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REACTIONS OF THE MEXICAN STOCK EXCHANGE AGGREGATE MARKET TO LARGE DAILY PRICE SHOCKS: A BEHAVIORAL FINANCE ANALYSIS

HONOURS PROGRAMME THESIS

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To my family, friends, academics and practitioners in the field.

Declaration of Authorship

I hereby declare that the thesis titled **"Reactions of the Mexican Stock Exchange Aggregate Market to Large Daily Price Shocks: A Behavioral Finance Analysis"** represents my own work in accordance with regulations. This Bachelor Thesis was realised in partial fulfilment of the requirements for graduation from the Honours Program of the Universidad de las Americas Puebla, UDLAP.

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"An investment in knowledge pays the best interest."

Benjamin Franklin

Abstract

This thesis analyses the post reactions to large daily price shocks on the Mexican capital aggregate market using data on daily returns of its main Index (IPC) from 2009 through 2018. It uses a variety of statistical tests and an event and post event study based on the means from the returns of both event and post event returns. On the whole, this thesis suggests that the market tends to both overreact and underreact to price shocks, in both cases, positive and negative price shocks. In essence, when there is a negative price shock, the market tends to overreact a slightly more than half of the times, while the rest of the times underreacts. While on the other side, when there is a positive price shock, the market underreacts slightly more than half of the times while the rest of the times overreacts. As new negative information appears, it causes prices to significantly drop, the panic and fear among market participants rise which is the cause of overreaction. On the other side, as new positive information is released, it causes prices to rise, thus, investors to feel more confident on gains, and there is a rise in greed among market participants pushing prices higher as under reaction occurs. Theories from Behavioral Finance can potentially explain the relationship between the market price shocks and the post event market reactions. Although the mentioned above may be true, one possibility to explain the market anomalies are the deviations to be expected under the Efficient Market Hypothesis. However, this thesis work is based on behavioral finance theories which suggest potential explanation on this work.

“Investing is the intersection of economics and psychology.”
Seth Klarman

1. Introduction

Behavioral Finance is indeed a contrast to the efficient market hypothesis, as it proposes that the reason for market inefficiencies are the not fully rational market participants. The traditional finance paradigm seeks to explain financial markets using models in which agents are fully rational. Granted this view, if the Efficient Market Hypothesis holds, prices are fair and reflect all available information, given that, there would be no investment strategy which could earn abnormal returns.

However, it can be said that markets are not fully efficient, moreover, an idea of having market participants whom account for the characteristics needed in order to have an efficient market mentioned by Barberis and Thaler (2005), are characteristics which are rarely seen on financial market participants. Certainly, new information is not instantaneously and fully incorporated into stock prices in an unbiased fashion. Thus, prices are likely not to be fair in al cases. In account of the research of this thesis, it can be suggested that traditional finance theories and the efficient market hypothesis do not fully explain Financial Markets.
Hence, with the intention of achieving a better understanding of the capital market functioning, this thesis suggests behavioral finance as a supplement and more logic explanation of the capital market functioning and its significance for price fluctuations. There needs to be a huge attention on market participants’ behaviour. In essence, behavioral finance replaces “perfectly rational” economic agents from traditional finance theories for “normal” people. “Specifically, it is the study of how psychology affects financial decisions, corporations, and the financial markets.” *(*Nofsinger, 2001)

Behavioral finance emerged from the contributions of the two psychologists Daniel Kahneman and Amos Tversky in finance field. Their work served as foundation in the field and gave rise to the new paradigm known as “Behavioral Finance”. The rise of this field has its roots on the difficulties faced by the traditional finance theories to explain various finance phenomena which were better explained when the assumption of full rationality is relaxed.

Very important to realize and put emphasis on, the main purpose of behavioral finance is not to prove any of the existence theories are obsolete, since those theories explain successfully various scenarios to a good extent. Hence, the objective of behavioral finance theories is to supplement the traditional theories by incorporating the cognitive psychology into those theories, so thereafter, create a more complete model of the investors behaviour in the process of decision making as market participants.

Thus, the rationale of the behavioral finance study would be that "In the field of investments, the implications of behavioural finance are substantial, analysing investor behaviour is an essential key in order to understand the sometimes rare and unexplainable fluctuations of financial markets. Hence, understanding behavioural finance can provide significant advantages for investors to the end of taking better investment decisions."

One key factor which caused the interest to realise this thesis work, are the psychological bias which strongly influence on market participants, whom have a strong tendency to fail into those when taking investment choices. As human beings, there is a "Systematic error in judgment and decision-making common to all human beings which can be due to cognitive limitations, motivational factors, and/or adaptations to natural environments." Wilke A. and Mata R. (2012).

For the purpose of improving the understanding on the field, and behavioral finance perspective on the capital market, the need to understand the main behavioral finance theories arises. Thereafter, further on in this thesis the following theories and bias will be broadly explained.

- **Prospect Theory**: Anchoring, Loss Aversion, Frame Dependence, and Mental Accounting.
- **Heuristics Theory**: Misperceiving Randomness, Herding, and Overconfidence.

The mentioned behavioral theories and bias can be seen as the causes of overreaction and under reaction in capital markets. In the same manner, contrarian investing and momentum investing.

Although the mentioned above may be true, one possibility to explain the market anomalies are the deviations to be expected under the Efficient Market Hypothesis (Fama 1998). However, this thesis aims to provide information suggesting that those market anomalies are not caused by those deviations under market efficiency. A central theme on this work is that prices sometimes overreact or underreact to some signal, moreover, often prices over and underreact simultaneously.

As a consequence, this thesis focuses on the Mexican capital market´s short term responses to large daily price shocks on its main index (IPC), which can be seen as an image of the aggregate market. Price shocks in the capital market can cause investors to either gain or lose wealth, which naturally causes emotional responses among market participants. Therefore, market participants are likely to be driven by emotions such as fear and greed which can lead to erroneous choices. Consequently, the investors behaviour in response to price shocks will usually be a key factor on defining the direction of the post event reaction. This thesis extends a literature review with the purpose of contributing a conclusion on the reasons provoking overreactions or under reactions in capital markets, and if these reactions can be explained by the aggregate behaviour of individuals.

Finally, the main hypothesis is that markets usually tend to overreact to bad news and underreact to good news. Thus, some behavioral theories can explain the results of this market reactions when comparing the relationship between the direction of the event and the direction of the market responses post event. The mentioned relationship will be analysed in three different tests further on in this thesis. This relationship has also been a debate in the field when similar tests have used the behavioral theories to explain abnormal returns caused post price shocks.

The already mentioned price shocks to the capital market can certainly cause market participants to gain or lose large amounts of money, hence this thesis can also contribute to the reader, if it is an investor, to understand the significance of their own responses, and the responses of the aggregate market.

1.1. Limits of the Study

The main weakness and advantage of this study is the fact that it is realized on the main index of the Mexican stock exchange, representing the aggregate market. Therefore, the timeframe post event to analyze the market reactions are just one-day and two-days window analysis, this is due to the fact that there are various factors affecting the index, thus a longer window for the analysis would not be accepted, since it would mean that the reactions post event are just attributed to the price shock, which is certainly not true as there are several other reasons causing price fluctuations in the index.

A second limitation arises out of the fact that the analysis is done on the current “bull” market, given the points of view presented on the data and methodology chapter which explain the reasons to choose this timeframe.

2. Literature Review

It has long been known by researchers in behavioural economics that the importance of less than fully rational behaviour depends on the extent to which rational actors can profit from the suboptimal choices of others, especially if in the act of profiting, rational individuals push the quasi-rational agents to behave more rationally.

Richard H. Thaler

Rationale of the study. In the field of investments, the implications of behavioural finance are substantial, analysing investor behaviour is an essential key in order to understand the fluctuations of capital markets. Hence, understanding behavioural finance can provide significant advantages for investors to the end of taking better investment decisions.

The traditional finance paradigm seeks to explain financial markets using models in which agents are fully rational. Hence, agents update their beliefs correctly and make choices for their best interests, which usually does not happen in reality. According to Barberis and Thaler (2005), rationality means two things: First, investors update their beliefs correctly when they receive new information, and they do so in the manner described by the Bayes's Law. Second, given their beliefs, investors make normatively acceptable choices, in the sense that they are consistent with Savage's notion of Subjective Expected Utility (SEU).

Therefore, two key paradigms within traditional finance would be enough to model behaviour and therefore fully explain financial markets' behaviour: (1) All new information is available for everyone, thereupon, interpreted correctly, uniformly and instantly. Hence, (2) Markets are efficient: new information is instantaneously and fully incorporated into stock prices in an unbiased fashion. When the Efficient Market Hypothesis holds, prices are fair and reflect all available information, granted so, there would be no investment strategy which can earn abnormal returns.

"An 'efficient' market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which,

as of now, the market expects to take place in the future. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value." (Fama, 1965)

Unfortunately, or maybe fortunately for some, the mentioned above does not fully represent financial market fluctuations. Traditional Finance Theory is nowadays appealing to be simple and incomplete. After years of research it has become very clear that traditional finance theories do not fully explain Financial Markets.

The Efficient Market Hypothesis and Behavioural Finance theories are negatively correlated inasmuch as one excludes the other. Traditional finance theory and behavioural finance theory stand for contrarian thoughts that aim to explain investor behaviour. Probably the simplest way to provide explanation of the main differences is to see traditional finance theory as how markets would work in the ideal world. While, on the contrary, Behavioral finance would be more accurate to provide knowledge of how markets work in the real world. Although, having a wide understanding of both theory and reality, can help investors to better understand fluctuations in the view of taking more optimal investment decisions.

Behavioural Finance is the approach to financial markets that argues that some financial phenomena, meaning market anomalies, can be better explained by using models which take into consideration investor psychology. Thus, incorporate models in which some agents are not fully rational in order to examine what occurs when one or the two key tenets that underlie individual rationality are soften or left apart.

2.1.1. Overview of Behavioral Finance

"Behavioral Finance is the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets".

(Sewell, 2007)

Behavioral finance aims to supplement the standard theories of finance by introducing behavioural theories to the investment decision making. Behavioral Finance identifies the potential reasons of stock market crashes and booms. According to Shiller (2003), the stock crashes and booms have their roots in human errors, suggesting those errors are influenced by behavioral finance bias. Statman (2014) says that behavioral finance replaces "perfectly rational" economic agents from traditional finance theories for "normal" people. Statman also suggest that the problem is not that normal people are completely irrational, but that, people tend not to be completely rational, since they can be affected by some cognitive errors clarified by behavioral finance theory.

According to Baber and Odean (1999), “Behavioral Finance relaxes the traditional assumptions of financial economics by incorporating these observable, systematic, and very human departures from rationality into standard models of financial markets. The tendency for human beings to be overconfident causes the first bias in investors, and the human desire to avoid regret prompts the second”

2.1.2. Behavioral Finance Theories and Bias

Psychologists Daniel Kahneman, Paul Slovic, and Amos Tversky (1982) first introduced the thought of psychological bias in the early 1970s. Later on, they published their findings in their 1982 book: "Judgment Under Uncertainty." They explained that psychological or cognitive bias are the tendency to make decisions in an illogical way.

According to Wilke A. and Mata R. (2012), Cognitive bias are defined as the “Systematic error in judgment and decision-making common to all human beings which can be due to cognitive limitations, motivational factors, and/or adaptations to natural environments.”

With the purpose of explaining the irrational behaviour from investors in financial markets, behavioral economists rely on the knowledge of human cognitive behavioral theories from psychology. Thus, this section of the thesis provides some information of the major behavioral theories and the psychological bias that support the given theories.

