2017-03-22	0.1962	84.44%	0.4791	64.05%	-1.4401	17.54%	-0.6661	51.79%	0.3047	76.58%	0.7260	48.17%
2017-04-07	0.9053	36.53%	-0.3422	73.81%	-0.6882	50.44%	0.6329	53.87%	0.4574	65.55%	1.1198	28.47%
2017-05-22	1.1647	24.41%	-0.1476	88.51%	0.4621	65.23%	0.5374	60.08%	1.1747	26.29%	1.8055	9.61%
2017-08-17	-0.3297	74.16%	0.7503	46.75%	-0.0332	97.40%	-1.5664	14.32%	1.0604	30.99%	-1.5826	13.95%
2017-09-10	-2.5244	1.16%	0.4665	64.92%	-2.4503	3.06%	-1.6925	11.63%	-1.9600	7.36%	1.2048	25.15%
2018-03-22	-0.5086	61.10%	0.0938	92.76%	0.8217	43.51%	-1.2402	25.00%	-0.9373	37.60%	-0.5230	61.51%
2018-10-10	2.4093	1.60%	-0.0772	93.97%	-0.9116	37.99%	0.6187	54.77%	1.7988	9.72%	0.7149	48.83%
2018-11-08	2.0265	4.27%	0.6478	52.93%	1.1666	26.60%	1.2508	23.48%	1.7831	9.99%	0.9878	34.27%
2019-08-09	-1.0579	29.01%	-1.1651	27.75%	0.6493	53.44%	-0.9848	35.36%	1.0816	31.10%	-1.0969	30.46%
2019-10-10	0.5334	59.38%	-0.7376	47.49%	0.7059	49.37%	1.1600	26.86%	-0.1762	86.31%	-0.0491	96.16%