Prospect Theory

Prospect Theory was first conceived by Kahneman and Tversky (1979), later on, their work resulted in Daniel Kahneman being awarded a Nobel Prize for Economics. The theory aims to explain the irrational human behaviour when assessing risk under uncertainty. In essence, it proposes that investors are not persistently risk averse; instead they are risk averse in gains but risk takers in losses.

The main idea of prospect theory is that people tend to take too much into consideration their changes in wealth, instead of just their comprehensive level of wealth (Jordan et al. 2015).

This theory can be seen in four main psychological bias: Anchoring, loss aversion, frame dependence, and mental accounting.

- **Anchoring** tends to happen when agents fix a certain reference point for investments. Investor will receive utility from gains and loses due to that reference point. According to Duxbury (2015) that reference point is usually the share price. Hence, the problem occurs as the investor will be putting too much focus on the given reference point instead of taking into consideration the level of his wealth. This can be explained when an investor who has held a winner stock for a long time in relation to its purchase price will refuse to sell the given stock. Thus, the stock's price could have a substantial factor on the decision making process of whether selling or keeping the stock (Kliger et al. 2014). Hirshleifer (2015) suggested that market participants should focus more on where the stock value lies in reference to its current covariance with their portfolios.
- **Loss Aversion.** As a matter of fact, people hate losing. Actually people even hate losing more than they enjoy winning. Thaler (1999) said that losses negatively affect investors more or less as twice as wins positively affects them. Moreover, media encourages this loss aversion by causing panic on financial news when the market is going down (Doviak, 2016). Basically, loss aversion occurs when invertors are reluctant to sell any stock that could result in a loss.
- **Frame dependence** is a theory which suggests that depending how a problem is described will affect how an individual will react to it. Some frame dependence may be caused by highlighting a reference point or simple approaching a decision while isolating the factor which is related to (Hirshleifer, 2015). Frame dependence is strongly related to anchoring. A good example of the already mentioned above would be when an invertor looks at a stock`s performance in reference to its purchase price instead of taking in account the diversification it adds to his portfolio.
- **Mental Accounting.** According to Jordan et al. (2015), mental accounting is the tendency to separate money into "mental buckets" resulting in a different approach of value and risk for each of the buckets differently. The most common mistake among market participants is not to threat money as fungible, meaning "freely exchangeable by another of like nature". Hence, investors tend to fail in keeping a general view of all of their assets and desired outcomes together.

  Thaler (1999) displayed another example of mental accounting with the "house money effect", which basically proves that when gambler is winning, thus "playing with house money”, they tend to become risk seeking with their money. Likewise, investors who are having high returns tend to become much less risk averse in their investments (Thaler, 1999).

The explanation for the mentioned above is because individuals usually threat money differently depending on how it was earned or lost.

Heuristics Theory

“Heuristics are simple efficient rules of the thumb which have been proposed to explain how people make decisions, come to judgments and solve problems, typically when facing complex problems or incomplete information. These rules work well under most circumstances, but in certain cases it leads to systematic cognitive biases”

Daniel Kahneman (Parikh, 2011).

Heuristics is a problem solving method based on shortcuts in order to simplify the decision making process. Thus, heuristics can provide good enough solutions for taking choices when there is a limited time frame for the decision making process.

According to Greenwood and Nagel (2009), prior experience affects investors' decision, and oftentimes this prior experience leads to heuristic investment strategies. Investors can also rely too much on certain habits without giving them enough thought (Hirshleifer, 2015). Investors usually tend to take into consideration the short sighted belief that “the majority is always right”, which also leads them to fall into herding (Andersson, Hedesstrom, and Garling 2014). Choi, Laibson, and Madrian (2009), say that investors could over extrapolate their own prior investment performance when making decisions.

Thus, everyone could well fall into heuristics when making investment decisions, and they can do so unintentionally. Therefore, investors are strongly suggested to become aware of their own heuristics so as to make more accurate investment decisions.

Misperceiving Randomness

"Thus, the representativeness heuristic can encourage people to expect intuitively past price changes to continue, even if they know, from professional training, that they should not expect this."

Robert Shiller

Misperceiving Randomness is also known as the representative heuristics, Kahneman and Tversky (1979) were the pioneers to define it. They defined representative heuristics as the action of people trying to predict future outcomes based off random past events. Shiller (2003) suggested that human minds can be seen as a patter seeking device. When investors are trying to estimate future outcomes based off technical analysis (past data and/or graphs), the human mind tends to fall for the actual poor probability that the current pattern will continue (Shiller, 2003).

Market participants tend to have a combination of recency bias, which is defined as putting too much attention on recent events when forecasting future outcomes (Sinha, 2015), and use the law of small numbers. This occurs as people rely too much on small samples to draw conclusions (Tversky and Kahneman, 1971).

Herding

"Most people get interested in stocks when everyone else is. The time to get interested is when no one else is. You can't buy what is popular and do well."

Warren Buffett

"By the time any view becomes a majority view, it is no longer the best view: somebody will already have advanced beyond the point which the majority have reached."

Friedrich Hayek

The herding bias is among the most common mistake within the investors' community as usually they tend to follow the investment decision of the majority. According to Jordan et al. (2015) investors constantly fall into herding by being subsequent to do what the majority are doing with their investments. The fundamental reasons market participants fall into herding is because they believe that their own information is incomplete or has a lack of quality, henceforth, they assume other investors have higher quality information (Sinha, 2015). Herding also tends to happen due to the lack of information at all.

Roider and Voskort (2016) tested the theory of herding among a group of investors and successfully proved it. There are tons of evidence suggesting that analysts are strongly persuaded by others as they fix their forecasts to follow the herd. One of the main reasons of herding is the fear to fail on their own.

Herding causes several issues to capital markets by destabilizing prices and causing bubbles (Andersson et al. 2014). This occurs as investors make decisions based off of the majority's decisions which have been proved not to be right all the time. Thus, herding can cause volatility and strong movements in prices if the herd changes beliefs or confidence in a given stock or the aggregate market. Conforming to Venezia et al. (2011), herding is significantly positive correlated to market volatility in capital markets. In conclusion, this could create a never-ending cycle as investors panic while falling into herding and therefore potentially increase market volatility.

Overconfidence

"It's not how right or how wrong you are that matters but how much $ you make when right and how much you do not lose when wrong"

George Soros

One of the most common mistakes among the investors community is the overconfidence nature in relation to their own investment strategies and market estimates. According to Thaler and Barberis (2002), the events that people believe will occur 98% of the times only happen 60% of the times. Moreover, events that people are certain that will not occur actually happen 20% of the times (Thaler and Barberis, 2002). Therefore, the mentioned overconfidence among investor may lead them to take inappropriate decisions.

"In this business if you're good, you're right six times out of ten. You're never going to be right nine times out of ten"

Peter Lynch

Another sing of overconfidence is when an investor is familiar with a stock and therefore the perception of risk decreases. Investors are more likely to bet on financial instruments they are familiar with instead of taking a better gamble in something unfamiliar

(Heath and Tversky, 1991). Also, overconfidence can lead to affect diversification as investors tend to place larger investments on individual securities they feel more familiar with (Hirshleifer, 2015). The familiarity with a stock has no relation to its performance, thus investors should see all financial instruments as equal.

2.1.3. From Traditional Finance Theory Towards Behavioural Finance Theory

Kahneman and Tversky (1979) were the first to challenge the EMH with their blockbuster report on prospect theory. Their work proposed Prospect Theory as an alternative to the Expected Utility Theory. They found that investors tend to weight alternatives wrong in relation to dealing with risk.

Later on, Thaler (1980) contributed to Behavioral Finance by arguing the prevalent economic theory from that time of how consumers made their purchasing decisions. This preponderating theory was the rational maximizing model, which stated that consumers use all available information for any purchasing decisions, hence they make the most rational decision. Thaler (1980) found many decision making errors people tend to do, mistakes such as underweighting opportunity costs, regret aversion, and fail to ignore sunk costs.

De Bondt and Thaler (1985) realized a study of how individual's cognitive bias could produce mispricing of equities in the New York Stock Exchange to prove overreactions in the stock market. Their study proved that people in fact overreact to bad news. This study is mention with further detail in the section of Evidence of Overreaction.

Andreassen and Kraus (1988) also challenged the EMH by proving that when investors analyse historical prices, they tended to behave as if they extrapolate past price changes when the prices appear to exhibit a trend relative to period-to-period variability. Hence, they let that have an impact on their decision making in their investments. This also suggests, that bubbles can be generated if agents are preconditioned by past experience to form expectations of bubbles.

Shiller (2003) stated that academic discussion began to shift towards an analysis of human psychology role in the financial markets' fluctuations in the 1990s. Thaler (1999) applied behavioural finance theory to successfully predict the crash of the Internet stock boom, he blamed the irrational investor to be the cause of the bubble. Finally, behavioural finance is nowadays clearly a legitimate tool to be used in investment theory.

2.1.4. Evidence of Overreaction and Reversals

"The contrary investor is every human when he resigns momentarily from the herd and thinks for himself"

Archibald MacLeish

DeBondt and Thaler (1985) split stocks by their previous returns over the past 3 years, they separated stocks in winners and losers depending on their previous returns. In the mentioned analysis, they find that over a long term, stocks that had performed poorly (losers) go on to outperform stocks that had performed very well (winners). Therefore, it could be said that investors' overreactions are the causes of the already mentioned above. Also, this would suggest evidence of Contrarian Investment. The reason for this is because winner stocks are over bought (Above fair value) and loser stocks are oversold (under fair value), hence profits occur as winner stocks retreat to their fair value and loser stocks rally to their fair value.

As well as, there are studies that show evidence of overreactions when analysing shorter periods of time. Zarowin (1989) realises an analysis as the mentioned above by Debondt and Thaler, but he does it by analysing the performance of stocks over the previous month and then examines returns over the next month. Once again, he finds that previous losers outperform previous winners. Bremer and Sweeney (1991) state that after a ten percent daily decline in prices, stocks perform a reversal to initial prices by having positive abnormal returns for the next two days.

2.1.5. Evidence of Under reaction and Momentum in prices

As well as Overreaction, empirical studies have also found examples of under reaction. Under reaction causes momentum in prices as stock prices keep on moving in the same direction as the information is slowly incorporated into stock prices. Momentum could be seen as the first stage in the short term market's reactions to price changes. Jegadeesh and Titman (1993) build portfolios just as Debondt and Thaler but used the prior six months returns and examined the reaction for the following six months return. Jegadeesh and Titman found evidence of momentum in the short term, meaning prior winners outperform and prior losers underperform. Since momentum has been proved to exist in the short term, it could be seen also as the first stage of overreaction. As it is mentioned above, winner stocks are over bought (Above fair value) and loser stocks are oversold (under fair value). This causes Momentum in prices, hence it could be seen as the period of time where investors cause a tendency in prices due to short term under reaction.

Underreaction and price drifts are usually related to important public announcements. Therefore, positive news can lead to subsequent positive abnormal returns, and negative news lead to subsequent negative abnormal returns. Some examples of negative events that could lead to negative abnormal returns include stock splits (Grinblatt, Masulis, and Titman 1984), open market repurchases (Ikenberry, Lakonishok, and Vermaelen 1995), public announcements of previous insider trades, analyst recommendations, among some others. However, the most famous and most well known and studied market anomaly is the Post Earnings Announcement Drift (PEAD). PEAD is the tendency of a stock's cumulative abnormal returns to drift in the same direction of the earnings surprise (positive or negative) for a considerable period of time. Brown (1997) states that the drift following standardized unexpected earnings is very significant, hence it can also lead to momentum in prices.

According to Kim (2002), the firms which consistently achieve or beat analysts' expectation earn a market premium in proportion to the times the firms have met their target. Anyhow, the mentioned premium is lost when firms miss their target earnings, suffering a proportionate reversal. Rapidly appreciating growth stocks tend to outperform during a boom, but also they tend to underperform in the long term if they do not meet expectations.

Empirical studies from the earnings surprise propose that investors use heuristics as they behave by the rule of the thumb, meaning the future will represent the past. Consequently, this causes momentum in prices while the market responds and incorporates information into prices. Finally, prices tend to continue moving in the same direction for a period of momentum while investors fully incorporate the event´s information.

2.1.6. Over and Under reaction at the same time

One possibility to explain the market anomalies already mentioned are the deviations to be expected under the Efficient Market Hypothesis (Fama 1998). However, this thesis aims to provide information suggesting that those market anomalies are not a caused by those deviations under market efficiency. A central theme on this work is that prices sometimes overreact or underreact to some signal, moreover, often prices over and underreact simultaneously.

Daniel, Hirshleifer, and Subrahmanyan propose a model in which overconfidence causes overreaction, and self attribution leads to underreaction. "Stock prices tend to overreact to private information signals and underreact to public signals, thus positive return autocorrelations can be a result of continuing overreaction." (Kent, Hirshleifer, and Subramanian 1998).

According to Porterba and Summers (1998), there is a transitory part of prices which leads to positive autocorrelation over short terms, but negative autocorrelation over long terms. A Non-Random Walk Down Wall Street by Andrew W. Lo and Craig Mackinlay is compound by eleven papers which all come to the same overall conclusion that there is positive autocorrelation in stock prices over short terms, but negative autocorrelation over long terms.

Also, Barberis, Shleifer, and Vishny (1998), suggest a model which integrates anchoring and heuristics where conservatism first causes underreaction but trend chasing leads to overreaction in the long term. By the same token, Hong and Stein (1999) propose a model of over and under reaction suggesting that fundamental analysis is the reason of underreaction while technical analysis leads to overreaction.

In brief, the mentioned above suggests that there is momentum in the short run but mean reversion in the long term. Stock prices tend to first drift (sign of underreaction), but thereafter prices correct (sign of overreaction).

Moreover, Kaestner (2006) suggests that the market whether over or underreact to an earnings surprise depends on how surprising is the event. He finds that the level of surprise is what defines the level of over or underreaction. Thus, it can be said that the greater the surprise from the price announcement, the stronger the market reaction.

Although this behavioural models may be true, traditional finance models also suggest explanation to those movements in prices dismissing them as methodological or statistical flaws. Some authors of traditional finance models believe that changes in risk that are compensated by changes in returns appear to be abnormal. As an example, it could be argued that prior losers are riskier than prior winners, hence they explain momentum as a compensation for risk in a given period of time.

"From a simplistic point of view, consider a bull market in which stock prices have been rising. Investors see their portfolio values increasing. Those who have been sitting on the side-lines hear how their friends have made money in the stock market. Not wanting to miss out on these returns, they join in. The average investor is hopeful and confident that the trend of rising stock prices will continue. Of course, as these investors place more and more money in the

market, stock prices do rise; in economic jargon, as the quantity of investors in the marketplace increases, the demand for stocks increases, driving stock prices even higher. The optimistic view of the market participants drives prices even higher. Seeing that they were correct, investors become overconfident and greedy and purchase even more stocks. At the peak of optimism, investors have placed all their available money in the stock market. At this point, there is no new money coming into the market to continue fuelling the increase in demand that has been driving price upward. Thus, there is no more fuel to keep stock prices rising, and the stock market reaches a peak."

"Conversely, when investors are pessimistic and fearful, they begin to sell stock. As the level of pessimism rises in the market and more investors sell, stock prices fall. These falling prices lead more and more investors to feel fearful and decide to sell their shares. When investors are the most pessimistic and fearful, they have withdrawn all of their money out of the market. The downtrend that has been fuelled by investors leaving the markets ends, and the market reaches a bottom."

Charles Kirkpatrick and Julie Dahlquist

2.2. The Role of Behavioral Finance in The Markets and its Implications for Price Shocks

"One of the funny things about the stock market is that every time one person buys, another sells, and both think they are astute"

William Feather

The Decision making process is a various steps process which implicates the analysis of diverse factors influencing a given problem. Probably taking investment decisions is one of the most crucial decisions for everyone. Optimal decision making for investing in the stock market requires a deep understanding of investors rationality and more important, irrationality in a global perspective. Given the past market crashes, there is been a lot of attention on studying irrational investor behaviour. "Behavioral Finance is becoming an integral part of decision-making process because it heavily influences the investors' performance" (Banerjee, 2011).

This section aims to explain the role of behavioral finance in capital markets, in the foreground of market reactions following significant price shocks. Thus, this part is split into the most inclusive factors causing the reactions following a price shock.

2.2.1. Prospect Theory

It could be said that if investors behave as explained in prospect theory, they would react differently to positive and negative price shocks. This behavioral theory suggests that following significant gains, such as a strong positive price shock, investors would become more risk averse, thereafter, they would sell in order to obtain profits. For the cases of analysis provided further on in this thesis, this would imply a negative mean of the returns from the following days after positive events.

On the contrary, this theory implies that investors tend to become more risk seeking following losses. Thus, instead of selling after a negative price shock, investors would hold the stock or even buy more with the purpose of gambling back their losses (Gambler's Fallacy). Therefore, since market participants tend to become more risk seeking after looses and improve their confidence on the market, this would manifest itself in the analyses provided further on in this thesis as a very poor market reaction following a negative event, resulting in a very small mean, either a positive or a negative mean close to 0 of the returns from the following days after negative events.

2.2.2. Overreaction and Contrarian Investing

Overreaction would imply similar results as in Prospect theory in terms of the tests provided further on in this thesis. Overreaction in the market would imply the initial price shock to be too strong mainly caused by emotions on the day of a price shock. As a result, prices would drift towards unfair value on the event day, as well as in the same direction of the event, meaning overvalued for positive events or undervalued for negative events. According to Atkins and Dyl (1990), whom examined the behaviour of common stock prices following a large change in prices in single days of trading, they found evidence suggesting that the stock market appears to overreact, especially following a negative price shock. In accordance to their study, prices should fall following positive events and raise after negative events as to return to fair value. Thus, returns of the days of the events would be negatively correlated with the returns of the days following the event. In the cases of analysis in this thesis, this would suggest a positive mean of the returns from the following days of the events in the case for negative events, likewise a negative mean for the case of positive events.

Finally, if there is overreaction in the market this would suggest prove and efficiency of contrarian investing strategies. This would happen as stocks that had performed poorly (losers) go on to outperform stocks that had performed very well (winners). The reason for this is because winner stocks are over bought (Above fair value) and loser stocks are oversold (under fair value), hence profits occur as winner stocks retreat to their fair value and loser stocks rally to their fair value.

2.2.3. Under reaction and Momentum Investing

Under reaction mainly implies a price drift following a price shock in the same direction of the price shock. The magnitude and length of the period of time for the price drift would be mainly attributed to the magnitude on the news' information impact which causes the original price shock. At the same time, this would cause momentum following price shocks. According to Bernard and Thomas (1990), prices would continue to increase following positive price shocks, as well as, prices would continue to fall after negative price shocks due to too moderate initial reactions in events.

2.2.4. Casual Attribution

Casual attribution could be seen as the logic-sequence explanation of both under and over reaction. This theory explains the market reaction in relationship to whether the investors attribute the price shock to a stable or non- stable cause. Given the prior day's return can significantly impact investor's expectation on the market, but those expectations did not account during the prior day shock, drifts or reversals in prices post event might be attributed to whether the price shock had a stable or non-stable cause.

Since investors usually use hindsight (understanding of a situation or event only after it has happened or developed), and tend to fail into herding when a significant price shock occurs, they usually do not absorb information and their future expectation on the day of the event.

Henceforth, if investors attribute the cause of the event is stable (solid fundamentals and technical analysis supports the cause), they would believe the past results will repeat. As a consequence, positive events would lead investors to expect more gains and increase optimism, while on the other side, negative events would lead investors to expect more losses and increase pessimism. Taking this into consideration, it could be said that the behaviour would be similar to under reaction, prices would continue to increase following positive price shocks, as well as, prices would continue to fall after negative price shocks.

On the other hand, when investors believe the cause of the event is non-stable, the same behaviour of overreaction would happen, there would be a reversion to the mean pattern. This would imply positive market reactions following negative events, and negative reactions following positive events. This tends to occurs because investors usually believe that non-stable causes do not repeat. Since they look back in time and do not expect the extreme results of the prior events will happen again. This may also have relationship to whether the cause of the event had solid fundamentals or not. Thus, this could be seen as the logic in the market reactions post an overreaction.

3. Data and Methodology

In this chapter, the data and methodology used in the thesis for analysis, and hypothesis testing will be explained in detail.

3.1. Data

The data used for this Thesis analysis are the closing prices and returns of the S&P/BMV IPC (Índice de Precios y Cotizaciones). The time frame to analyse market reactions is from 2009 to March 2018, closing prices were retrieved from the S&P Dow Jones Indices official site. The IPC is closely followed by investors, as well as, it is very well known to be the best composite index to represent the Mexican aggregate capital market. It is the best single gauge of Mexican equities. Thus, daily changes within the IPC are widely recognized by market participants causing some vast different reactions to changes over significant daily percentage changes.

The reasons for choosing this period of time for the analysis are: firstly, to exclude the events near to the 2008 crash, which produced returns so extreme that would strongly affect the results for this post-event analyses. Secondly, it is certainly known that before the 2008 crash there were far less regulations in stock markets. Thus, the market from before 2008 does not represent the same context as the market from the last few years after the crash. Hence, this analysis aims to provide results which represent the current context of the actual capital market.

3.2. Methodology

Events in daily price changes are defined in a similar manner as Lowe (2008), who also defined events similarly to Bremer and Sweeny (1991), Cox and Peterson (1994), Larson and Madura (2002), and Sturm (2003). The mentioned above besides Lowe, analysed single securities for which they used price shocks of 10% to individual securities to define an event, however, this criterion can not be used for an aggregate index which is by far less volatile. By the same token, Lowe (2008) classified events as a daily percent change greater than 2% or less than -2%. Also, with the purpose of analysing mild events, he uses a 3% edge to define positive and negative events and examine the 1.5% to 3% range to which he calls mild events.

This thesis defines events in a similar same manner as Lowe (2008), but with a slide change on the event definitions for the return percentages. There are two different groupings for the event definitions. The Grouping 1 and Groping 2 are classified as following in Table 1:

Table 1

Event Definitions				
Grouping 1				
Events	**Negative Event**	**Negative No Event**	**Positive No Event**	**Positive Event**
Prior Day Returns	NEG<=-1.2%	-1.2%<NNE<0%	0%<PNE<1.2%	1.2%<=PE
Groping 2				
Events	**Negative Event**	**Negative No Event**	**Positive No Event**	**Positive Event**
Prior Day Returns	NEG<=-1.5%	-1.5%<NNE<0%	0%<PNE<1.5%	1.5%<=PE

Thus the events showed above are defined in relation to the daily return on the IPC. The daily raw return is calculated as in the following formula (equation 1):

$$\text{Daily Return}_{t+1} = \frac{PC_{t+1} \;\; -IPC_{t=0}}{IPC_{t=0}} \qquad (1)$$

This thesis analysis the post-event market returns based on the given event in order to asses the market reaction to significant daily price changes. To the end of analysing the market behaviour following the event, two post event windows are used. This criterion is also used in Sturm (2003), Chen and Siems (2002), and Lowe (2008) in a similar manner. Thus, the post event windows are in the following manner:

- ❖ The IPC raw return on the following day of the event (RR1)
- ❖ The average IPC raw returns (ARR2) for the following 2 days of the event.

If events are defined to take place at t=0, then the RR1 is simply the raw return on the following day, and ARR2 is obtained as in the following formula (equation 2):

$$ARR2_{t=} \;\; 1/2* \sum_{t=1}^{2} RR_t \qquad (2)$$

The raw return on the following day of the event (RR1) and the average raw returns on the following 2 days (ARR2) are taken for reference to asses the market reaction to the events already mentioned above. The market performance following the events is statistically analysed in order to gauge whether there is any evidence suggesting Under reaction for the Positive Events or Overreaction for the negative events. Hence, under reaction would suggest momentum investment, and on the other hand overreaction would suggest contrarian investment.

All the statistical tests analysis done in this thesis are realised with the following alpha values (Table 2):

Table 2

Rejection Regions to the Null Hypothesis for the given α (alfa) Values				
	Alternative Hypothesis (Ha)			
	Lower Tailed $Z<-Z\alpha$	Upper Tailed $Z>Z\alpha$	Two-Tailed $Z<-Z\alpha/2$ or $Z>Z\alpha/2$	
$\alpha=0.05$	$Z<-1.645$	$Z>1.645$	$Z<-1.96$	$Z>1.96$
$\alpha=0.1$	$Z<-1.280$	$Z>1.280$	$Z<-1.645$	$Z>1.645$

Firstly, a single mean analysis is conducted in order to asses if the post event reactions are positive or negative. However, in order to gauge the statistical significance, a Z test for one sample mean hypothesis testing is conducted as following (Table 3):

Table 3

Single Mean Hypothesis Testing							
Test Statistic: Z test: One Sample Mean			Behavioral Finance Suggested Cause for market				
Event Definition	Null Hypothesis (Hn)	Alternative Hypothesis (Ha)	Ivestor Type	Causal Attibution	Market Reaction	Emotions	Prospect Theory
Negative Event (NE)	$\bar{x}$NE=0	$\bar{x}$NE>0	Contrarian	Non-stable	Overreaction	Fear, panic	Applies
		$\bar{x}$NE<0	Momentum	Stable	Underreaction	Greed	N/A
Positive Event (PE)	$\bar{x}$PE=0	$\bar{x}$PE>0	Momentum	Stable	Underreaction	Greed	N/A
		$\bar{x}$PE<0	Contrarian	Non-Stable	Overreaction	Fear	Applies

Secondly, a Z test for two sample means is done in order to compare the Negative Events' post event reaction mean against the Negative No Events' post event reaction mean. Also, the test compares the Positive Events' post reaction mean against the Positive No Events' post reaction mean.

The mentioned analysis has the purpose of assessing the main Alternative Hypothesis' of this thesis, which are described in the following table (4):

Table 4

Hypothesis Testing							
Test Statistic: Z test: Two Sample for Means			Behavioral Finance Suggested Cause for Market Post Event Reactions				
Event Definition	Null Hypothesis (Hn)	Alternative Hypothesis (Ha)	Ivestor Type	Causal Attibution	Market Reaction	Emotions	Prospect Theory
Negative Event (NE)	$\bar{x}NE=\bar{x}NNE$	$\bar{x}NE>\bar{x}NNE$	Contrarian	Non-stable	Overreaction	Fear, panic	Applies
		$\bar{x}NE<\bar{x}NNE$	Momentum	Stable	Underreaction	Greed	N/A
Positive Event (PE)	$\bar{x}PE=\bar{x}PNE$	$\bar{x}PE>\bar{x}PNE$	Momentum	Stable	Underreaction	Greed	N/A
		$\bar{x}PE<\bar{x}PNE$	Contrarian	Non-Stable	Overreaction	Fear	Applies

This thesis aims to find evidence on Overreaction for Negative Events and Under reaction for positive events. Thus, in the same manner, Contrarian Investing following Negative Events, and Momentum Investing following Positive Events.

Therefore, in order to support the mentioned hypothesis, the RR1 and ARR2 means from Negative Events must be statistically higher than the same means from the Negative No Events when tested in the Z test. Thus, if results are as mentioned, it would suggest there is more overreaction for big falls on the index than with small drops of the IPC.

On the other hand, in order to support the under reaction hypothesis for Positive Events, the RR1 and ARR2 means from Positive Events must be statistically higher than the means from the Positive No Events when tested in the Z test. Thus, if results are as mentioned it would suggest there is more under reaction, and therefore momentum for big price drifts upwards on the index than with small drifts upwards of the IPC.

3.3. Magnitude of the Positive and Negative Market Reactions Post Event

A third analysis is done with the purpose of assessing the market reactions post Negative and Positive Events. Thus, this analysis is realized for a third grouping of data (Grouping 3), which is classified as the following table:

Table 5

Event Definitions for Groping 3

Event Definitions	Negative Event	Positive Event
Prior Day Returns	**NEG<=-1.2%**	**1.2%<=PE**

As it can be seen in the table above (5), grouping 3 is very similar to grouping 1 in terms of the range for classifying events. However, groping 3 does not take into consideration the days between the negative and positive events, thus the range from -1.2% to 1.2% is not taken into consideration for this model. The reason for the already mention is because the purpose of this model is to asses the market reactions post event, hence, the range between events is considered as non significant events. In conclusion, this groping is focused merely on price shocks, both positive and negative, thereafter, the post event market reactions can be judged in terms of their relationship to behavioral finance theories.

The post event window to analyse will be just the following day after the event. In that case, the post event window is in the following manner:

- The IPC raw return on the following day of the event (RR1)

Once defined the returns to analyse, the post event given window analysis for returns is split into positive and negative reactions, meaning the positive those returns above 0, and negative those below 0. Hence, the returns to analyse would be in the following manner (Table6):

Table 6

Data from Groping 3

Event Definitions		Negative Event			Positive Event		
Prior Day Returns		**NEG<=-1.2%**			**1.2%<=PE**		
Number of Events		195			201		
Mean of the Event		**-1.9391%**			**1.9155%**		
Market Reactions		%	Mean	n	%	Mean	n
Positive Reactions	%RR1>0	51.282%	0.8549%	100	55.224%	1.0358%	111
Negative Reactions	%RR1<0	48.718%	-0.9804%	95	44.776%	-0.7964%	90

Thereupon, with the intention of analysing if the mentioned market reactions suggest any evidence of over and/or under reaction for the given events a magnitude analysis of means is done. This analysis consists in comparing the means of the positive and negative post event reactions in comparison to the mean of the Event. Consequently, if there is a significant price drift both in magnitude of means and economically significant in the same direction of the event (Ex: positive for positive events), then it would suggest evidence of underreaction. On the other hand, if it occurs a mean reversal, which would mean a price drift on the opposite direction of the event, same as the case before, it would need to be significant both in magnitude of means and economically, this would suggest evidence of overreaction.

Finally, a set of graphics is shown in order to provide a wider panorama from a visual perspective to asses the magnitude for post event reactions. First, in each graphic, the mean of the whole IPC returns for the period of analysis is shown for reference. Second, the graphics illustrate the events' mean followed by the post event mean (one graphic for negative post event and one for positive post event).

4. Results

In this chapter the results from the statistical analysis will be provided with a short interpretation and comments of each statistical test. First, the results from the single mean hypothesis testing will be shown in order to asses whether the post event reaction is positive or negative. Second, the two sample mean hypothesis testings are provided with the purpose of gauging whether there is supporting evidence on Overreaction for Negative Events and Underreaction for positive events when comparing the means of the Negative Events against the means of the Negative No Events; on the other hand, the means from the Positive Events against the means from the Positive No Events. Thus, likewise, Contrarian Investing following Negative Events, and Momentum Investing following Positive Events. Finally, a third analysis is provided with the purpose of assessing the direction of the market reactions post Negative and Positive Events in a different grouping of data. The purpose of this last model is to asses the market reactions post event, focusing merely on price shocks, both positive and negative, thereafter, the post event market reactions can be judged in terms of their relationship to behavioral finance theories.

4.1. Single Mean Hypothesis Testing, Z test: One Sample Mean

Table 7

Single Mean Hypothesis Testing							
Test Statistic: Z test: One Sample Mean			Behavioral Finance Suggested Cause for market				
Event Definition	Null Hypothesis (Hn)	Alternative Hypothesis (Ha)	Ivestor Type	Causal Attibution	Market Reaction	Emotions	Prospect Theory
Negative Event (NE)	$\bar{x}NE=0$	$\bar{x}NE>0$	Contrarian	Non-stable	Overreaction	Fear, panic	Applies
		$\bar{x}NE<0$	Momentum	Stable	Underreaction	Greed	N/A
Positive Event (PE)	$\bar{x}PE=0$	$\bar{x}PE>0$	Momentum	Stable	Underreaction	Greed	N/A
		$\bar{x}PE<0$	Contrarian	Non-Stable	Overreaction	Fear	Applies

Note: For the following Tables the "Non-Rejection" Region means accepting the Null Hypothesis; therefore, the "Rejection" region refers to reject the reject the null hypothesis and accept the alternative hypothesis.

4.1.1. Groping 1

Table 8

Results for Groping 1

Event Definitions		Negative Event		Negative No Event		Positive No Event		Positive Event	
Prior Day Returns		NEG<=-1.2%		-1.2%<NNE<0%		0%<PNE<1.2%		1.2%<=PE	
Number of Events	Total= 2321	195	8.402%	907	39.078%	1018	43.860%	201	8.660%

Table 9

Hypothesis Testing for Post Event One Day Raw Returns Reactions						
		Negative Event			Negative No Event	
Mean		-0.03923%			-0.02892%	
Z score		-0.452840845			-0.875286124	
Z test	Lower Tailed	Upper Tailed	Two- Tailed	Lower Tailed	Upper Tailed	Two- Tailed
α=0.05 Results	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection
α=0.1 Results	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection
		Positive Event			Positive No Event	
Mean		0.21539%			0.07106%	
Z score		2.374866224			2.506956614	
Z test	Lower Tailed	Upper Tailed	Two- Tailed	Lower Tailed	Upper Tailed	Two- Tailed
α=0.05 Results	Non-Rejection	Rejection	Rejection	Non-Rejection	Rejection	Rejection
α=0.1 Results	Non-Rejection	Rejection	Rejection	Non-Rejection	Rejection	Rejection

Hypothesis Testing for Post Event Two Day Raw Returns Reactions						
		Negative Event			Negative No Event	
Mean		0.04783%			-0.00114%	
Z score		0.76392435			-0.048185621	
Z test	Lower Tailed	Upper Tailed	Two- Tailed	Lower Tailed	Upper Tailed	Two- Tailed
α=0.05 Results	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection
α=0.1 Results	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection
		Positive Event			Positive No Event	
Mean		0.15186%			0.04262%	
Z score		2.217375796			2.03839941	
Z test	Lower Tailed	Upper Tailed	Two- Tailed	Lower Tailed	Upper Tailed	Two- Tailed
α=0.05 Results	Non-Rejection	Rejection	Rejection	Non-Rejection	Rejection	Rejection
α=0.1 Results	Non-Rejection	Rejection	Rejection	Non-Rejection	Rejection	Rejection

As it can be seen above, results from the Z test do no vary between the post event one day and the post event two days. In both cases the means from the negative events and negative no events are not indistinguishable from cero. Hence, this statistical test would suggest that there is no supporting evidence of significant strong market reactions following negative events. On the other hand, in the case for the Positive Events, the statistical test proves that there is a positive market reaction. (Table 9)

Additionally, for both cases, one and two days' analysis for the positive events and the positive no events the results show that the means are indistinguishable from cero; more over, the means are statistically higher than cero in all cases. This result would suggest there is a positive market reaction following positive events. However, this is not enough evidence for suggesting either underreaction nor momentum following a positive price shock.

4.1.2. Grouping 2

This section displays the results of the Grouping 2 for the single mean hypothesis testing. First, in the following table (10) comes the general information and data for grouping 2

Table 10

Results for Groping 2

Event Definitions		Negative Event		Negative No Event		Positive No Event		Positive Event	
Prior Day Returns		NEG<=-1.5%		-1.5%<NNE<0%		0%<PNE<1.5%		1.5%<=PE	
Number of Events	Total= 2321	124	5.343%	978	42.137%	1097	47.264%	122	5.256%

Table 11

Hypothesis Testing for Post Event One Day Raw Returns Reactions

	Negative Event			Negative No Event		
Mean		-0.01340%			-0.03295%	
Z score		-0.119913482			-1.023323741	
Z test	Lower Tailed	Upper Tailed	Two- Tailed	Lower Tailed	Upper Tailed	Two- Tailed
α=0.05 Results	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection
α=0.1 Results	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection
	Positive Event			Positive No Event		
Mean		0.23978%			0.07874%	
Z score		2.09929408			2.771417029	
Z test	Lower Tailed	Upper Tailed	Two- Tailed	Lower Tailed	Upper Tailed	Two- Tailed
α=0.05 Results	Non-Rejection	Rejection	Rejection	Non-Rejection	Rejection	Rejection
α=0.1 Results	Non-Rejection	Rejection	Rejection	Non-Rejection	Rejection	Rejection

In the case for Grouping 2, the Z tests' results are the same as in for Grouping 1. Thus, short interpretation of the results can be found in t section 5.1.1.

Table 12

Hypothesis Testing for Post Event Two Day Raw Returns Reactions

	Negative Event			Negative No Event		
Mean		0.04990%			0.00216%	
Z score		0.596507635			0.094579706	
Z test	Lower Tailed	Upper Tailed	Two- Tailed	Lower Tailed	Upper Tailed	Two- Tailed
α=0.05 Results	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection
α=0.1 Results	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection	Non-Rejection
	Positive Event			Positive No Event		
Mean		0.17270%			0.04817%	
Z score		2.054460047			2.278937475	
Z test	Lower Tailed	Upper Tailed	Two- Tailed	Lower Tailed	Upper Tailed	Two- Tailed
α=0.05 Results	Non-Rejection	Rejection	Rejection	Non-Rejection	Rejection	Rejection
α=0.1 Results	Non-Rejection	Rejection	Rejection	Non-Rejection	Rejection	Rejection

In the case for Grouping 2, the Z tests' results are the same as in for Grouping 1. Thus, short interpretation of the results can be found in t section 5.1.1.

4.2. Two Sample Mean Hypothesis Testing, Z test: Two Sample Means

This part shows the results from the two sample mean hypotheses testing. (table 13)

Table 13

Hypothesis Testing							
Test Statistic: Z test: Two Sample for Means			Behavioral Finance Suggested Cause for Market Post Event Reactions				
Event Definition	Null Hypothesis (Hn)	Alternative Hypothesis (Ha)	Ivestor Type	Causal Attibution	Market Reaction	Emotions	Prospect Theory
Negative Event (NE)	$\bar{x}$NE=$\bar{x}$NNE	$\bar{x}$NE>$\bar{x}$NNE	Contrarian	Non-stable	Overreaction	Fear, panic	Applies
		$\bar{x}$NE<$\bar{x}$NNE	Momentum	Stable	Underreaction	Greed	N/A
Positive Event (PE)	$\bar{x}$PE=$\bar{x}$PNE	$\bar{x}$PE>$\bar{x}$PNE	Momentum	Stable	Underreaction	Greed	N/A
		$\bar{x}$PE<$\bar{x}$PNE	Contrarian	Non-Stable	Overreaction	Fear	Applies

The following Z tests results have the purpose of assessing the means of the "events" in relationship with the means of the "no events". Therefore, the Negative Events' post event reaction mean against the Negative No Events' post event reaction mean. Also, the test compares the Positive Events' post reaction mean against the Positive No Events' post reaction mean. The results' interpretation is based on the table of hypothesis testing above. However, even if the statistical results support the alternative hypothesis', there needs to be use of criteria in terms of means' magnitude and economic significance for real life model applications.

4.2.1. Grouping 1

The following table (14) provides the general information and date of Grouping 1

Table 14

Results for Groping 1

Event Definitions		Negative Event		Negative No Event		Positive No Event		Positive Event	
Prior Day Returns		NEG<=-1.2%		-1.2%<NNE<0%		0%<PNE<1.2%		1.2%<=PE	
Number of Events	Total= 2321	195	8.402%	907	39.078%	1018	43.860%	201	8.660%

4.2.1.1. Negative Events

Table 15

α=0.05

z-Test: Two Sample for Means

	Negative One Day	*Negative No Event One Day*
Mean	-0.000392304	-0.00028924
Known Variance	0.000146349	9.89339E-05
Observations	195	906
Hypothesized Mean Difference	0	
z	-0.111155694	
P(Z<=z) one-tail	0.455746442	
z Critical one-tail	1.644853627	
P(Z<=z) two-tail	0.911492885	
z Critical two-tail	1.959963985	

z-Test: Two Sample for Means

	Negative CRR 2 Days	*Negative No Event CRR 2 Days*
Mean	0.000478319	-1.13612E-05
Known Variance	7.64484E-05	5.03663E-05
Observations	195	906
Hypothesized Mean Difference	0	
z	0.731897176	
P(Z<=z) one-tail	0.232115665	
z Critical one-tail	1.644853627	
P(Z<=z) two-tail	0.46423133	
z Critical two-tail	1.959963985	

In the case for the Negative Events' Z test analysis for a given alpha of 5%, the results above demonstrate that the difference between the mean of the Negative One Day and the Negative No Event One Day is not indistinguishable from 0. The already mentioned is confirmed in the P-Value for one tail and the obtained z. (Table 15)

As well as, in the case for the Negative CRR 2 Days in comparison with the Negative No Event CRR 2 Days, the result is the same: the difference in means is not indistinguishable from 0.

Table 16

α=0.10

z-Test: Two Sample for Means

	Negative One Day	*Negative No Event One Day*
Mean	-0.000392304	-0.00028924
Known Variance	0.000146349	9.893E-05
Observations	195	906
Hypothesized Mean Difference	0	
z	-0.111155694	
P(Z<=z) one-tail	0.455746442	
z Critical one-tail	1.281551566	
P(Z<=z) two-tail	0.911492885	
z Critical two-tail	1.644853627	

z-Test: Two Sample for Means

	Negative CRR 2 Days	*Negative No Event CRR 2 Days*
Mean	0.000478319	-1.13612E-05
Known Variance	7.64484E-05	5.03663E-05
Observations	195	906
Hypothesized Mean Difference	0	
z	0.731897176	
P(Z<=z) one-tail	0.232115665	
z Critical one-tail	1.281551566	
P(Z<=z) two-tail	0.46423133	
z Critical two-tail	1.644853627	

As it can be seen above in the given table, the results from the Z test for a given alpha of 10% do not vary from those already mentioned above with a given alpha of 5%. (Table 16)

4.2.1.2. Positive Events

Table 17

α=0.05

z-Test: Two Sample for Means

	Positive One Day	Positive No Event One Day
Mean	0.002153877	0.000710625
Known Variance	0.000165333	8.17966E-05
Observations	201	1018
Hypothesized Mean Difference	0	
z	1.518873825	
P(Z<=z) one-tail	0.064397129	
z Critical one-tail	1.644853627	
z Critical two-tail	1.959963985	

z-Test: Two Sample for Means

	Positive CRR 2 Days	Positive No Event CRR 2 Days
Mean	0.001518644	0.000426227
Known Variance	9.42821E-05	4.45093E-05
Observations	201	1018
Hypothesized Mean Difference	0	
z	1.525526479	
P(Z<=z) one-tail	0.063563917	
z Critical one-tail	1.644853627	
P(Z<=z) two-tail	0.127127834	
z Critical two-tail	1.959963985	

In the case for the Positive Events' Z test analysis for a given alpha of 5%, the results above demonstrate that the difference between the mean of the Positive One Day and the Positive No Event One Day is not indistinguishable from 0. The already mentioned is confirmed in the P-Value for one tail and the obtained z. (Table 17)

As well as, in the case for the Positive CRR 2 Days in comparison with the Positive No Event CRR 2 Days, the result is the same: the difference in means is not indistinguishable from 0.

Table 18

α=0.10

z-Test: Two Sample for Means

	Positive One Day	*Positive No Event One Day*
Mean	0.002153877	0.000710625
Known Variance	0.000165333	8.17966E-05
Observations	201	1018
Hypothesized Mean Difference	0	
z	1.518873825	
P(Z<=z) one-tail	0.064397129	
z Critical one-tail	1.281551566	
z Critical two-tail	1.644853627	

z-Test: Two Sample for Means

	Positive CRR 2 Days	*Positive No Event CRR 2 Days*
Mean	0.001518644	0.000426227
Known Variance	9.42821E-05	4.45093E-05
Observations	201	1018
Hypothesized Mean Difference	0	
z	1.525526464	
P(Z<=z) one-tail	0.063563919	
z Critical one-tail	1.281551566	
P(Z<=z) two-tail	0.127127838	
z Critical two-tail	1.644853627	

In the case for a given alpha of 10%, the results differ from those with an alpha of 5%. In this case, the mean in both cases, the Positive One Day and the Positive CRR 2 Days are statistically larger than the means of the Positive No Event. (Table 18)

4.2.2. Grouping 2

In the case for Grouping 2, the results are the same for the given statistical Z tests as in Grouping 1. However, even if results are the same in term of the Z tests, they are not for the rest of the statistical information provided for reference; such as means, variances, and z's. Therefore, results are shown below with the purpose of providing the reader the rest of the statistical data for any further reference and/or interpretation.

Table 19

Results for Groping 2

Event Definitions		Negative Event		Negative No Event		Positive No Event		Positive Event	
Prior Day Returns		NEG<=-1.5%		-1.5%<NNE<0%		0%<PNE<1.5%		1.5%<=PE	
Number of Events	Total= 2321	124	5.343%	978	42.137%	1097	47.264%	122	5.256%

4.2.2.1. Negative Events

Table 20

α=0.05

z-Test: Two Sample for Means

	Negative One Day	*Negative No Event One Day*
Mean	-0.00013404	-0.000329508
Known Variance	0.000154937	0.000101298
Observations	124	977
Hypothesized Mean Difference	0	
z	0.168034889	
P(Z<=z) one-tail	0.433277916	
z Critical one-tail	1.644853627	
P(Z<=z) two-tail	0.866555832	
z Critical two-tail	1.959963985	

z-Test: Two Sample for Means

	Negative CRR 2 Days	*Negative No Event CRR 2 Days*
Mean	0.000498963	2.16043E-05
Known Variance	8.67615E-05	5.09776E-05
Observations	124	977
Hypothesized Mean Difference	0	
z	0.550522004	
P(Z<=z) one-tail	0.290980694	
z Critical one-tail	1.644853627	
P(Z<=z) two-tail	0.581961389	
z Critical two-tail	1.959963985	

Table 21

α=0.10

z-Test: Two Sample for Means

	Negative One Day	*Negative No Event One Day*
Mean	-0.00013404	-0.000329508
Known Variance	0.000154937	0.000101298
Observations	124	977
Hypothesized Mean Difference	0	
z	0.168034889	
P(Z<=z) one-tail	0.433277916	
z Critical one-tail	1.281551566	
P(Z<=z) two-tail	0.866555832	
z Critical two-tail	1.644853627	

z-Test: Two Sample for Means

	Negative CRR 2 Days	*Negative No Event CRR 2 Days*
Mean	0.000498963	2.16043E-05
Known Variance	8.67615E-05	5.09776E-05
Observations	124	977
Hypothesized Mean Difference	0	
z	0.550522004	
P(Z<=z) one-tail	0.290980694	
z Critical one-tail	1.281551566	
P(Z<=z) two-tail	0.581961389	
z Critical two-tail	1.644853627	

4.2.2.2. Positive Events

Table 22

α=0.05

z-Test: Two Sample for Means

	Positive One Day	*Positive No Event One Day*
Mean	0.002397801	0.000787433
Known Variance	0.000159162	8.85584E-05
Observations	122	1097
Hypothesized Mean Difference	0	
z	1.368194806	
P(Z<=z) one-tail	0.085625554	
z Critical one-tail	1.644853627	
P(Z<=z) two-tail	0.171251107	
z Critical two-tail	1.959963985	

z-Test: Two Sample for Means

	Positive CRR 2 Days	*Positive No Event CRR 2 Days*
Mean	0.001727047	0.00048172
Known Variance	8.6213E-05	4.90152E-05
Observations	122	1097
Hypothesized Mean Difference	0	
z	1.43669214	
P(Z<=z) one-tail	0.075402745	
z Critical one-tail	1.644853627	
P(Z<=z) two-tail	0.150805489	
z Critical two-tail	1.959963985	

Table 23

α=0.10

z-Test: Two Sample for Means

	Positive One Day	Positive No Event One Day
Mean	0.002397801	0.000787433
Known Variance	0.000159162	8.85584E-05
Observations	122	1097
Hypothesized Mean Difference	0	
z	1.368194806	
P(Z<=z) one-tail	0.085625554	
z Critical one-tail	1.281551566	
P(Z<=z) two-tail	0.171251107	
z Critical two-tail	1.644853627	

z-Test: Two Sample for Means

	Positive CRR 2 Days	Positive No Event CRR 2 Days
Mean	0.001727047	0.00048172
Known Variance	0.000086213	4.90152E-05
Observations	122	1097
Hypothesized Mean Difference	0	
z	1.436691913	
P(Z<=z) one-tail	0.075402777	
z Critical one-tail	1.281551566	
P(Z<=z) two-tail	0.150805554	
z Critical two-tail	1.644853627	

4.3. Magnitude of the Positive and Negative Market Reactions Post Event

Finally, a third and last analysis' results are provided in this section with the purpose of assessing the market reactions post Negative and Positive Events for a different Grouping of data (Grouping 3), which is already explained in the data and methodology chapter.

In the following table (24) are the results from the post event returns already split into positive and negative reactions, meaning the positive those returns above 0, and negative those below 0. As well as the number of days with a positive reaction and those with a negative reaction post event. Also, the means of the already mentioned returns from one day after the events divided into positive and negative returns for both Positive and Negative Events.

Table 24

Groping 3

Event Definitions		Negative Event			Positive Event		
Prior Day Returns		**NEG<=-1.2%**			**1.2%<=PE**		
Number of Events		195			201		
Mean of the Event		**-1.9391%**			**1.9155%**		
Market Reactions		%	Mean	n	%	Mean	n
Positive Reactions	%RR1>0	51.282%	0.8549%	100	55.224%	1.0358%	111
Negative Reactions	%RR1<0	48.718%	-0.9804%	95	44.776%	-0.7964%	90

In the following two sections graphics are provided with the purpose of giving the reader a visual aid to graphically analyse the positive reaction post event and the negative reaction post event for each event classification. In each section comes first the table for the given event, in which the means of the returns from the days of the events are provided. As well as, the two means of the events' following days' returns (Post Event Positive and Negative Reactions). In the same table comes also de percentage in which the post event reactions are distributed. Which can be seen as the chance of occurrence of either a negative post event reaction or a positive post event reaction.

Furthermore, tables which provide information on the magnitude of the reactions are displayed in order to better understand the graphics. Each table of the "Magnitude of Reactions" is classified in either Positive or Negative, depending on the case of analysis. Important to realize, in the tables already mentioned above and for the graphics, the first input is the mean from the day of the event, henceforth, the second (Post Event in the table) is the mean of the event plus the mean of the post event reactions (either positive or negative, depending on the case). This can help to analyse the post event reactions while taking into consideration also the magnitude of the event itself.

4.3.1.1. Negative Events

Table 25

Negative Event				
t=	Post One Day RR Means	Event	N	Chance of Ocurrence % of Ocurrence
0	-0.019391044	Negative Event	195	1
1	0.008548872	Post Event Positive Reactions	100	0.512820513
1	-0.009804068	Post Event Negative Reactions	95	0.487179487

Table 25 provides the data for the Negative Event's analysis post event reaction. As can be seen the means of the returns from the days of the events are provided. As well as, the two means of the events' following days' returns (Post Event Positive and Negative Reactions). In the same table comes also de percentage in which the post event reactions are distributed.

Table 26

Magnitude of Positive Reactions		
	0	0.0000%
Event	1	-1.9391%
Post Event	2	-1.0842%

Figure 1

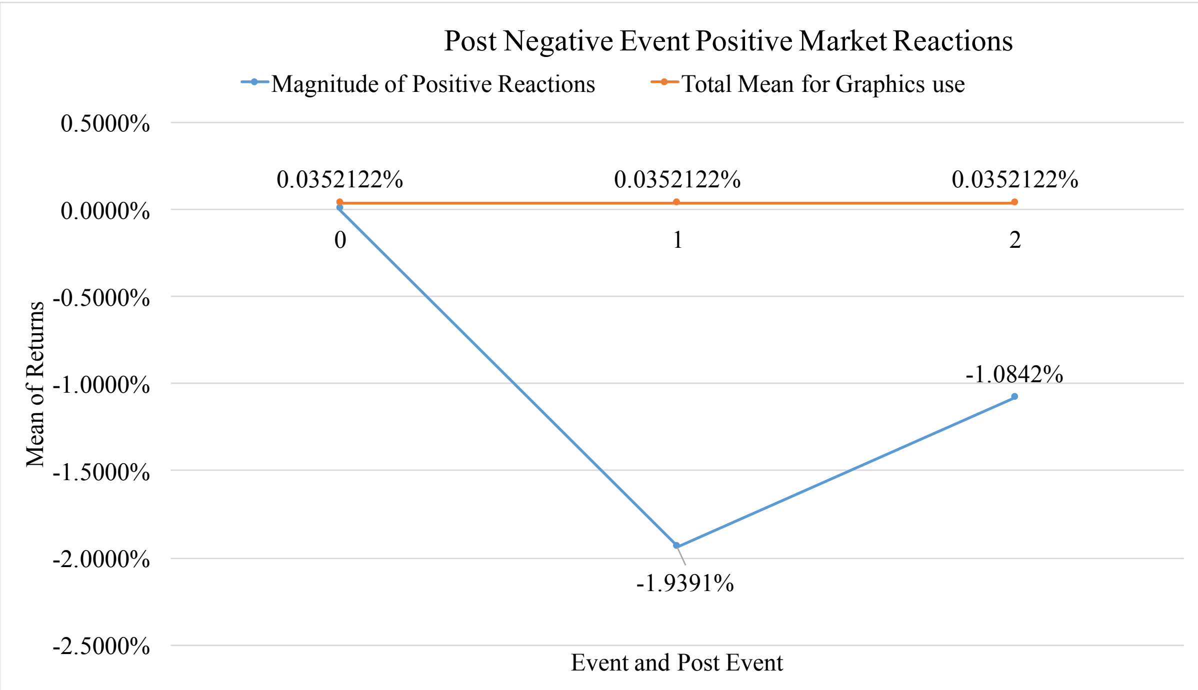


Figure 1 and Table 26 display the observed positive post Event market reaction for the negative price shocks, in which the mean reversion to the mean pattern can be assessed.

Table 27

Magnitude of Negative Reactions		
	0	0.0000%
Event	1	-1.9391%
Post Event	2	-2.9195%

Figure 2

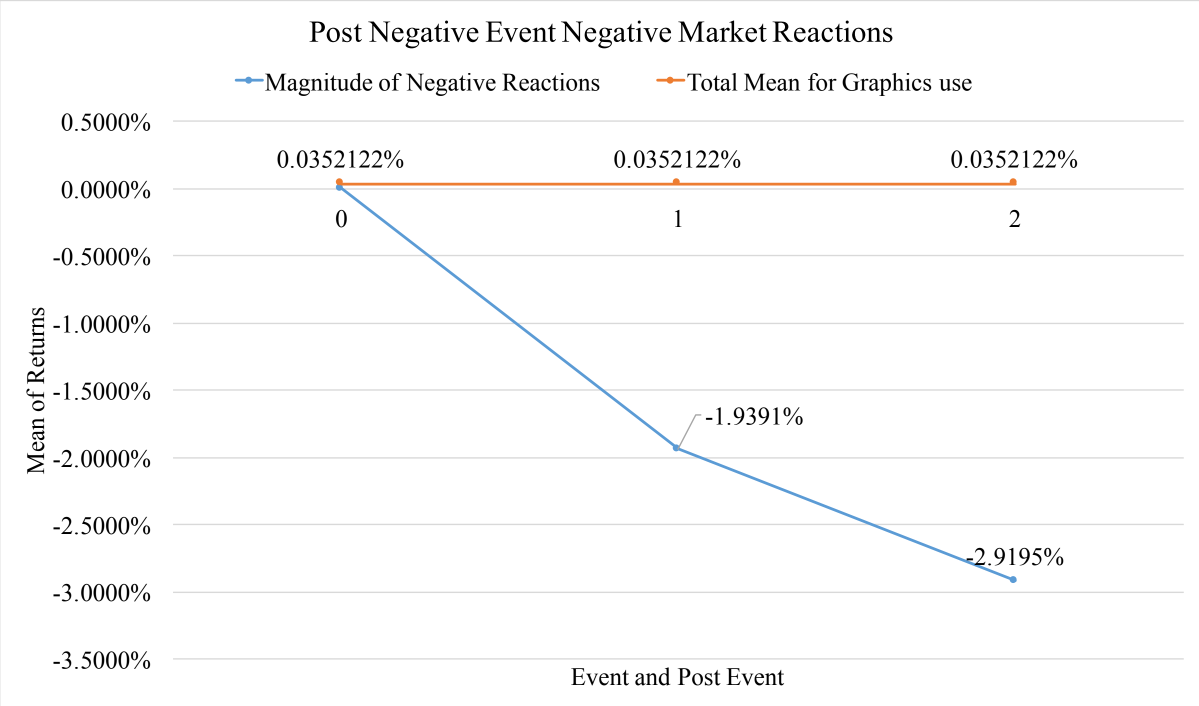


Figure 2 and table 27 provide information of the positive post Event market reaction in the case for negative price shocks, in which the price drift in the same direction of the price shock can be seen.

4.3.1.2. Positive Events

Table 28

Positive Event

t=	Post One Day RR Means	Event	N	Chance of Ocurrence % of Ocurrence
0	0.01915507	Positive Event	201	1
1	0.010357579	Post Event Positive Reactions	111	0.552238806
1	-0.007964022	Post Event Negative Reactions	90	0.447761194

Table 28 provides the data for the Positive Event's analysis post event reaction. As can be seen the means of the returns from the days of the events are provided. As well as, the two means of the events' following days' returns (Post Event Positive and Negative Reactions). In the same table comes also de percentage in which the post event reactions are distributed.

Table 29

Magnitude of Positive Reactions		
	0	0.0000%
Event	1	1.9155%
Post Event	2	2.9513%

Figure 3

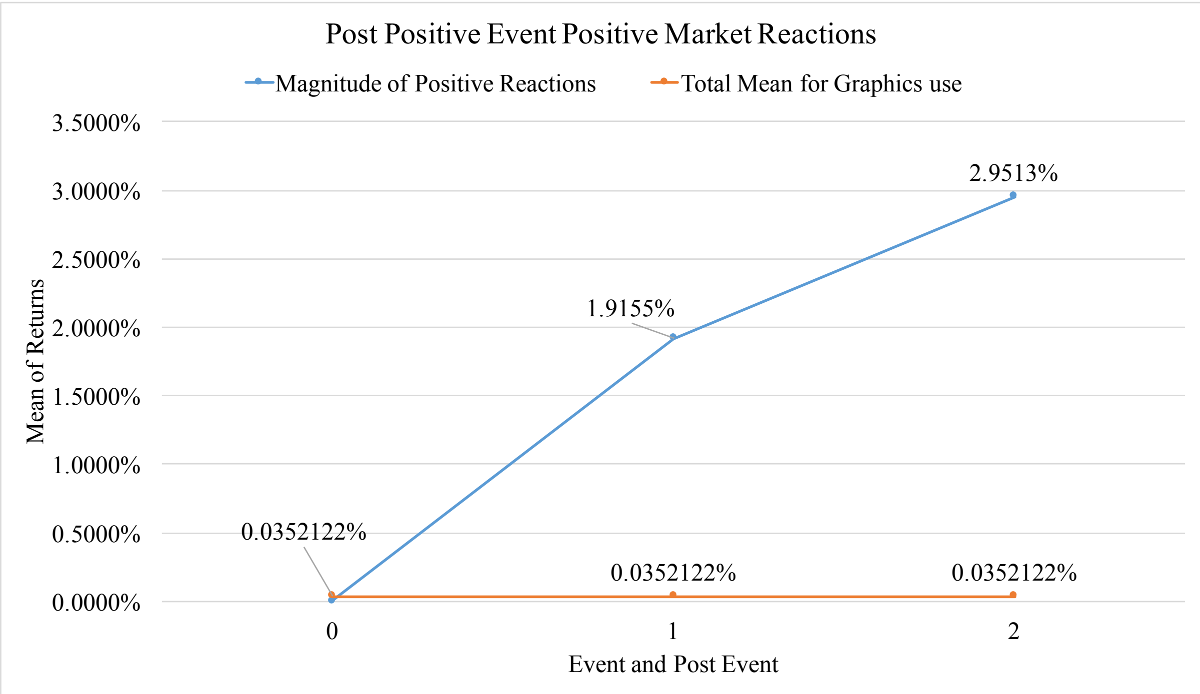
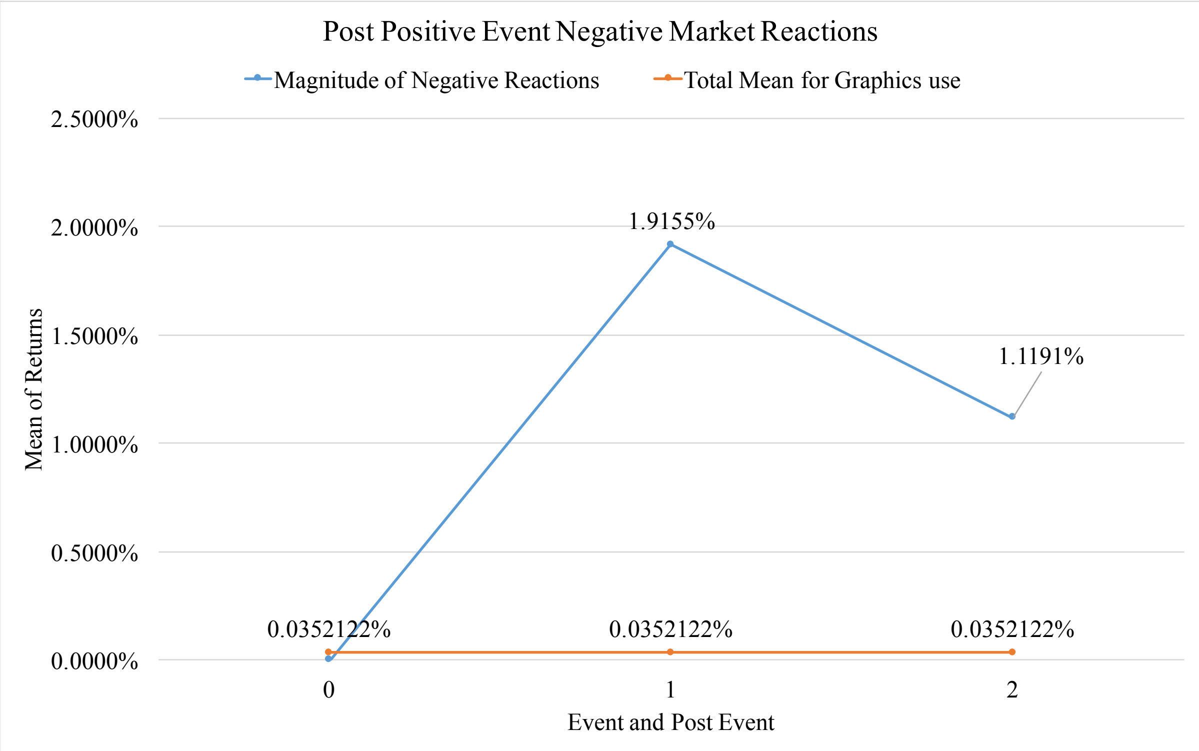


Figure 3 and table 29 shown above give the results of the positive post event market reaction in the case of positive price shocks. As can be seen in figure 3, there is a price drift in the same direction of the price shock.

Table 30

Magnitude of Negative Reactions		
	0	0.0000%
Event	1	1.9155%
Post Event	2	1.1191%

Figure 4



As provided above in figure 4 and table 30, it can be said that there is a mean reversion to the mean pattern for the negative post event market reactions in the case of the positive price shocks.

5. Results Analysis

In this section, the analysis and comments on the already given results in the previous chapter will be provided. This analysis is in order to gauge the market reactions post price shocks from the three different studies done in the thesis.

5.1.1. Single Mean Hypothesis Testing, Z test: One Sample Mean

As it is already mentioned above, results from the Z test do no vary between the post event one day and the post event two days. As well as results do not vary between Grouping 1 and Grouping 2, either from one day and two days' analysis. In both cases the means from the negative events and negative no events are not indistinguishable from cero. In like manner, the results are the same for the two given alphas, 0.05 and 0.1 used in this analysis.

Taking into consideration the given results, this statistical test would suggest that there is no supporting evidence of significant market reactions following either negative events nor negative no events. Hence, this statistical test suggests that there is a very poor market reaction following a negative price shock

On the other side, for both cases, one and two days' analysis for the positive events and the positive no events the results show that the means are indistinguishable from cero; more over, the means are statistically higher than cero in all cases. This result would suggest there is a positive market reaction following positive events. However, this is not enough evidence for suggesting either under reaction nor momentum following a positive price shock.

5.1.2. Two Sample Mean Hypothesis Testing, Z test: Two Sample Means

First, for the analysis of the negative events, the results demonstrate that the difference between the mean of the Negative One Day and the Negative No Event One Day is not indistinguishable from 0. As well as, in the case for the Negative CRR 2 Days in comparison with the Negative No Event CRR 2 Days, the result is the same: the difference in means is not indistinguishable from 0. In the same fashion, the results from the Z test for a given alpha of 10% do not vary from those with an alpha of 5%.

Therefore, with attention to the already seen results from this statistical test, in the case of the Negative Events, there is no significant evidence suggesting either overreaction nor under reaction following a negative price shock in the Mexican Capital Market for the given period of time used in this analysis. On the contrary, when assessing just the mean on its own, the evidence suggests a poor market reaction following a negative price shock. Finally, this statistical test would suggest there is no difference in terms of the magnitude of market reactions following either a negative price shock nor a negative no event price shock.

On the other side, in the case for the Positive Events' Z test analysis for a given alpha of 5%, the results above demonstrate that the difference between the mean of the Positive One Day and the Positive No Event One Day is not indistinguishable from 0. As well as, the results are the same for the Positive CRR 2 Days in comparison with the Positive No Event CRR 2 Days.

Different from the Negative Events analysis, in the statistical test with a given alpha of 10%, the results differ from those with an alpha of 5%. Taking into account an alpha of 10%, the means in both cases, the Positive One Day and the Positive CRR 2 Days are statistically larger than the means from the Positive No Event.

Given the obtained results, it can be said that in the case for the Positive Events, there is no significant evidence supporting stronger positive market reactions following a positive price shock than when there is a positive no event price shock for a given alpha of 5%. However, when taking the statistical with an alpha of 10%, the statistical tests confirm that the means for the Positive Event's case are larger than from those of the Positive No Events. This would suggest that the market reactions are stronger in the same directions of the event following a positive price shock than when there is no significant positive price shock. Hence, from a statistical point of view, the null hypothesis can be rejected in the case of positive events, and thereafter consider the suggested behavioral finance causes from the hypothesis testing table already displayed earlier. Nonetheless, when taking into consideration just the mean on its own, the evidence suggests a poor reaction following a positive price shock. Since the positive price shock range is at least equals or above 1.2%, and the mean of the following days of the price shocks is very low (0.21%). This would indicate a poor reaction, which implies that there is not enough evidence in terms of magnitude when comparing the mean against the Positive Event Range of 1.2%. Finally, the behavioral finance suggested causes on the hypothesis testing can not be accepted taking into consideration the already mentioned in terms of magnitude. Thus, it can be said there is just a mild positive market reaction following a positive price shock.

Note: In the case of Grouping 2, the results are the same for the given statistical Z tests as in Grouping 1. Thus, there is no need of providing result analysis again for Grouping 2 since the analysis would be the same as in for Grouping 1.

5.1.3. Magnitude of the Positive and Negative Market Reactions Post Event

In the case of this third analysis, with the purpose of assessing the market reactions post Negative and Positive Events for a different Grouping of data (Grouping 3), the results completely differ from the two statistical tests already mentioned above in terms of providing supporting evidence for Over and Under reaction in the Mexican capital market.

When analysing the Negative Events, its been found that the post event market reactions can not be attributed to only one type of reaction (over or under reaction) since the reactions following a negative price shock can be either positive or negative, depending on each case. For the given period of analysis, its been found that about a bit more than half of the times the market reaction following a negative price shock is positive; likewise, the other half of the times the market reaction is negative. To put it into numbers, 51.2% of the times the reaction is positive, while 48.8% of the times the reaction is negative.

In the case for the positive reactions, when analysing the magnitude of the mean of the negative events itself (-1.94%) in comparison to the mean of the positive reactions (0.86%), the positive reaction is found to be very significant, it represents about half of the mean from the negative events in terms of magnitude. This result would suggest prove of overreaction for negative events as following a negative price shock there is a reversal to the mean pattern for the given cases of positive market reactions.

On the other hand, in the case for the negative reactions its been found that those are stronger than the positive reactions following a negative price shock when anchoring the comparison to the mean of the negative event (-1.94%). The mean of the negative reactions (-0.98%) is more than half of the mean of the negative events. Since prices would continue to fall following a negative price shock, this would suggest evidence of momentum and under reaction following a negative price shock for the given cases of negative market reactions.

Note: For graphic reference of the mentioned in the two paragraphs above see **4.3.1.1.**

At the same time, when analysing the Positive Events, its been found that the post event market reactions can not be attributed to only one type of reaction (over or under reaction) since the reactions following a negative price shock can be either positive or negative, depending on each case. For the given period of analysis, its been found that slightly more than half of the times the market reaction following a positive price shock is positive; likewise, slightly less than half of the times the market reaction is negative. To put it into numbers, 55.2% of the times the reaction is positive, while 44.8% of the times the reaction is negative.

When analysing the positive reactions, the magnitude of the mean of the positive events itself (1.92%) in comparison to the mean of the positive reactions (1.04%), the positive reaction is found to be very significant, it represents more than half of the mean of the positive events in terms of magnitude. This result would suggest prove of momentum and under reaction following a positive price shock since there is a positive price drift towards the same direction of the event for the given cases of positive market reactions.

On the other hand, in the case for the negative reactions, its been found that those are weaker than the positive reactions following a positive price shock when anchoring the comparison to the mean of the positive event (1.92%). The mean of the negative reactions (-0.80%) is less than half of the mean of the positive events. Since prices would drop following a positive price shock, this would suggest evidence of overreaction for positive events as following a positive price shock there is a reversal to the mean pattern for the given cases of negative market reactions.

Note: For graphic reference of the mentioned in the two paragraphs above see **4.3.1.2.**

"Investors should remember that excitement and expenses are their enemies. And if they insist on trying to time their participation in equities, they should try to be fearful when others are greedy and greedy when others are fearful."

"Cash combined with courage in a time of crisis is priceless."

Warren Buffett

6. Conclusions

"The fact that people will be full of greed, fear or folly is predictable. The sequence is not predictable."

Warren Buffett

After the deep research, analysis, and long learning process on which this thesis is based, there is a need to retrieve what is been said in the beginning: In the field of investments, the implications of behavioural finance are substantial, analysing investor behaviour is an essential key in order to understand the sometimes rare and unexplainable fluctuations of financial markets. Hence, understanding behavioural finance can provide significant advantages for investors to the end of taking better investment decisions. Optimal decision making for investing in the stock market requires a deep understanding of investors rationality and more important irrationality in a global perspective. Behavioral Finance is an integral part of the decision-making process because it heavily influences the investors' performance.

Generally speaking, it can be said that markets are not fully efficient, moreover, several studies have fail to the same conclusion, market participants are not fully rational. The idea of having market participants whom account for the characteristics of full rationality are rarely seen. Certainly, new information is not instantaneously and fully incorporated into stock prices in an unbiased fashion. Thus, prices are likely not to be fair in al cases.

The most compelling evidence suggests that market participants are not fully rational. Actually, there have been considerable studies which advocate stock crashes and booms to human errors, proposing those errors are influenced by behavioral finance bias. After the research gone through, it can be said that market participants have a strong tendency to fail into the psychological bias already explained in this thesis, studies suggest there is a Systematic error in judgment and decision-making common to all human beings which can be due to cognitive limitations, motivational factors, and/or adaptations to natural environments. The mention cognitive bias have their roots in Prospect Theory and Heuristics theory. The conducted studies on these two theories support the following human cognitive bias: Anchoring, Loss Aversion, Frame Dependence, Mental Accounting, Misperceiving Randomness, Herding, and Overconfidence.

Studies propose the mentioned behavioral theories and bias to be the causes of overreaction and under reaction in capital markets. In the same manner, the roots of contrarian investing and momentum investing. As a result of this, prices may well not represent their fair value at times due to these market reactions in the capital market. As well as, its been found that in some cases there is momentum in the short run but mean reversion in the long term. Stock prices tend to first drift (sign of under reaction), but thereafter prices correct (sign of overreaction).

In the case of overreaction and contrarian investing there are tons of research providing evidence proposing that often times winner stocks are over bought (Above fair value) and loser stocks are oversold (under fair value), hence profits occur as winner stocks retreat to their fair value and loser stocks rally to their fair value. As well as, empirical studies have also found examples of under reaction. Causing momentum in prices as stock prices keep on drifting in the same direction as the information is slowly incorporated into prices. From this view, prior winners outperform and prior losers underperform. The evidence proposes that under reaction and price drifts are usually related to important public announcements. Therefore, positive news lead to subsequent positive abnormal returns, and negative news lead to subsequent negative abnormal returns.

Although the mentioned above may be true, one possibility to explain these market anomalies are the deviations to be expected under the Efficient Market Hypothesis. However, this thesis aimed to provide information suggesting that these market anomalies are not caused by those deviations under market efficiency. A central theme on this work was to prove that prices sometimes overreact or underreact to some signal. Thus, the main questioning is *What is the role of Behavioral Finance in the capital market, and what are its implications for price shocks?*

First, when taking into consideration the evidence on Prospect theory, it could be said that if investors behave as explained in prospect theory, they would react differently to positive and negative price shocks. This theory suggests that following significant gains, such as a strong positive price shocks, investors would become more risk averse, thereafter, they would sell in order to obtain profits. On the contrary, this theory implies that investors tend to become more risk seeking following losses. Thus, instead of selling after a negative price shock, investors would hold the stock or even buy more with the purpose of gambling back their losses.

Second, when studying overreaction and contrarian investing, it would imply the initial price shock to be too strong mainly caused by emotions on the day of a price shock. As a result, prices would drift towards unfair value on the event day, hence, prices should fall following positive events and raise after negative events in order to return to fair value.

Third, when taking into consideration the evidence in reference to under reaction and momentum, it would imply a price drift following a price shock in the same direction of the price shock. The magnitude and length of the period of time for the price drift would be mainly attributed to the magnitude of the new information's impact which causes the original price shock. At the same time, this would cause momentum following price shocks.

Finally, a complete explanation of markets' post reaction to price shocks would be causal attribution. This explains the market reaction in relationship to whether the investors attribute the price shock to a stable or non- stable cause. If investors attribute the cause of the event is stable, they would believe the past results will repeat. As a consequence, positive events would lead investors to expect more gains and increase optimism, while on the other side, negative events would lead investors to expect more losses and increase pessimism. On the other hand, when investors believe the cause of the event is non-stable, it would imply positive market reactions following negative events, and negative reactions following positive events.

Thereafter, this thesis displays three different analyses in order to suggest proof the main hypothesis of this thesis: Markets tend to overreact to bad news, and underreact to good news. The three analyses provided were done on the Mexican Capital Market main index (IPC) with a time frame from 2009 to 2018. First, a single mean hypothesis testing, with the purpose to asses whether the post event reaction was positive or negative. Second, two sample mean hypothesis testing, which had the target of gauging whether there was supporting evidence on Overreaction for Negative Events and Under reaction for positive events when comparing the means of the Events in contrast to the No Events. Finally, a third analysis based on the means of the price shocks and the post one-day reaction in order to assess the magnitude of the positive and negative market reactions post event. The function of this last analysis was to asses the market reactions post event, focusing merely on post price shocks reactions, both positive and negative, thereafter, the post event market reactions can be judged in terms of their relationship to behavioral finance theories.

First, the single mean hypothesis testing suggests that following a negative price shock the statistical evidence suggests a poor market reaction, thus, this evidence would propose that the market incorporates the bad news on the same day of the event. On the other hand, in the case for the positive price shocks, the evidence advocates a mild positive market reaction following positive events, which is not enough evidence to propose signs of either under reaction nor momentum following positive price shocks.

Similarly, the two sample mean hypothesis testing failed to the same conclusions in the analysis of the negative events, there is no significant evidence on either overreaction nor under reaction in the case of negative price shocks. The evidence suggests a poor market reaction following a negative price shock. Finally, this test would again suggest that there is no difference in terms of the magnitude of market reactions following either a negative price shock nor a negative no event price shock.

On the side, in the case of positive events, in the statistical test with a given alpha of 10%, the market reactions are stronger in the same directions of the event following a positive price shock than when there is no significant positive price shock. Thereafter, from a statistical point of view, the null hypothesis applied to this test could be rejected in the case of the positive events. Hence, the suggested behavioral finance causes from the hypothesis testing table already displayed earlier on this thesis could be accepted. Nonetheless, when taking into consideration just the mean on its own, the evidence suggests a poor reaction following a positive price shock. Finally, this test does not provide enough evidence on under reaction following a positive price shock, and it can be said there is just a mild positive market reaction following a positive price shock.

Although it may be true that sometimes there are just mild market reactions following strong price shocks, this thesis aims to prove the contrary. The assumption that markets react poorly following strong price shocks truly contradicts all the provided evidence in the literature review.

In contrast to the mentioned tests, the results from the third analysis completely differs in terms of providing supporting evidence for Over and Under reaction. When analysing the market reactions, it was found that in both cases, the Negative Events and Positive Events, the event market reactions can not be attributed to only one type of reaction (over or under reaction) since the reactions following a significant price shock can be either positive or negative. It was found that about slightly more than half of the times the market reactions following a price shock are positive; likewise, the other half of the times the market reactions are negative.

When analysing the negative price shocks from the days of the events, the two market post event reactions, both positive and negative account to be very significant. The positive reactions mean represents about half of the mean from the negative events. This result would suggest proof of overreaction for negative events following a negative price shock since there is a reversal to the mean pattern for the given cases of positive market reactions. On the other hand, in the case for the negative reactions its been found that those are stronger than the positive reactions following a negative price shock when anchoring the comparison to the mean of the negative event. The mean of the negative reactions is more than half of the mean of the negative events. Since prices would continue to fall following a negative price shock, this would also suggest evidence of momentum and under reaction following a negative price shock for the given cases of negative market reactions.

On the side, for the positive price shocks, the two market post event reactions, both positive and negative post event account to be very significant. The positive reactions account for a mean of more than half of the mean of the positive events. This result would suggest proof of under reaction and momentum following a positive price shock since there is a positive price drift towards the same direction of the event for the given cases of positive market reactions. On the other hand, in the case for the negative reactions, its been found that those are weaker than the positive reactions following a positive price shock when anchoring the comparison to the mean of the positive event. The mean of the negative reactions is less than half of the mean of the positive events. Since prices would drop following a positive price shock, this would suggest evidence of overreaction for positive events since following a positive price shock there is a reversal to the mean pattern for the given cases of negative market reactions.

Finally, in the light of this last analysis, the evidence suggests proof of both under and overreaction in the Mexican stock capital market. On the whole, the market tends to both overreact and underreact to price shocks, in both cases, positive and negative price shocks. In essence, when there is a negative price shock, the market tends to overreact a bit more than half of the times, while the rest of the times underreacts. In the same order, it suggests contrarian investing and momentum. While on the other side, when there is a positive price shock, the market underreacts slightly more than half of the times while the rest of the times overreacts. Likewise, in the same manner it suggests momentum slightly more than half of the times while the rest of the times it can suggest contrarian investing.

Finally, all in all, to put a very simple explanation of the market possible reaction to price shocks comes the following process interpretation. When there is new substantial information, the market may either underreact or overreact to this new information causing a price shock. The price shock may be either negative or positive, depending on the new information. Greed comes into play when good new information arrives while panic and fear do so when bad news arrive. This price shock will lead to substantial post event reactions which can be either positive or negative. In the case of negative price shocks, if the market underreacted the post event reaction will be negative; on the contrary, if the market overreacted, the post event reaction will be positive. On the other side, in the case of a positive price shock, if the market underreacted the post event reaction will be positive; on the other hand, if the marked overreacted, the post event reaction will be negative.

Finally, there are various different approaches to analyse the capital market from a behavioral finance perspective in contrast to the efficient market hypothesis. After deep research and learning process gone through this thesis, a few different possible topics for further research emerged. Among the ideas for further research, it would be very interesting to build up portfolios from the Mexican capital market based on momentum and/or contrarian investment strategies with the purpose of evaluating its performance against the market. As well as, do the same analyses from this thesis but in single securities and in different groups of securities.

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